Automatic Generation of Personalized Recommendations in eCoaching

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UiA University of Agder

Doctoral Dissertations at the University of Agder 421

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Automatic Generation of Personalized Recommendations in eCoaching

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Dedicated to my parents
Amit Chatterjee and Kalpana Chatterjee

my loving wife
Nibedita Pahari

my affectionate son
Aranno Chatterjee (Tintin, Megh, Mana)

my caring
Teachers, Professors, Supervisors, Research Collaborators, and Friends

and my late grandparents
Madhab Chandra Chatterjee and Jayaboti Chatterjee
Sambhu Nath Biswas and Shanti Biswas

"The ***highest education*** *is that which does not merely give us information but* ***makes our life in harmony*** *with all existence".*
– Rabindranath Tagore (Nobel Laureate)

Preface

This thesis is submitted to the University of Agder (UiA) for partial fulfillment of the requirements for the degree of philosophiae doctor.

This dissertation is a result of the research work carried out at the Department of Information and Communication Technology (ICT), University of Agder (UiA), Grimstad, Norway, from February 2019 to September 2022. During my PhD study, my supervisors have been Professor Andreas Prinz (University of Agder), Associate Professor Martin W. Gerdes (University of Agder), and Associate Professor Santiago G. Martinez (University of Agder).

During my PhD study, I was a visiting scholar at Simula Research Laboratory (Oslo), Norwegian University of Science and Technology (Gjøvik), and University of Tromsø (Tromsø) from October 2021 to December 2021. The research visits were hosted by Chief Research Scientist (Research Professor) Michael A. Riegler (SimulaMet), Professor Raghavendra Ramachandra (NTNU), and Professor Gunnar Hartvigsen (UiT), respectively. Furthermore, in 2019, I attended the Not-Equal summer school on Rewriting Our Digital Society For Social Justice at Swansea University, United Kingdom.

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Ayan Chatterjee
Grimstad, Norway
December 2022

Abstract

The emerging role of Information and Communication Technology has significantly impacted several industrial areas, and the healthcare industry is no exception. Research in electronic health can provide methods to strengthen personal healthcare with Information and Communication Technologies. The concept of automatic coaching (eCoaching) is a very promising initiative of eHealth research for real-time personalized lifestyle support. An eCoach system may generate automatic and personalized lifestyle recommendations based on the insight from individual time-variant (e.g., sensor observation) and time-invariant (e.g., personal and preference data) health and wellness data to reach their lifestyle goals. Personalized recommendations in eCoaching can be specific to many health domains − mental health, physical training, and general lifestyle, to name a few examples. However, the generation of such personalized recommendations comes with common technological requirements. This study focuses more on the contributions towards the recommendation generation technology, the evaluation of the contributions to the recommendation generation technology, and their outcomes, rather than the evaluation of the content and quality of specific recommendations.

The generation of personal or group-level recommendations for a healthy lifestyle has been a promising concept and is a decision-making approach in complex information environments. The recommendation techniques can be classified as rule-based and data-driven. Over time, recommendation technology has become an efficient and scalable option for intensive human behavior analysis. Automatic generation of behavioral recommendations is a research challenge in eCoaching, where the recommendations can be either personalized or community-driven. According to the literature search, its application domain in health eCoaching can comprise nutrition coaching, activity coaching, mental health coaching, coaching for daily living activities for the elderly, diabetic coaching, and cardiac rehabilitation. However, most of such concepts are in the conceptual stage. Besides, several mobile health applications and wearable devices for health monitoring and recommendation generation are available. However, they are too generic, and problems exist in standardization, method selection, data governance, data annotation, data integration, continuous processing of data, and a proper presentation of the insights from the data back to the users to make them understand what is going on and what recommendations to follow.

This study looks at theoretical foundations and practical implementations following the *Design Science Research Method,* which is well-established in the fields of information systems and software engineering research. We primarily focused on the hypothesis that an eCoach system can generate adaptive and personalized recommendations, and to prove

this hypothesis we considered physical activity as a study case. The selection of the case study narrowed down the scope to identify the key concepts and themes associated with eCoaching in general. The research outcome is the verification of the hypothesis and the answers to the research questions. Therefore, we focused on the proposal and experimental evaluation of an algorithm for the automatic generation of personalized recommendations in eCoaching, the design, and development of an eCoach system based on user needs, integration of the algorithm in the eCoach system, and the technical evaluation of the designed and developed eCoach prototype. For the collection of user requirements, we used the iterative *User-Centered Design* approach and turned the user inputs into design requirements with the *Volere Requirement Templates*.

This research focuses on collecting personal and person-generated health data, data governance, semantic annotation, data integration, processing of data to generate automatic activity recommendations to manage personalized activity goals and visualization of actionable recommendations. The technical validation is performed in controlled laboratory settings to test the accuracy, precision, and reliability of the technology under different conditions and compare its performance to a reference standard. We have not focused on the evaluation of clinical impacts or outcomes of the designed and developed eCoach prototype. Such preliminary and case-based scientific mixed method research (theoretical and experimental) helps to understand and check the relevant technological feasibility of the “automatic and personalized recommendation generation” concept in eCoaching. The obtained results can be further extended to a broader perspective in other study cases.

Sammendrag

Denne avhandlingen omhandler eCoaching for personlig livsstilsstøtte i sanntid ved bruk av informasjons- og kommunikasjonsteknologi. Utfordringen er å designe, utvikle og teknisk evaluere en prototyp av en intelligent eCoach som automatisk genererer personlige og evidensbaserte anbefalinger til en bedre livsstil. Den utviklede løsningen er fokusert på forbedring av fysisk aktivitet. Prototypen bruker bærbare medisinske aktivitetssensorer. De innsamlede data blir semantisk representert og kunstig intelligente algoritmer genererer automatisk meningsfulle, personlige og kontekstbaserte anbefalinger for mindre stillesittende tid. Oppgaven bruker den veletablerte designvitenskapelige forskningsmetodikken for å utvikle teoretiske grunnlag og praktiske implementeringer. Samlet sett fokuserer denne forskningen på teknologisk verifisering snarere enn klinisk evaluering.

List of Publications

The author of this dissertation is the first author and the principal contributor of all the included papers listed below. Papers A-F in the first set of the following list are selected to present the state-of-the-art and main research achievements and are presented in Part II of this dissertation. Other papers which are listed in the second set are other contributions towards Interoperability, Applied Security, and Artificial Intelligence in eHealth Research.

Papers Included in the Dissertation

Paper A A. Chatterjee, M. Gerdes, A. Prinz, and S. Martinez. Digital Interventions on Healthy Lifestyle Management: Systematic Review. *Journal of Medical Internet Research*, vol. 23, no. 11 (2021): e26931.

Paper B A. Chatterjee, M. Gerdes, A. Prinz, and S. Martinez. Human coaching methodologies for automatic electronic coaching (eCoaching) as behavioral interventions with information and communication technology: systematic review. *Journal of Medical Internet Research*, vol. 23, no. 3 (2021): e23533.

Paper C A. Chatterjee, A. Prinz, M. Gerdes, and S. Martinez. An automatic ontology-based approach to support logical representation of observable and measurable data for healthy lifestyle management: Proof-of-concept study. *Journal of Medical Internet Research*, vol. 23, no. 4 (2021): e24656.

Paper D A. Chatterjee, and A. Prinz. Personalized Recommendations for Physical Activity e-Coaching (OntoRecoModel): Ontological Modeling. *JMIR Medical Informatics*, vol. 10, no. 6 (2022): e33847.

Paper E A. Chatterjee, A. Prinz, M. Riegler, and Y.K. Meena. An automatic and personalized recommendation modelling in activity eCoaching with deep learning and ontology. *Scientific Reports, Nature*, vol. 13, (2023): 10182.

Paper F A. Chatterjee, A. Prinz, M. Gerdes, S. Martinez, N. Pahari, and Y.K. Meena. ProHealth eCoach: user-centered design and development of an eCoach app to promote healthy lifestyle with personalized activity recommendations. *BMC Health Services Research*, vol. 22, no. 1120 (2022).

Other Publications

Paper G A. Chatterjee, M. Gerdes, and S. Martinez. eHealth initiatives for the promotion of healthy lifestyle and allied implementation difficulties. *In 2019 IEEE International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*, pp. 1-8 (2019).

Paper H A. Chatterjee, M. Gerdes, A. Prinz, S. Martinez, and A.C. Medin. Reference Design Model for a Smart e-Coach Recommendation System for Lifestyle Support based on ICT Technologies. *In Proceedings of The Twelfth International Conference on eHealth, Telemedicine, and Social Medicine (eTELEMED)*, pp. 52-58 (2020).

Paper I A. Chatterjee, M. Gerdes, and S. Martinez. Development of a Smart e-Coach Recommendation System for Obesity. *Digital Personalized Health and Medicine. IOS Press (Medical Informatics Europe Conference (MIE) – EFMI)*, pp. 1259-1260 (2020).

Paper J A. Chatterjee, M. Gerdes, and S. Martinez. Identification of risk factors associated with obesity and overweight—a machine learning overview. *Sensors*, vol. 20, no. 9 (2020): 2734.

Paper K A. Chatterjee, A. Prinz, and M. Riegler. Prediction Modeling in Activity eCoaching for Tailored Recommendation Generation: A Conceptualization. *2022 IEEE International Symposium on Medical Measurements and Applications (MeMeA)*, pp. 1-6 (2022).

Paper L A. Chatterjee, N. Pahari, and A. Prinz. HL7 FHIR with SNOMED-CT to Achieve Semantic and Structural Interoperability in Personal Health Data: A Proof-of-Concept Study. *Sensors*, vol. 22, no. 10 (2022): 3756.

Paper M A. Chatterjee, M. Gerdes, P. Khatiwada, and A. Prinz. SFTSDH: Applying Spring Security Framework With TSD-Based OAuth2 to Protect Microservice Architecture APIs. *IEEE Access*, vol. 10 (2022): 41914-34.

Paper N A. Chatterjee, and A. Prinz. Applying Spring Security Framework with KeyCloak-Based OAuth2 to Protect Microservice Architecture APIs: A Case Study. *Sensors*, vol. 22, no. 5 (2022): 1703.

Paper O A. Chatterjee, N. Pahari, M. Riegler, and A. Prinz. LSTM Step Prediction and Ontology-Based Recommendation Generation in Activity eCoaching. *In 2022 IEEE International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*, pp. 13-18 (2022).

Paper P A. Chatterjee, N. Pahari, M. Gerdes, and R. Bajpai. Analyze the Effect of Healthy Behavior on Weight Change and Its Conceptual Use in Digital Behavioral Intervention. *In 2022 IEEE International Conference on E-health Networking, Application & Services (HealthCom)*, pp. 222-228 (2022).

Paper Q A. Chatterjee, N. Pahari, A. Prinz, and M.Riegler. Machine learning and ontology in eCoaching for personalized activity level monitoring and recommendation generation. *Scientific Reports (Nature)*, vol. 12 (2022): 19825.

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PART I

Chapter 1

Introduction

Coaching is a form of development in which a coach acts as a trusted role model or adviser to facilitate experimental learning that results in future-oriented abilities. Coaches can shape new visions and plans to achieve desired results [5]. Among other fields, coaching has been implemented in management, leadership, entrepreneurship, and health care. It helps participants to cultivate themselves and become more successful in achieving their set goals. Effective coaching may lead to excellent performance, self-motivation, and self-correction. Coaching processes can be generally distinguished into two categories - traditional human coaching (coaching made by humans) and coaching via an electronic medium (eCoaching). The process associated with coaching by humans can be achieved either face-to-face or remotely (via telematic means). Traditional human coaching is a dialogue-based, goal-oriented, and pragmatic learning practice. Therefore, an electronic medium can play an important role in remote coaching. The human coaching process can further be enhanced through electronic modes, such as video, audio, email, chatbot, and text, with the support of information and communication technologies (ICTs), which is referred to as eCoaching. In the last decade, personal coaching for behavioral intervention has been increasingly used to promote a healthy lifestyle. eCoaching is a promising eHealth research direction for continuously customized ways of lifestyle support. A health eCoach system is a complex system with a set of partially connected computerized components that interact across a diversity of interaction loops (e.g., preferences, recommendations, feedback). It is based on an artificial unit that can perceive, reason about, learn and predict individual behavior in context and over time. It proactively engages in a conversation with the individual to support planning and promote effective goal management using, for instance, persuasive techniques. eCoaching technologies represent an evolving trend in the domain of human behavioral intervention.

1.1 Background

Research in eHealth has come up with a new dimension to improve personal healthcare with ICTs. eHealth is an evolving field in public health, medical informatics, and medical business, referring to health services and information delivery or enhancement with the internet and related technologies [6]. WHO defines[1] eHealth as the cost-effective and secure use of information and communication technologies to support health and health-related sectors, including health services, health surveillance, health documentation, and health education, knowledge, and research. The triple aim of eHealth is to improve the quality and efficacy of healthcare and the patient experience of care [6]. eHealth monitoring has become increasingly popular, providing ICT-based remote, timely care support to patients and healthcare providers with reduced cost and convenient maintenance. The practical implementation of different eHealth innovations has often been challenging to establish prophesied benefits [6]. The concept of health eCoaching is a promising initiative of eHealth research for real-time personalized lifestyle support [6]. Health monitoring and fitness coaching with artificial intelligence have a great future in the coming decades.

Health monitoring and automatically personalized lifestyle coaching (eCoaching) considering ethical and clinical guidelines, individual health status, health condition, context, and preferences may successfully help participants to follow lifestyle recommendations to maintain a healthy lifestyle [6, 5]. Studies in eCoaching can offer methods to enhance individual healthcare with ICTs [5]. The leading methods of eCoaching processes are monitoring, decision-making, goal setting, persuasion, awareness provision (intervention), goal evaluation, and learning for future actions [5]. The pillars of eCoaching initiatives are data collection, logical representation of data, analysis of data, personalized recommendation generation (sending the right message to the right people in the proper context and time), and data governance [6, 5]. eCoaching processes may ideally influence health outcomes, for which aspects, such as usability, efficacy, and adherence, may play important roles to influence health and/or health behavior. "Efficacy" means the effects of behavioral intervention following any coaching process (of any method, not only of eCoaching). "Usability" means effectiveness, efficiency, and satisfaction when using technology. "Adherence" means the degree to which the technology is used as intended or how much the recommendations are followed [5].

eCoaching is rewarding for participants to change negative behavior using a goal-based approach and to observe the increase in their health and strength. Therefore, different research groups have conducted projects on health eCoaching to generate a recommendation plan for a healthy lifestyle. The idea is to give remote care to the participants with a suggestion for healthy lifestyle management. Behavior and health are strongly associated. Having proper eCoaching recommendation plans may help people accomplish health goals and maintain healthy behavior. Recommendations can be defined as a suggestion or proposals as to the best course of action in complex information environments, and their generation techniques can be classified as data-driven and rule-based [6, 5, 7, 8, 9, 10]. Each of the techniques has its own merits and demerits. Therefore, a hybrid approach can be adequate to overcome the shortcomings of both data-driven and rule-based recommendation generations.

Recommendation design and its effective representation to increase healthy lifestyle and reduce negative behavior vary significantly in context, content, and usefulness [11]. Different mobile applications are available online for self-monitoring of behavioral pat-

[1]http://www.emro.who.int/health-topics/ehealth/

terns; however, they require proper standardization and methodologies for personalization, data governance, decision-making, and feedback presentation [9, 12, 13]. Moreover, only a few mobile applications for behavioral monitoring have been evaluated, and the evidence is of poor quality of the evaluation [9]. By supporting the improvement of personalized lifestyle with wearable activity sensors, digital trackers, automation, security and privacy, interoperability, machine learning and deep learning algorithms, statistical metrics, semantic rules, and design flexibility, the recommendation generation in eCoaching can be promising and motivating to the participants.

1.2 Problem Description

This section describes the research gap which helps to frame the research problem, scope and limitations, and research questions to address the identified research problem. Considering the broader aspect of eCoaching, defining the scope and limitations for this research project is critical to ensure that this research is focused, manageable, ethical, and valid.

1.2.1 Identification of Research Problem

The concept of intuitive coaching (eCoaching) is inspired by the traditional offline human coaching processes. A detailed and comprehensive systematic literature review of human coaching methodologies for eCoaching as behavioral interventions with ICTs has been performed in [5]. It entails different coaching methods to understand the necessary coaching processes for healthy lifestyle management using ICTs. The most appropriate eCoaching methods are personalization, interaction and co-creation, technology adaption for behavioral change, goal setting and evaluation, persuasion, automation, and lifestyle change. Furthermore, knowledge, observation, coaching skills, ethics, interaction, credibility, efficacy evaluation, coaching experience, pragmatism, intervention (or recommendation generation), goal setting, and evaluation are key coaching processes relevant to eCoaching. The aspects of eCoaching are automation, behavior change with technology, and promoting a healthy lifestyle. The point of interest of eCoach initiatives is to deliver high-quality, evidence-based, comfortable, economical, and timely care to assist human beings in maintaining a healthy way of life.

Different health monitoring and feedback generation smartphone applications are available in the market; however, they are too generic and not personalized (or personally adaptive). Gerdes et al. proposed a holistic theoretical concept of a personalized eCoach system for wellness promotion in [1]. They combined specialized medical evidence from randomized controlled trials with personal and referenced knowledge to create and strengthen wellness-based recommendations [1]. Their conceptualized eCoach system (see Figure 1.1) adapts such recommendations in a continuous personalized coaching dialog addressing participant's requirements and preferences [1]. Their proposed eCoaching concept outlines *How to personalize the coaching* for the determination of *What to coach*, and the validation approach of the eCoach in the respective field of study [1]. Their study [1] leaves an automatic generation of personalized lifestyle recommendations as a future scope. Therefore, we extend Gerdes et al.'s work for this dissertation to address the

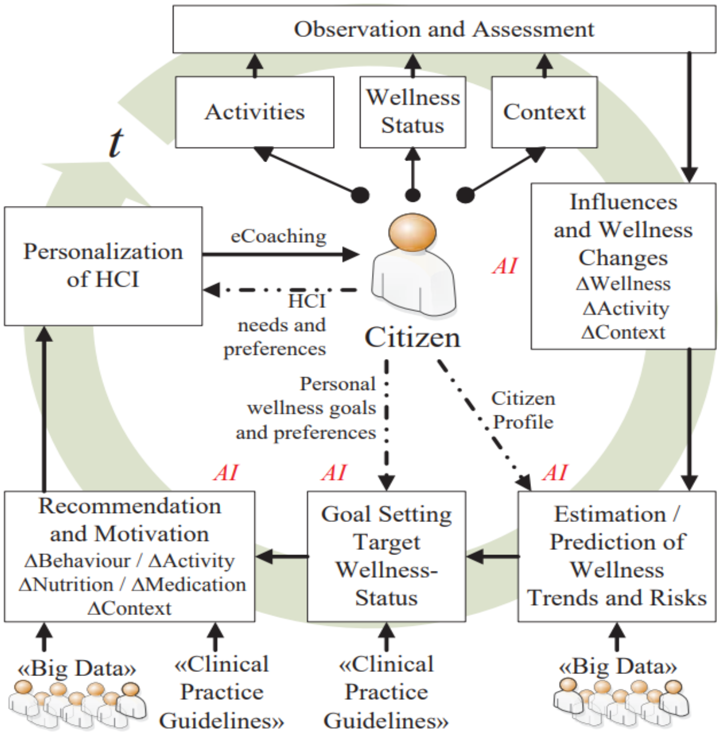

Figure 1.1: Wellness management in the eCoach System [1].

following scientific research problem with technological verification rather than a clinical evaluation.

How to generate automatic and personalized recommendations in eCoaching?

The identified research problem has been set from the perspective of a "general eCoaching system"; however, considering the robustness and time-constrains, we relied on a case-based study to address the research problem. Recommendations are specific to a domain, but recommendation generation is more technical in nature. This study is more concerned with the technology contributions to the recommendation generation (or the enabling technologies, in other words), the evaluation of the technology contributions, and the results associated with these outcomes. To guide the research work within this dissertation and to contribute to achieving the identified research goals based on a study case, research questions (RQs) have been formulated to address the identified research problem and elaborated in the subsequent sub-sections with scope, limitations, and study case selection. The case study helps to narrow down the scope to identify the key concepts and themes associated with eCoaching in general. The obtained results on the automatic and tailored recommendation generation process in eCoaching can be further extended to a broader perspective in other study cases, such as Mental health, Diabetes Type II, Sleeping Apnea, and Cardiovascular diseases.

1.2.2 Scope and Limitations

This scientific study is strictly based on the technical verification of an automatic and personalized recommendation generation process in an eCoach prototype, rather than the clinical evaluation of the generated recommendation content in controlled trials (or with other methods). This includes in particular the selection of the following –

1.2.2.1 Selection of Study Case

The application area of automatic coaching is broad. Therefore, to address the identified research problem, the selection of a study case is essential. A case study captures a range of perspectives and provides an opportunity to better understand relevant issues and reduces the potential for bias. It is a research approach that aims at developing a deep and multifaceted understanding of complex real-life problems. Therefore, we approach the DSRM methodology to design and develop an eCoach prototype system for a study case on a defined study group to answer our research questions. The application of eCoaching in eHealth is new. It can be promising in personalized behavioral monitoring and the automatic generation of customized recommendations to attain a healthy lifestyle goal, considering clinical and ethical guidelines, individual health status, health condition, context, and preferences. A healthy lifestyle leads to eating a balanced diet, getting regular exercise, and healthy habits (e.g., avoiding tobacco, drugs, and alcohol) to avoid chronic diseases and long-term illnesses. Therefore, continuous health monitoring is required. Regular physical activity (or non-sedentary lifestyle) contributes to preventing and managing lifestyle diseases, such as obesity, diabetes type II, high blood pressure, depressive state, and cardiovascular risks[2]. Therefore, to complete the eCoaching cycle in Figure 1.1 and address the research problem, we consider "Physical Activity (getting regular exercise)" as a study case for this dissertation. We exclude other healthy lifestyle aspects, such as eating a balanced diet and healthy habits, for our future research focus.

1.2.2.2 Purpose of the eCoach Prototype

The design and development requirements (basic functional and certain non-functional) of the eCoach prototype are collected from end-users in iterative workshops for the identified study case. Our designed and developed eCoach prototype mainly addresses the proposal and experimental evaluation of an algorithm for the automatic generation of personalized recommendations, integration of the algorithm in the eCoach prototype, and the technical evaluation of the eCoach prototype. Moreover, the design and development cover the main eCoach components as identified through the systematic literature review of established human coaching models. Certain aspects and characteristics (and related research questions) of the eCoach design are evaluated with corresponding methods – some theoretically, and some experimentally. Besides the theoretical evaluation of our proposed recommendation algorithm, the design and development of our prototype have involved users, providing also the evaluation of user aspects with experimental methods. The handling of the problem is done within the scope of the case. This approach leads to the following **limitations**.

[2]https://www.who.int/news/item/04-04-2002-physical-inactivity-a-leading-cause-of-disease-and-disability-warns-who

1.2.2.3 Study Limitations

The technical research outcomes and knowledge can further be extended in different eCoaching study cases for automatic and personalized recommendation modeling and representation. However, this study has certain limitations. The limitations help to draw a boundary between a technological verification study and a clinical evaluation study. The main **limitations** of this dissertation consist of the excluded evaluation of aspects, which have been explicitly marked as **out of the scope (excluded)** in the following −

- Usability and acceptability evaluation of the designed and developed eCoach in the usability lab settings on controlled trials **out of the scope (excluded)**,
- Detailed evaluation and scaling down of the performances of non-functional test cases **out of the scope (excluded)**,
- Clinical evaluation (medical efficiency and improvements of the health and wellness) of eCoaching on different cases in the direction of adequacy, reliability, and effectiveness of the automatically generated/delivered recommendations in controlled or uncontrolled trials **out of the scope (excluded)**,
- Evaluation of automatic and personalized recommendation generation algorithm on other study cases (on top of the considered study case) **(excluded due to the time limitations)**,
- We set up a digital infrastructure to host the eCoach prototype system in a secure environment, performed semantic and structural interoperability [14] and security testing on it [15][16]; however, we have **excluded** their detailed elaboration in this dissertation as they are not our main research focus,
- We performed version controlling (e.g., Git), auto-deployment (e.g., Jenkins), and code quality checking with standard tools (e.g., SONAR) to analyze various aspects of the code, such as code coverage, code duplication, logging, and code complexity under lab settings; however, we have **excluded** their detailed elaboration in this dissertation as they are not our main research focus,
- We performed performance testing of the eCoach system under lab settings to capture the response time under various loads and stress conditions [15][16]; however, we have **excluded** their detailed elaboration in this dissertation as they are not our main research focus,
- We performed compatibility testing of the eCoach system under lab settings against different web browsers, and hardware configurations [14][17]; however, we have **excluded** their detailed elaboration in this dissertation as they are not our main research focus, and
- We performed transfer and incremental learning methods for handling growing datasets and scalability testing on different machine learning models [18] in the laboratory settings; however, we have **excluded** their detailed elaboration in this dissertation as they are not our main research focus.

1.2.3 Research Questions

In order to address the research problem within this dissertation and to contribute to achieving the overall goals focusing on a study case as a proof-of-concept, the following research questions have been formulated –

RQ-1: How can human coaching methods be used as a basis for automatic coaching (eCoaching)?
RQ-2: What data is needed for recommendation generation in physical activity eCoaching and how to annotate them semantically?
RQ-3: How to generate automatic personalized recommendations, and how to annotate recommendation messages semantically in an eCoach system for physical activity?
RQ-4: How to personalize the presentation of automatic recommendations in an eCoach system for physical activity?

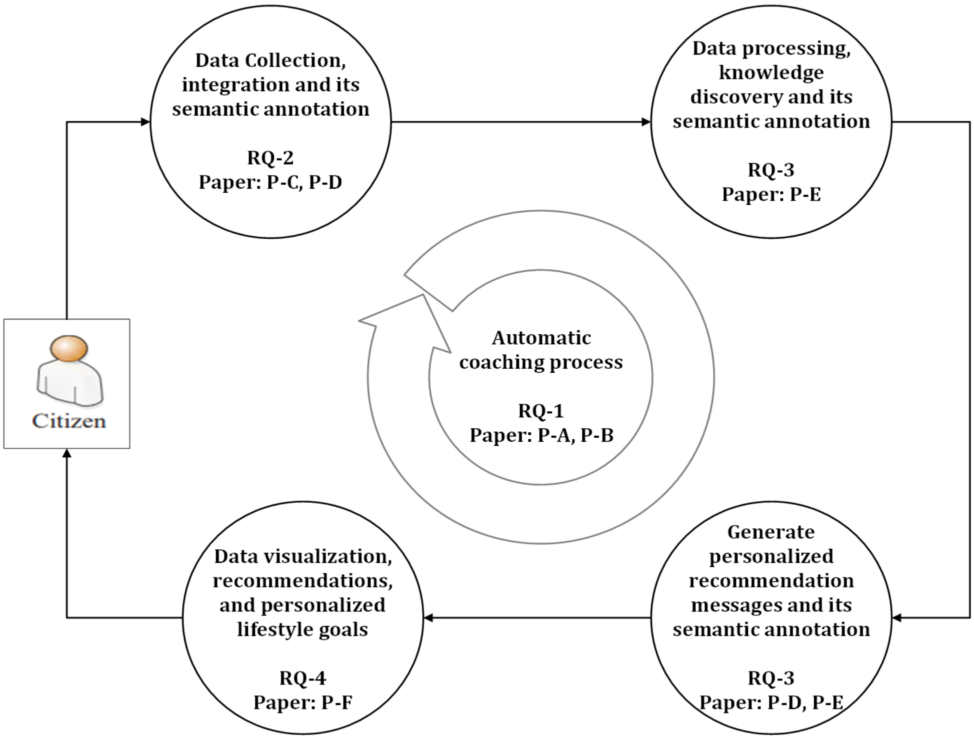

Figure 1.2: Data flow in our eCoach system and the assigned research questions.

The identified research questions answer eCoach conceptual modeling, data source handling, semantic modeling, knowledge discovery, data processing, and information provisioning in a physical activity eCoach system, automatic generation, and meaningful presentation of personalized recommendations to attain personal lifestyle goals. The identified research questions and associated contributions in the form of publications (Paper-A – Paper-F / P-A - P-F) are depicted in Figure 1.2. It illustrates a high-level design of our proposed solution and the assigned research questions (RQs).

RQ-1 aims at providing a basic understanding of the research problem with a focus on designing, developing, and technically evaluating the generation of personalized lifestyle recommendations in an eCoach system, in laboratory settings. RQ-1 identifies eCoaching processes, associated methods, strengths, and limitations from established human coaching models. The recognized methods of coaching point toward integrating human coaching processes in automatic coaching to design effective recommendation plans for sedentary lifestyle management and overcome the existing limitations of human coaching. Paper-A (P-A) and Paper-B (P-B) focus on RQ-1.

RQ-2 poses a fundamental problem in data integration from heterogeneous sources and of different formats. Collecting and transforming distributed, heterogeneous health and wellness data into meaningful information to train an artificially intelligent health risk prediction model is challenging in healthcare settings. RQ-2 focuses on the creation of a meaningful, context-specific ontology to model massive, intuitive, raw, unstructured observations of health and wellness data (e.g, sensors, interviews, questionnaires), preference information, and to annotate them with semantic metadata to create a compact, intelligible abstraction for health risk predictions for individualized rule-based recommendation generation. Paper-C (P-C) and Paper-D (P-D) focus on RQ-2.

Personalized lifestyle recommendations can be rule-based, data-driven, or hybrid. RQ-3 focuses on a fundamental problem in data processing, semantic modeling of processed data, automatic generation of personalized lifestyle recommendations, and semantic modeling of recommendation messages. Paper-D (P-D) and Paper-E (P-E) focus on RQ-3. P-C concentrates on rule-based personalized lifestyle recommendation generation and the semantic modeling of recommendation messages. P-E proposes deep learning-based time-series classification and forecasting, statistical metrics, and ontology-based hybrid personalized recommendation generation methodology in eCoaching. The proposed ontology model in P-F is an extension of the ontology model used in P-D. RQ-3 addresses the design, implementation, and technical evaluation of the automatic and personalized recommendation generation algorithm with real participant data (both public and private) against the standard and derived metrics under laboratory settings.

RQ-4 describes the user-centered design approach to cater to user needs at each phase of the design and development of an eCoach mobile application. Users have been involved throughout an iterative design process to create a working research eCoach prototype to improve the fit between technology, end-user, and researchers. Paper-F (P-F) focuses on RQ-4. RQ-4 addresses the basic functional and certain non-functional technical testing of the developed eCoach prototype under laboratory settings involving users.

1.3 Research Approach and Method

Research approaches are plans, decisions, and processes for research that span the steps from broad assumptions to detailed methods [19]. The selection of a research approach depends on the nature of the research problem. They help to identify and select appropriate research methods to answer the research questions. We approach our research with the well-accepted design science research methodology (DSRM) to connect objective, problem identification, theory, abstraction, eCoach design, development, and technical evaluation, considering physical activity as a case study. The DSRM consists of the following six common design process elements [2] – problem identification and motivation, the definition of the objectives for a solution, design and development, demonstration, evaluation, and communication. Figure 1.3 depicts the flowchart of the research methodology.

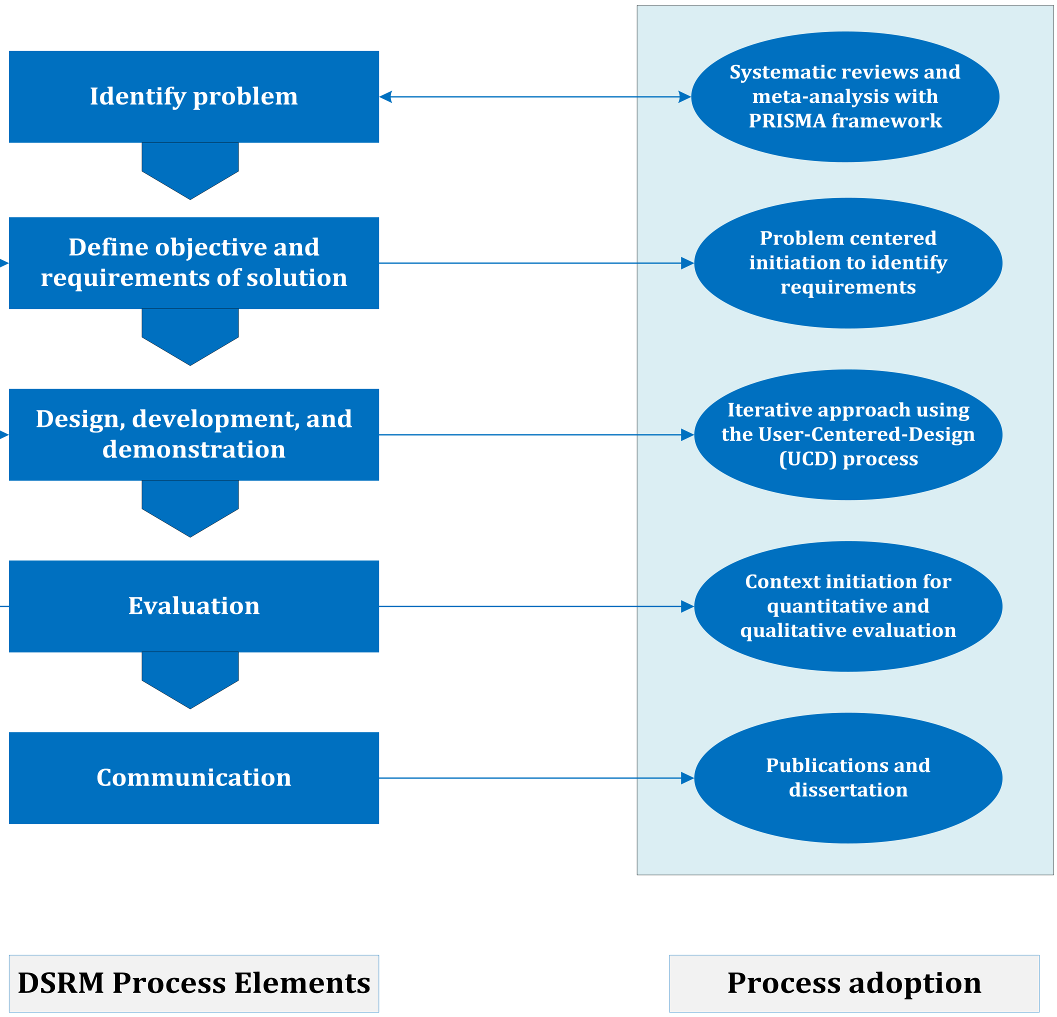

Figure 1.3: The flowchart of the research methodology. The left column illustrates the DSRM process sequence (and different possible iterations). The right column depicts the DSRM process adoption in this research.

For problem identification and motivation, we use a systematic literature review [5]. The preferred reporting items for systematic reviews and meta-analysis (PRISMA) framework [3] helps in evidence-based systematic review and meta-analysis. We identify general prerequisites to define the solution's objective and run the experiment. In the objective and requirements, we have concentrated on ensuring what to measure, how to measure, the recruitment criteria of participants in this study, the duration of data collection, and data governance. For eCoach prototype design, development, and demonstration, we adopt an iterative approach using the User-Centered Design (UCD) process. The adopted iterative UCD process adds a design focus on the user and their needs at each phase. The iterative design process has helped to develop a basic working prototype of an eCoach system that considers end-users' input toward meaningful recommendation visualization.

We use a mixed method to evaluate the designed and developed eCoach prototype system for personalized physical activity recommendation generation. The quantitative evaluation consists of state-of-the-art metrics focusing on the evaluation of the proposed recommendation algorithm and Ontology structure, and the qualitative evaluation focuses on the basic functional and certain non-functional technical testing on the primary working eCoach prototype. We focus on interdisciplinary cooperation in the whole design, development, and technical eCoach prototype evaluation process. We consider end-user's perspectives to visualize the personalized recommendations in the eCoach prototype for the selected study case. We scale down (0-5) the performances of basic functional test cases as a part of the qualitative evaluation process with end-users. Moreover, we add results of achieving certain identified non-functional technical test cases without any detailed elaborations. In detailed level, the methods associated with identified research questions in this dissertation are summarized in Table 1.1.

Table 1.1: The methods used to address research questions (RQs).

RQs	Methods
RQ-1	a. Review existing literature with appropriate selection criteria to understand the existing human coaching methods and processes, and b. understand the applicability of human coaching methods and processes in automatic coaching.
RQ-2	a. Identify a study case for eCoaching design and development, b. review existing methods of body sensor network data collection via the IoT, different ontology and their applicability to our case study, and c. analyze data and create a meaningful, context-specific ontology to model sensor observations and annotate sensor data with semantic metadata.
RQ-3	a. Understand the recommendation process in healthcare, review existing articles on human behavior change and its relationship with lifestyle changes, context, and age, b. identify study groups and develop a method for secure data collection and its governance, c. integrate the knowledge of human behavior change with AI to model meaningful, observational, and empirical evidence-based, context-specific recommendations that people will follow to achieve their individual health and wellness goals, d. propose a novel algorithm for hybrid recommendation generation with person-based heuristic configuration, and e. evaluate the performance of the developed AI and ontology models against established and derived metrics, on selected datasets, in lab settings.
RQ-4	a. Review existing articles on user-centered design methods on human behavior change, and b. conduct workshops to incorporate elements of the human process of coaching in our intended eCoach mobile app, such as feedback/rating, preference sharing, user-friendly human-computer-interaction, goal management, timely feedback generation, wellness vision, motivational suggestions, encouragement, assessing human thoughts to make the human-eCoach-interaction (HCI) effective for personalized lifestyle recommendations.

1.4 Dissertation Structure

In this research, *first*, the literature on human coaching to recognize existing coaching processes as behavioral interventions and methods within those processes has been systematically reviewed. It gives a broad aspect of human coaching processes and methods, and their applicability in automatic coaching. *Second*, relevant coaching processes for automatic health coaching to promote a healthy lifestyle with Information and Communication Technologies have been identified. It helps in problem identification. *Third*, As the application area and scope of eCoaching are very broad, we narrow down its scope to a physical activity eCoaching, and its design, development, and technological verification. In this regard, an iterative UCD approach focusing on the user aspects helps to prepare requirement specifications for data collection, data processing, data representation, algorithm design for recommendation generation, and their integration in an activity eCoach system design. We use a standard template to discover, specify, communicate, and document software requirements. *Fourth*, we plan to collect data from different formats and from various sources. Therefore, a framework for data integration and data annotation has been developed in the form of semantic ontology to explore the semantics of collected personal and person-generated health data. The proposed semantic ontology model enables knowledge sharing and reuse, enhanced search and retrieval, reasoning and decision-making, and data exchange (or interoperability) effectively. *Fifth*, we extend the semantic ontology design to model personalized physical activity recommendation message intent, components, and contents. The ontology-based approach has been effective in managing data and meta-data from heterogeneous sources and solving their semantic inconsistency in an activity eCoach prototype system. *Sixth*, we design an algorithm for personalized activity recommendation generation. We have conceptualized the design of a rule-based recommendation generation model with semantic ontology and, subsequently, extended it with deep learning time-series prediction and forecasting models, and statistical metrics for hybrid, personalized, and automatic recommendation generation. We have used an incremental approach to handle growing activity sensor data for deep learning model training, validation, and testing. *Seventh*, to represent the personalized recommendations using effective human-eCoach-interaction, we consider user aspects as obtained from the iterative UCD approach. *Eight*, all the outcomes are investigated against qualitative and quantitative approaches (under laboratory settings) to answer the identified research questions to address the research problem identified in this dissertation.

The basic form of this dissertation is a collection of scientific articles, such that this dissertation consists of two parts, where Part II contains the collected articles. Part I introduces the background of our research, research gaps, and the problems to be addressed. Moreover, Part I gives an overview of our accomplishments, presented in detail in Part II. Part I contains seven chapters: introduction, methodology, state of the art, objective and requirements, design and development, technical evaluation and discussion, and conclusions.

1. **Chapter 1: Introduction** introduces overview, background, the problem statement, research gaps, scope and limitations, selection of case study to address the research questions, and reference design approach and method.

2. **Chapter 2: Methodology** informs about the methodological framework, template for requirement specifications, explanation of the tools, and selected methods to address the research questions.

3. **Chapter 3: State of the Art** introduces basic coaching and eCoaching processes, methods, and terminologies that are used throughout the dissertation. Moreover, we introduce the existing works (to identify existing studies related to recommendation generation processes in activity eCoaching) and the novelty of this work. The chapter then represents the state-of-the-art aspects of data integration (semantics, and integration following health standards), and recommendation generation (data-driven, rule-based, and hybrid).

4. **Chapter 4: Requirements** informs about objectives and requirements to identify the implementation challenges associated with the project. Moreover, this chapter describes data collection, requirement collection, and documentation strategies to run the necessary experiments.

5. **Chapter 5: Development** describes our main achievements. An ontological representation and integration of personal, preference, behavioral, and recommendation messages are presented. Moreover, we extend the proposed ontology model to semantically annotate unprocessed and processed data for reasoning, knowledge representation, and personalized recommendation generation for the identified study case. Furthermore, the complete design and development of an eCoach prototype system are elaborated separately. In addition, a hybrid and automatic personalized recommendation generation technique is explained.

6. **Chapter 6: Evaluation** presents the following four things: outcomes from the systematic literature review on traditional human coaching methods relevant for automatic coaching, a quantitative evaluation of the deep learning models and ontology reasoning, and a qualitative evaluation of our eCoach prototype system.

7. **Chapter 7: Conclusion and Future Scope** briefly summarizes the presented contributions against research questions and describes potential future works.

Part II consists of six appendices A-F which represent our selected publications.

Chapter 2

Research Methodology

The importance of research methods lies in their ability to produce correct, reliable, and meaningful results that can inform decision-making, improve understanding, and drive innovation across a wide range of domains. This chapter explains the adopted research methodologies and approaches to answer the research questions to address our identified research problem for the dissertation.

2.1 Design Science Research Methodology

In Information Systems, to conduct design science research, Peffers et al. [2] proposed a methodology, called Design Science Research Methodology (DSRM). The DSRM satisfies the following three objectives −

- to be consistent with previous literature to identify the problem and define the objectives of a solution,
- to design and develop a basic model to perform design science research, and
- to evaluate and present the model to improve it further, iteratively.

The DSRM consists of the following six activities (see Figure 2.1) − problem identification and motivation, the definition of the objectives for a solution, design and development, demonstration, evaluation, and communication. According to Figure 2.1, the research process can start in almost any step, as reflected by different possible research entry points. The general sequence begins with the first activity in the case of a problem-centered approach.

This research is about self-management of physical activity level with a software system (called "e-Coach") for sedentary lifestyle observation and assessment, person-generated data (PGD) collection and governance, and the generation and provisioning of automatic and evidence-based personalized recommendations. We divide our research work into the following task groups based on the well-established design science research methodology − systematic literature review, design and development (data collection, data integration, development of a recommendation engine, and eCoaching through interaction), model testing with collected data, and quantitative and qualitative evaluation of the model with performance parameters and the qualitative evaluation of the eCoach prototype.

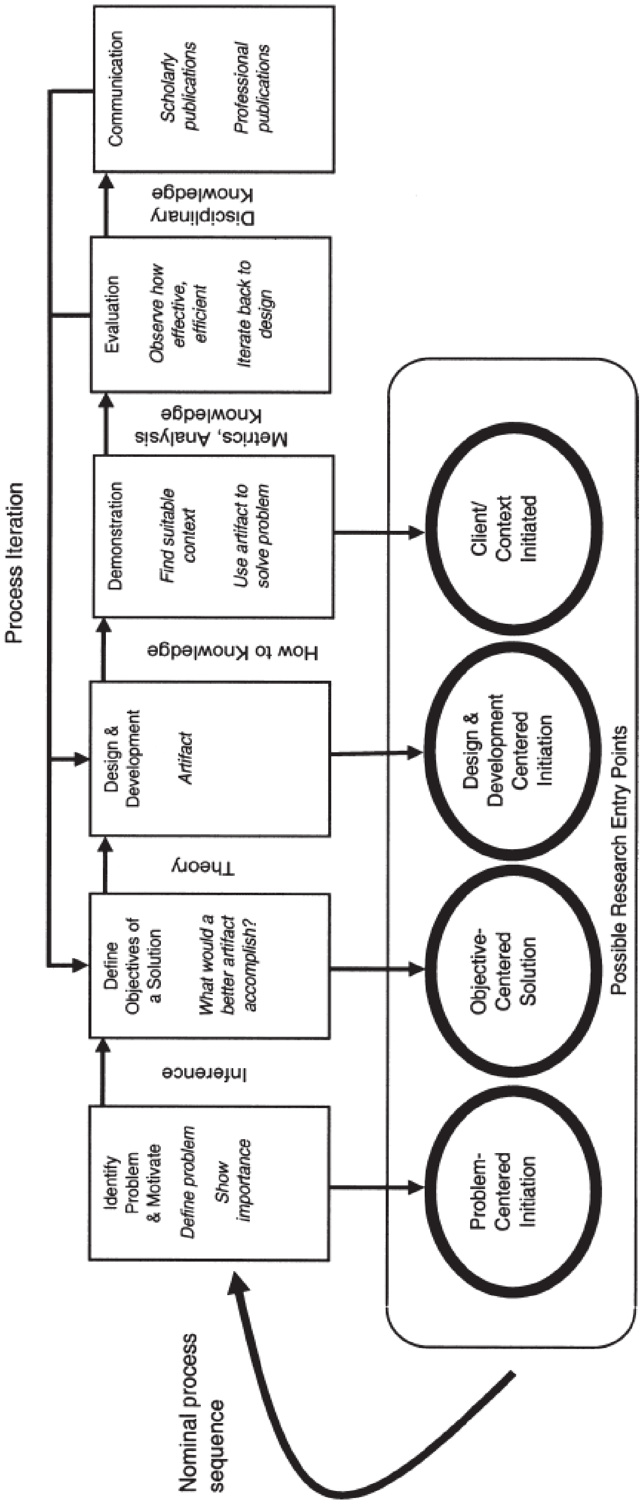

Figure 2.1: Design Science Research Methodology (DSRM) Process Model [2].

We use a systematic literature review to address RQ-1, and for the other RQs, we use other task groups. Due to the applicability of the objectives and context of this research project, we approach DSRM to initiate the research process with a problem-centric approach. The methods applied for this research project are elaborated in the following DSRM process steps.

2.1.1 Systematic Literature Review for Problem Identification

A systematic literature review is a scientific summary of evidence on a presented topic, using critical methods to identify, define and evaluate research on that topic [20]. It examines other authors' data and findings related to a specific research question. To understand the digital interventions on healthy lifestyle management and human coaching methodologies for eCoaching as behavioral interventions with ICTs, we perform a systematic literature review to search the following scientific databases − Scopus, Science Direct, EBSCOhost, ACM, SpringerLink, Nature, IEEE Xplore, Google Scholar, JMIR, and PubMed for publications. During the literature search process in the electronic databases, we use proper inclusion and exclusion criteria to avoid research overlap and to generate solution ideas and potential approaches. The preferred reporting items for systematic reviews and meta-analysis (PRISMA) framework [3] help in evidence-based systematic review and meta-analysis (see Figure 2.2). We document our findings in the *State-of-the-Art* (Chapter 3). The general Background and Problem Description (or Motivation) for this research are elaborated on in the Introduction (Chapter 1).

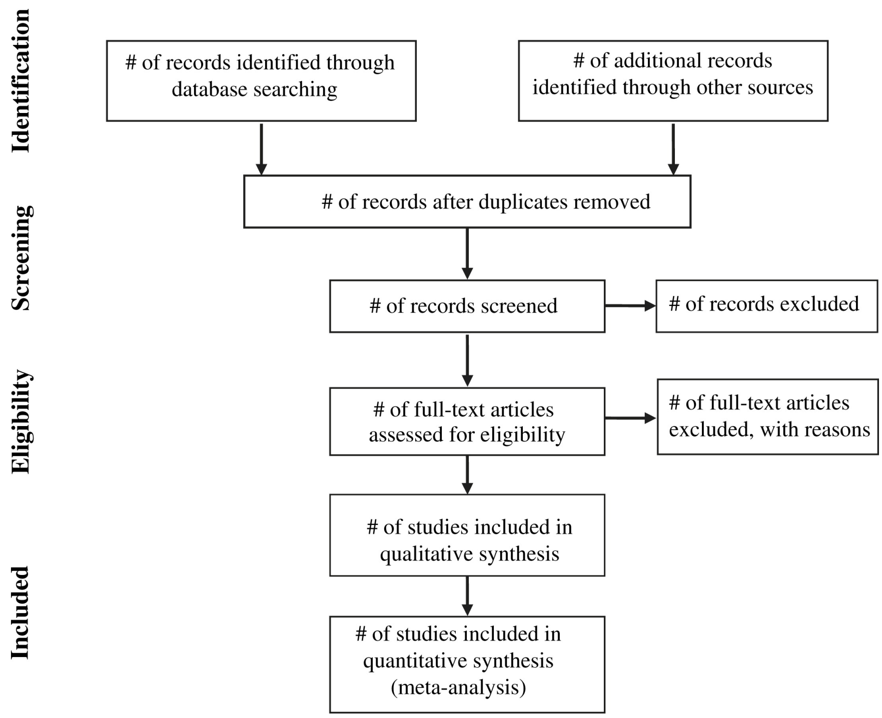

Figure 2.2: Processes in the PRISMA framework [3].

The literature review acts as a backbone to address RQ-1 − RQ-4. RQ-1 helps to understand the existing human coaching methods and processes and understand the applicability of human coaching methods and processes in automatic coaching. RQ-2 addresses research gaps and existing body sensor network data collection methods via the IoT, different ontologies, and their applicability to our case study. RQ-3 helps to understand recommendation generation processes on human behavior change and its relationship with lifestyle changes, context, and demography. RQ-4 helps to gain knowledge from the existing articles on user-centered design methods for human behavior change. We turn the obtained knowledge into UCD workshop planning.

2.1.2 Objectives of the Solution

The overall objectives of the research project are to design, develop, and technically evaluate an intelligent eCoach prototype for the automatic generation of personalized and evidence-based lifestyle recommendations. The design and development of the eCoach prototype require support from individuals of different end-user groups and experts as a part of an iterative User-Centered-Design approach. The main identified challenges associated with the research project are −

- *Data collection and knowledge representation:* recruiting participants, type of data, devices to be used, preparing questionnaire set, defining the frequency of data collection, modeling of data, presenting continuous and discrete data, and governing data,

- *Personalized goal management and automatic recommendation generation:* a designing algorithm for personalized and automatic recommendation generation, presenting recommendations in an understandable format, and setting up needed infrastructure.

- Initiation of *multidisciplinary cooperation.*

A study design prerequisite is essential to formulate the research objective in a theoretical proof-of-concept (PoC) study. A research objective tells about "*What do we want from the research?*", and the requirements tell "*How we plan to make the objectives happen?*". We document basic functional and certain non-functional technical requirements obtained from the user workshops to run the experiment in the *Objective and Requirements* (Chapter 4). They work as a stepping stone to address RQ2, RQ3, and RQ4 by overcoming the identified challenges. Data collection, meaningful processing, and presentation are important for personalized activity recommendation generation. Such challenges are mitigated with the proper planning using this method by linking "*What*" and "*How*".

2.1.3 Design and Development

The design phase aims to transform documented requirements into a suitable structure to implement in some programming languages. Two well-established design approaches are [21] − the traditional (or structured) design approach and the object-oriented design approach. The development phase transforms the design into source code. The design and development processes help to learn and develop a working prototype but also help to discover new and unexpected outcomes. In this research, on top of the modular eCoach system design and development with an object-oriented design approach, we consider end-user engagement, data collection, data integration, data governance, and ethical requirements to convert them into technical requirements for solution design and development.

2.1.3.1 Overview of Established Methods and Techniques

In information systems and software engineering, the software development life cycle (SDLC), also known as the application development life cycle, is the process of planning, building, testing, and deploying information systems. SDLC is a set of steps used to build a software application. These steps break down the development process into tasks that can be assigned, completed, and measured. The SDLC process model is a descriptive diagram of the software life cycle. A life cycle model represents all the activities required to move a software product through its life cycle stages [21]. SDLC captures the order in which these activities should be performed. In a basic SDLC, the following processes are involved - study design prerequisites, requirement analysis and specification, design, development (or coding) and unit testing, integration, functional and non-functional testing, and maintenance. Some well-established SDLC models are [21]: classical waterfall model, iterative model, prototype model, incremental model, evolutionary model, spiral model, V-model, agile model, and RAD model. Requirements analysis is the most fundamental stage in SDLC. This information is used to plan a basic project approach. Planning for quality assurance requirements and identifying risks associated with the project is also done during the planning phase. The study design prerequisites identify different technical approaches that can be followed to implement the project with minimal risk successfully. The design method defines all architectural modules of the software and their communication and data flow mapping with external and third-party modules.

2.1.3.2 Templates for Documenting Software Requirements

Software Requirements Specification (SRS) is important in software engineering because it provides a clear and concise description of software requirements. It serves as the foundation for the entire software development lifecycle, ensuring that software under development meets the needs and expectations of stakeholders, is developed efficiently, and is maintained over time. There are the following different SRS templates that are commonly used in software engineering and each has its own unique format and content − IEEE Standard SRS Template (based on the IEEE 830-1998 standard), Volere Requirements Specification Template, MoSCoW Method, Rational Unified Process Template, and Agile User Story Template. The most popular SRS templates depend on the specific needs and requirements of the project, as well as the preferences and practices of the development team.

We have used the Volere template [4] because it is a widely used requirements specification template that emphasizes the importance of understanding stakeholder needs and expectations. It includes sections for defining project drivers, requirement types, and project issues. The Volere template includes the following sections −

- *Introduction*: This section provides an overview of the document and its purpose, and outlines the intended audience and scope of requirements.
- *Project Drivers*: This section describes the business, user, and system requirements that drive the software requirements. It contains information about business goals, objectives, constraints, user characteristics, needs, and expectations.

- *Project Constraints*: This section describes any constraints or constraints on the project, such as budget, schedule, technical or legal requirements,
- *Functional Requirements*: This section specifies the software features and functions required to meet the business and user needs to be identified in the project-driven section.
- *Non-Functional Requirements*: This section describes the quality attributes that the software must have, such as ease of use, reliability, performance, security, and maintainability.
- *Project Issues*: This section lists any unresolved issues, risks, or assumptions that may affect the success of the project. It also outlines any contingency plans or mitigation strategies that have been implemented.
- *Sign-off*: This section provides a space for stakeholders to indicate their agreement and approval of the requirements document.

The Volere Template can be useful in this research to document all the requirements as obtained from the selected design method for eCoach prototype design and turn the design into software implementation. The key attributes of the Volere Template are presented in Figure 2.4.

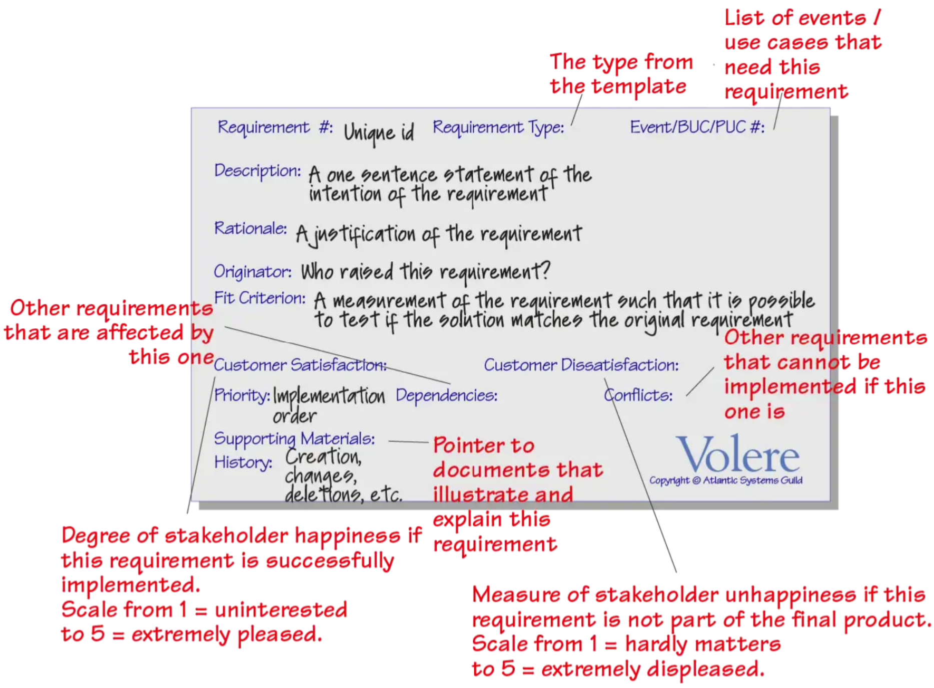

Figure 2.3: The structure of a sample Volere requirement template [4]

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User requirements are an important aspect of user-centered design because they provide a clear understanding of users' needs and expectations for a product or service. UCD workshops are an excellent opportunity to document user needs, as designers, engineers, researchers, and stakeholders can work with users to identify their needs and expectations. Therefore, we have carried out UCD workshops to collect user needs and expectations for an eCoach system for physical activity. The following steps may help us to collect and document user requirements obtained from the iterative UCD workshops – identification of target user group (e.g., users' characteristics, such as age, gender, occupation, present health status, and level of experience) and experts, objectives of the workshop (e.g., opportunities of an eCoach app. in eHealth, type of goal setting for the self-weight-management, feedback generation to motivate self-management, and feedback presentation and information visualization), preparation of the workshop materials to facilitate the ideation and documentation process, workshop planning and execution (e.g., various activities, such as brainstorming, group discussions, and role-playing), documenting user requirements in a standard template, verification approach for the requirements to reflect user needs and expectations, and setting priorities and categorization of user requirements.

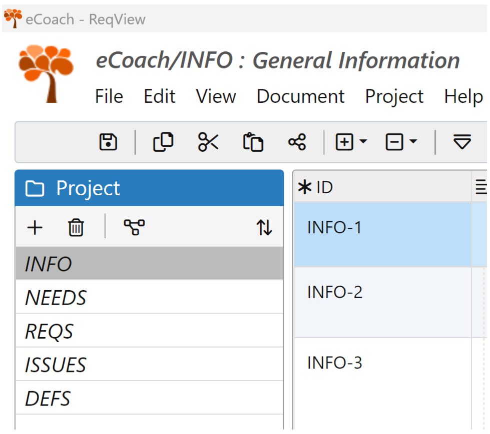

Figure 2.4: The use of ReqView software for requirements engineering in eCoach prototyping using the Volere requirement process.

Documenting user requirements in the "Volere Shell" is a systematic task. We have used the ReqView (V. 2.16.2) requirements management software for Windows OS to streamline the process. The "eCoach project" in the ReqView software consists of the following documents (see 2.4) – Project Information (INFO), Project Needs (NEEDS), Project Requirements (REQS), Project Issues (ISSUES), and Naming Conventions and Definitions (DEFS); however, we have focused only on the "REQS". We have performed the following steps to document identified requirements under the "eCoach project" –

- Create Project Needs: Here, we plan to update the product use case (PUC) table against a NEEDS-ID (#) (e.g., NEEDS-1). Each table has the following entries: PUC Name (e.g., User Login to the eCoach system), Actor/s (e.g., USER/ADMIN), and Input & Output (e.g., credentials with an authorization token (in), and successful login message and access the system (out)).

- Create Project Requirements: Here, we plan to update the requirements against their REQS-ID (#). Each row has the following entries: ID (e.g., REQS-1), Type (e.g., Functional Requirement), Use Case (e.g., NEEDS-1: User Login to the eCoach system), Description (e.g., The eCoach system will accept valid user credentials and access token to allow legitimate users in the system), Status (e.g., New, Planned, Implemented, or Verified), Rationale (e.g., To allow legitimate users in the system), Originator (e.g., name of the project owner), and Fit Criterion (e.g., A legitimate user is one who has valid authentication and authorization information).

- Traceability Configuration: We plan to create a NEEDS-ID and REQS-ID for all the identified issues using reference links. Afterward, we plan to connect REQS-IDs with corresponding REQS-IDs via a satisfaction link.

2.1.3.3 Application of Selected Design Method and Techniques

Design[1] is the intersection of understanding and creation, and design methods are the broader study of design methods − the study of design principles, practices, and procedures. The development of design methods[2] is closely related to the specification of the system design process. Design methods offer many different activities that designers can use throughout the design process. Design methods stem from new approaches to problem-solving in engineering, industrial design, architecture, and communications. The design and development of a health eCoach system require integration between technologies (e.g., mobile phone, computer, wearable and non-wearable sensors, tablet), concepts, and strategies from interdisciplinary domains (health informatics, computer science, software engineering, persuasive technologies, networking, and human-computer-interaction (HCI)), and of users' preferences and requirements in an engaging manner. The UCD approach may solve such an integration challenge by positioning the end-users centrally for designing, developing, testing, and evaluating an eCoach prototype. It may promote interactive digital services and applications with Internet-of-Things (IoT) connected sensors and actuators to open new opportunities for HCI. A user-centered design framework integrates a wide range of practices around understanding the needs, requirements, and limitations of end-users. It can improve strategic decisions and increase the effectiveness of individual projects and services. As a prerequisite for the eCoach prototype design, it is essential to involve the end-users and subject-matter experts throughout the design process. Therefore, we use an iterative UCD approach to understand the context of the user and collect qualitative data to develop a road map for self-management with eCoaching. The UCD process involves problem context, user identification, workshop planning, participant recruitment and grouping, group work, prototyping, interviews, domain analysis, task analysis, communication and understanding, introspection, and prototype evaluation. Following the UCD approach, we plan to implement the functionalities for activity eCoaching, and iteratively refine and test the prototype. We involve researchers, non-technical and technical, health professionals, subject-matter experts, and potential end-users in the iterative design process. We design and develop the eCoach prototype in multiple stages, adopting different phases of the iterative design process. The iterative design approach in the UCD process can help to develop a working prototype of an eCoach system that meets end-users' requirements and expectations towards an effective

[1]https://en.wikipedia.org/wiki/Design
[2]https://en.wikipedia.org/wiki/Design_methods

recommendation visualization, considering diversity in culture, quality of life, and human values. The design can provide an early version of the solution, consisting of wearable technology, a mobile app, and web content for self-monitoring, goal setting, and lifestyle recommendations in an engaging manner between the eCoach app and end-users. The adopted iterative design process brings in a design focus on the user and their needs at each phase. Throughout the design process, users are involved at the heart of the design to create a working research prototype to improve the fit between technology, end-user, and researchers. In the next subsection, we describe the process of participant recruitment for the UCD workshops. The UCD workshops help us to create a set of personal and person-generated health data to be used in a personalized recommendation generation algorithm in eCoaching to address RQ-3. Moreover, the identification of potential data and their sources helps us to create a semantic domain Ontology to model sensor observations and annotate sensor data with semantic metadata to address RQ-2. Furthermore, we integrate the knowledge of human activity change with AI to model meaningful, observational, and empirical evidence-based, context-specific semantic recommendation structures that people can follow to achieve their individual health and wellness goal(s). The UCD workshops help to incorporate elements of the human process of coaching in our intended eCoach mobile app, such as feedback/rating, preference sharing, user-friendly human-computer-interaction, goal management, timely feedback generation, wellness vision, motivational suggestions, encouragement, assessing human thoughts to make the HCI effective for personalized lifestyle recommendations (RQ-4).

2.1.3.4 Process of Participant Recruitment in UCD Workshops

Participation in this study is voluntary. Notifications related to the recruitment of participants are given in the following ways − advertisement on the "*UiA Notice Board*", advertisement on the "*UiA web portal (i4Helse)*", advertisement through internal email via "*tekreal-ikt@uia.no*", advertisement through internal cross-faculty level email communication, and advertisement through UiA in house health providers at "*Grimstad Kommune*". Advertisements maintained kept as short as possible. In the advertisement, inclusion criteria have been mentioned clearly to avoid confusion. Participants who fulfill the inclusion criteria are asked to provide their signed consent for participation. During the recruitment, basic training is given to the participants related to the participation guidelines, the use of the eCoach prototype and activity device, and how to submit the self-reporting questionnaire online. The number of selected participants for each iteration is described elaborately in *Paper-F (P-F)*. We have focused on recruiting male and female participants to avoid gender biases. In the next subsection, we mention the requirement criteria and duration for the participant (or end-user) recruitment in the UCD workshops.

2.1.3.5 Criteria and Duration for Participant Recruitment

We involve end-users in UCD workshops to understand their thinking and expectations. The professional background and the area of expertise of each end-user are different. Therefore, we decide to recruit participants from the following occupations – student, researcher, health professional, educationalist, and IT professional, to bring diversity to the UCD workshops. Our study targets adult participants with standard body mass (BMI) ranges [18.5 – 25 kg/m2] as well as obese and overweight [25 – 35 kg/m2]. The initial selection criteria are described below, and the recruited participants satisfied them.

Inclusion criteria:

- Participants registered to a general practitioner (GP) with BMI > 18.5.
- Age group 18-64 with targeted BMI range.
- Participants having Wi-Fi or wireless BB at home.
- Participants in South-Norway.
- Participants motivated for self-monitoring and data collection.
- Participants without a prescribed major chronic condition or current disease episode.
- Can speak, write, and read English in an understandable way.

We turn the entire process user-friendly and interactive. One future objective of the research about the use of this eCoaching app will be to perform a usability study followed by a longitudinal study on a controlled group of participants to verify the practical effectiveness of using this app toward a healthy lifestyle with self-management, self-motivation, and self-correlation. Therefore, in our study, end-users are a potential subset of actual eCoach participants for our future studies. We decide to conduct two virtual workshops for the iterative UCD process for 2 hours. For the workshops, we invite the recruited end-user volunteers (or participants) and the required number of experts. The UCD workshops are described in the subsequent subsections.

2.1.3.6 UCD Workshops

At the end of Workshop 1 (iteration 1), the research team collects user needs and preferences. An engineering team helps to translate the needs into initial technical solution requirements. The initial solution is developed based on continuous interaction and feedback generation between the engineering team and the research team. Afterward, the initial solution is utilized in Workshop 2 (iteration 2) to gather feedback on the gap between the technical solution and the user requirements (particularly on the recommendation visualization). The result of the second iteration helps us to mature the design and the technical solution. The structure of the workshops is based on the *dialogue-labs* methods from Lucero et al. [22], which facilitate the generation of participants' ideas by stimulating their creative thinking through a sequence of design activities.

At the end of the first workshop, materials from respective folders are assembled and analyzed to understand themes and categories. Also, we discuss and refine our understanding with the research team. We synthesize the most general scenarios and interaction styles. We use Workshop 1 as input for the next workshop. The data from Workshop 2 helps to refine the design and implementation of the working research prototype of eCoach

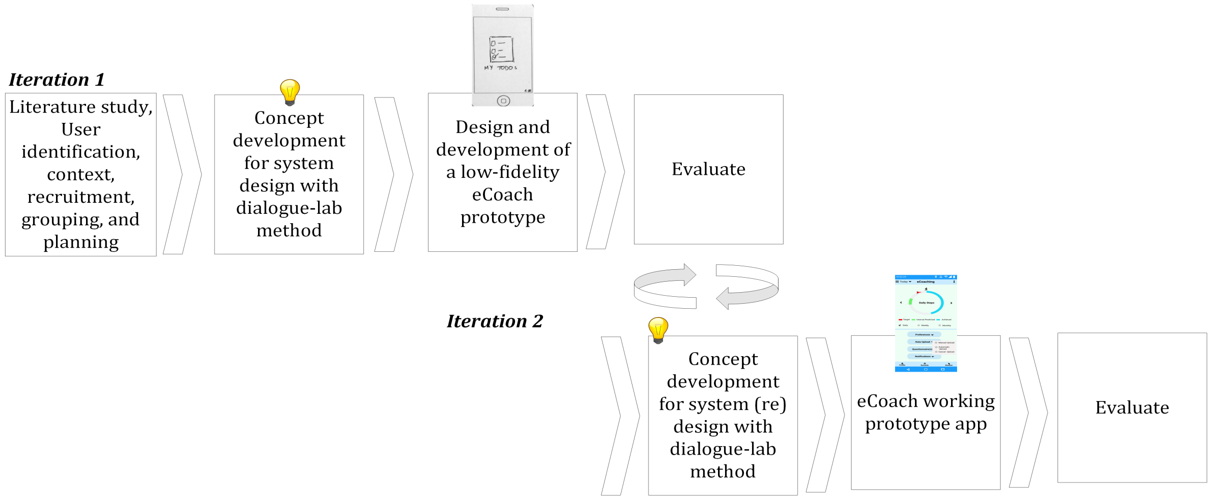

Figure 2.5: Adopted design process for the eCoach prototype design and development.

system. The workshop planning (e.g., participant selection, time management) and execution criteria for UCD Workshop 1 and UCD Workshop 2 are elaborated in *Paper-F (P-F)*. Researchers collect data from text notes (Notepad++, Google Docs, and digital Sticky Notes), videos, and images during the design workshops following the General Data Protection Regulation (GDPR). We maintain two separate folders (for two iterations) in Microsoft Teams to store the materials safely with access control rules. The adopted iterative UCD approach is illustrated in Figure 2.5 and has been described and evaluated in [17] with a specific focus on usability aspects. Following the UCD approach, the functionalities for activity eCoaching are implemented in our eCoach prototype system and iteratively refined and tested.

2.1.3.7 User-Centered Design Workshop - 1

The UCD Workshop 1 consists of the following phases –

1. *Concept Development for System Design*: In this workshop (iteration 1), we integrate the identified behavior change strategies and technologies in the eCoaching prototype design to stimulate a healthy lifestyle (physical activity, proper diet, and healthy habit) corresponding to users' context and needs (e.g., overweight and obesity risk management). *Paper-F (P-F)* gives further insight on it. Based on the *Workshop 1 (iteration 1)*, we develop an eCoach prototype app as an initial solution based on the first draft of user expectations to improve it further based on the feedback from end-users in the next iteration.

2. *Iteration 1 for Scenario Design*: From workshop 1 we identify end-users and their context and, followed, develop a concept based on the focus group discussion. The same is described elaborately in *Paper-F (P-F)*.

3. *Concept Design for Recommendation Generation*: The discussion opened a broad scope for the eCoach system to promote a healthy lifestyle, and the same has been elaborated in *Paper-F (P-F)*. This workshop helps to refine the data sources and data

types in the eCoach prototype design and development for meaningful, personalized recommendation generation.

We create a basic working eCoach prototype for personalized activity coaching given by the participant's discussion and design to capture the high-level plan for goal management and customized recommendations in activity coaching and interactions anticipated across groups. Researchers involved in Workshop 1 develop an eCoach prototype using data and objects from the workshop. The initial prototype is further updated based on the outcome of Workshop 2.

2.1.3.8 User-Centered Design Workshop - 2

The UCD Workshop 2 consists of the following phases −

1. *Concept Development for System (Re)-Design*: Workshop 2 (iteration 2) helps us to collect user input for the improvement of the quality of goal settings, motivational status visualization from self-monitoring, personalized feedback generation based on artificial intelligence (AI) technology, and recommendation visualization. *Paper-F (P-F)* gives further insight on it. Collected feedback from the end-users and experts generated ideas to (re)design the initial activity eCoach prototype based on selective considerations.

2. *Iteration 2 for Scenario Co-(re)Design*: We organize the workshop with a group discussion focusing on preference(s) and motivation. The re (design) comments are collected from considered user groups as detailed in *Paper-F (P-F)* to gather insights on personalized goal management, motivational feedback generation, and interaction models.

3. *Personalized Recommendation Planning*: From Workshop 2 we gather end-user feedback on the personal preference settings for personalized recommendation generation and visualization in a health eCoach app based on the focus group discussion, and the same is described in *Paper-F (P-F)*.

We integrate the solution for personalized and automatic activity recommendation generation and its delivery, in the eCoach prototype system. Different system components, such as eCoach mobile-tablet-PC solution and their needed infrastructure services for healthcare researchers and participants, are implemented in parallel and are integrated and evaluated in the workshops and beyond. We document our eCoach prototype design and development details in *Design and Development* (Chapter 5), and the requirements to meet the research objectives in *Objective and Requirements* (Chapter 4).

2.1.4 Evaluation

The objective of the evaluation process in DSRM is to observe, measure, and technically evaluate how well the designed and developed artifact represents a solution to our research problem. We will use quantitative and qualitative approaches to evaluate the performance of the eCoach prototype system and its automatic personalized recommendation generation. We have documented our evaluation results in *Experimental Evaluation, Results, and Discussion* (Chapter 6).

2.1.4.1 Quantitative

This study proposes a hybrid personalized recommendation generation method in eCoaching. To achieve that, this study will use a mixed activity prediction approach with the following methods – time-series prediction, time-series activity level classification, and statistical matrices (e.g., weighted mean, standard deviation, activity pattern, and similarity score). Furthermore, we plan to use interval prediction with residual standard deviation to make point prediction meaningful in the recommendation presentation. We will integrate the processed outcomes on activity datasets in an ontology for semantic representation and reasoning. SPARQL query protocol and RDF Query Language (SPARQL) may generate personalized recommendations in an understandable format.

We have planned to evaluate the performance of machine learning models against standard quantifiable metrics on public and private activity datasets. The performance of our proposed ontology will be evaluated with reasoning and query execution time. The quantitative evaluation methods are associated with RQ-2 and RQ-3 to technically evaluate the performances of proposed OWL Ontology, prediction, and forecasting models, and our proposed hybrid and personalized activity recommendation generation algorithm under lab settings with the private and public physical activity data of actual participants.

2.1.4.2 Qualitative

We will perform functional testing on the initial working eCoach prototype system against the participant's feedback in the UCD process. The feedback may consist of the following choices – passed (5), failed (0), and further scope of improvement (3). We will prepare a sample test set for the evaluation of the eCoach prototype with user involvement based on the collected functional requirements. Traditional activity-tracking smartphone apps focus more on data capturing and its representation; however, they suffer from the UCD approach, adequate data, data protection, data consistency, proper documentation, guidelines, and ethical approvals.

Therefore, we plan to qualitatively compare our designed and developed activity eCoach prototype system with commercial activity tracking mobile apps including smartwatches against generic eCoaching components to evaluate its performance. Moreover, we will add arguments for attaining certain non-functional technical features of the eCoach prototype (without detailed elaborations, as they are not the main research focus) under the qualitative evaluation outcomes. The qualitative evaluation methods are associated with RQ-4 to technically evaluate the basic functional and certain non-functional performances of our proposed activity eCoach prototype, rather than its clinical evaluation. Furthermore, we will perform a technological readiness study of our eCoach system against standard levels set by European Union (EU) [23].

2.2 Chapter Summary

In this chapter, we have discussed methodology selection to design and develop a PoC activity eCoach system as an artifact for this research project. Furthermore, we have discussed how DSRM processes are meaningfully integrated with eCoach prototype design, development, and technical evaluation! The adopted iterative UCD approach has extended the system demonstration and evaluation steps of the DSRM process. In the quantitative assessment, we have focused on evaluating the performances of deep learning models for time-series forecasting and classification, adopted statistical methods, ontology reasoning, and SPARQL query execution, with actual participant activity data. In contrast, the qualitative evaluation has focused primarily on technical evaluation and technological readiness study.

Chapter 3

State of the Art

Health eCoaching is not only about personalized recommendation generation for continuous lifestyle support, but it is also about appropriate method selection for system design and implementation, exploiting the semantics of data stored in the knowledge base to support a logical representation of observable and measurable data, processing of data for meaningful recommendation generation, and collaborative conversation with participants to aid planning and promote effective goal management using persuasive techniques. This chapter first presents high-level concepts that are used in this dissertation. It then elaborates on state-of-the-art eCoaching for health intervention, data integration with a focus on semantics, methods for data processing and time-series analysis, and personalized recommendation generation.

3.1 Concepts

Concepts are abstract ideas with principles, beliefs, and thoughts. Their meaning differs according to the contexts. Therefore, we briefly elaborate on all the necessary ideas used in this dissertation to avoid ambiguity.

- **Health Interventions**: *Digital health interventions (DHI)* are widely distributed, trusted, contextual, and personal well-being digital services for formal or informal care to fulfill individualized requirements to sustain a healthy lifestyle [5]. They can provide feasible and hypothetically cost-effective models to improve well-being [5].

- **Data - Information - Knowledge - Wisdom**: *Data* represents a collection of real-world facts with raw and unorganized symbols[1]. *Information* is a meaningful, contextual, organized, and processed form of data[2]. *Knowledge* is a subset of information in terms of perception and abstraction. A piece of knowledge can be turned into *wisdom* if it can conform to some actionable intelligence[3].

- **Data Integration - Semantics - Ontology**: *Data integration* brings data from

[1]https://www.systems-thinking.org/dikw/dikw.htm
[2]http://www.knowledge-management-tools.net/knowledge-information-data.html
[3]https://en.wikipedia.org/wiki/Wisdom

heterogeneous sources to provide a unified view[4]. Data integration can be performed with the following approaches, – of ontologies and web services. Ontologies are useful in data integration systems to give a semantic annotation to massive, raw, and unstructured data to create a compact, intelligible abstraction. Web services are a collection of open protocols and standards for exchanging data between applications or systems. *Semantics* is the study of reference, meaning, or truth[5]. In this dissertation, the semantics of personal and person-generated health data is being exploited to represent data in a more meaningful and structured way to extract more information from data. *Ontology* supports flexibility in its design to solve real-world modeling and knowledge representation problems [8, 24].

- **Data Processing**: Data processing occurs when data is collected and transformed into usable information. Data processing is generally managing and manipulating data elements to produce meaningful information. In this sense, it can be viewed as a subset of information processing, the modification of information identifiable to an observer in some way. Data processing must be performed correctly, not adversely affecting the final product or data output. We have integrated statistical, probabilistic, and deep learning methods in sensor data processing, obtained from wearable activity sensors for individual physical activity level monitoring.

- **Recommendations**: It is a suggestion or proposal for the best course of action, and especially one put forward by an authoritative body. Recommendations are statements designed to help end-users to make informed decisions on whether, when, and how to undertake specific actions or public health measures to achieve the best collective health outcomes.

- **Recommendation Generation**: Recommendation generation involves the suggestion or recommendation of products, services, or content to users based on their interests, goal, preferences, and behavior. Recommendation generation can be data-driven, rule-based, or hybrid.

3.2 eCoaching for Health Intervention

Digital intervention in healthcare is the intersection of healthcare, behavior science, computing, and engineering research and needs methods borrowed from all these disciplines. Digital interventions have effectively improved many health conditions and behaviors; besides, they are increasingly being used in different healthcare fields, including self-management of long-term conditions, prevention of lifestyle diseases, and health promotion. Persuasion studies instigate digital interventions for changing negative health behavior to advance a healthy lifestyle. They have gained acknowledgment in interventions for the management of a healthy lifestyle. The use of digital technologies offers new opportunities to improve people's health [9]. Digital interventions have been effectively implemented to enhance psychological well-being and enable self-management of persistent

[4] https://en.wikipedia.org/wiki/Data_integration
[5] https://en.wikipedia.org/wiki/Semantics

conditions [9]. Successful digital intervention methods include conceptualization, intervention strategies, policy design, understanding of the environment, motivation, satisfaction, behavioral determinants, psychology (competence, autonomy, and relationship), persuasion, self-determination, self-regulation, observation, participation (encouragement and engagement), human-centered design, exercise-related behavior in selected motivational profiles, decision-making, feedback generation and its meaningful delivery, goal setting, and evaluation, incorporation of digital technologies (e.g., smartphone, computers, wearable sensors), and evidence-based recommendation generation [9]. Its success depends on credibility, satisfaction, privacy, digital literacy, proper connectivity, co-creation, and efficacy evaluation [9].

A health intervention is performed for, with, or on behalf of a person or population whose purpose is to assess, improve, maintain, promote, or modify health, functioning, or health conditions [25]. Lifestyle or behavioral interventions include exercise, diet, and at least one other method (e.g., counseling, stress management, healthy habits). *Traditional Human Coaching* is a dialogic, goal-oriented, pragmatic learning practice to lead to excellent performance, self-motivation, and self-correlation [5]. The concept is well-accepted and implemented in management, leadership, entrepreneurship, performance management, and health care [5]. Coaching as human behavioral intervention is a personalized, planned process designed to reward and reinforce the positive behavior of human beings. Each behavior intervention differs from others based on the participants who are the primary target of the intervention, where psychology and context play crucial roles [5]. The coaching process for behavioral intervention should include appropriate guidelines, mutual trust, a rewarding plan, customized feedback, goal setting, and goal evaluation methods to make it worthwhile for coaching and eCoaching (coaching by an eCoach) processes [5].

eCoaching is inspired by traditional human coaching processes and methods [5, 9]. It is a promising eHealth research direction for continuous lifestyle support in a customized way [9]. Time is a critical factor in determining the format of coaching. Integration of coaching methodologies into persuasive eCoaching for electronic, personalized behavioral interventions creates new opportunities for a healthy lifestyle [5]. eCoaching has great potential to improve well-being and health meditation by increasing appropriateness, competence, usability, and personalization. An eCoach may develop optimized, real-time, comprehensible, automated, contextual, evidence-based, personalized intervention strategies for its participants. Moreover, it may address the challenges associated with coaching, such as scope, the volume of the target audience, bias, cost, automation, accessibility, security, flexibility, credibility, conceptual clarity, location, and time independence [5]. It is rewarding for participants to change negative behavior using evidence-based methods and to observe the boost in their health and strength [5]. This section gives an overview and, followed by, discusses existing human coaching methods and their adoption in eCoaching for the promotion of a healthy lifestyle with the support of ICTs. The process of human coaching includes an insight into how people learn and think, along with an understanding of what motivates them to achieve continuous high performance during behavior intervention. From the systematic literature search [5], the identified human coaching methods for the promotion of behavioral intervention are –

- Systematic observation: It helps researchers to identify the instructional behaviors utilized by coaching practitioners within the practice environment. Systematic observation must be capable of accurately and comprehensibly recording human behavior within a human coaching context.

- Interpretive interview: Achievement of the coaching process remains with observational data collection, supplied with in-depth interviews that allow for the acquisition and interpretation of rich qualitative data based on the behavioral strategies of coaching.

- Knowledge exchange: To understand the coaching process, it is necessary to analyze and investigate the shared experience between coach and participant.

- Pragmatism: Coaching is not a collection of techniques to apply or dogma to adhere to, rather, it is a discipline that requires freshness, innovation, and relentless correction according to the outcomes being produced.

- Understanding of human Psychology: Psychological principles, on which coaching is based, are essential. Without psychological understanding, coaches might go through the motions of coaching, or use the behaviors associated with coaching, such as questioning, but fail to achieve the intended results.

- Experience: It is a skill that helps to improve competence and coaching outcomes, such as future advancement.

- Trust: It is one of the complex issues for the coaches, whether internal or external. It teaches how not to use personal information and disclose it to illegitimate people.

- Relationship: The relationship must be based on mutual respect, trust, and mutual freedom of speech.

- Expression: Language impacts the goals of coaching by providing a means to assist the participant in self-correcting and self-generating. It is important to provide a new language for the participant for better understanding and learning.

- Mentoring: Mentoring is a more formal process, based on a one-to-one relationship with someone in the organization. While a mentor can use all the coaching types, their purpose is broader in scope than that of a coach.

- Values and Motivation: Values are ideas about what is good and bad and how things should be. Motivation is the internally generated feeling that stimulates participants to act. Motivation is related to the needs and values that correlate with intrinsic motivation.

- Feedback: It is important for coaches to improve their learning environment.

- Evidence-based: Evidence-based life coaching can enhance health, quality of life, and goal achievement.

- Context: Understanding the context is essential from a coaching perspective, as it provides insight into why participants either fail to use or resist the coaching approach.

- Decision-making: It includes data collection related to coaching, the privacy of collected data, data cleaning, statistical analysis of collected data, and the development of a machine learning model for prediction or regression analysis.

- Goal-based (Goal setting) and Evaluation: Goals include clearly stated pathways to the preferred alternative by identifying strategies. Goal setting and goal evaluation are two essential parts of a behavioral intervention to determine the effectiveness of coaching.

- Self-efficacy: It has its core in social learning theory. It can be explained as the general or definite belief that people have concerning their capability to accomplish assigned tasks.

- Personalization: The concept of personalization or user tailoring is used in coaching to explain the variation in preferences between groups of participants and within the groups of participants to make recommendations more effective.

- Persuasion: It is a process that has been designed to change the negative attitudes or behaviors of participants through advice, faith, and social influence. It is regularly used in the domain of public health where human-human or human-computer interaction is applied.

- Interaction and co-creation: Interaction is an integral part of pervasive computing that guides people to "do the right thing". It requires improving the automated logging of health (behavior) data and integrating this into coaching processes, designing more intelligent, interactive coaching processes which incorporate user preferences and plans, contextual/situational priorities, and health data consequences. For a successful design, the concept of co-creation is essential, where the system is designed together with its users.

Successful digital health intervention methods include conceptualization, intervention strategies, policy design, understanding of the environment, motivation, satisfaction, behavioral determinants and psychology (competence, autonomy, and relationship), persuasion, self-determination, self-regulation, observation, participation (encouragement and engagement), human-centered design, exercise-related behavior in selected motivational profiles, decision-making, feedback generation and its meaningful delivery, goal setting, and evaluation, incorporation of digital technologies (e.g., smartphone, computers, wearable sensors), and evidence-based recommendation generation [9]. Its success depends on credibility, satisfaction, privacy, digital literacy, proper connectivity, co-creation, and efficacy evaluation [9]. Therefore, effective intervention planning is essential for an eCoach system for behavioral intervention to promote a healthy lifestyle change. The concept of eCoaching is based on traditional coaching, and the technological revolution has boosted its performance and real-time acceptance. The pillars of eCoaching for behavioral intervention are mostly inspired by traditional human coaching methods. Lifestyle goal management and appropriate feedback generation are important in eCoaching. A goal type can be short-term (e.g., weekly) or long-term (e.g., monthly). Success in short-term goal attainment may help in achieving long-term goals. Different visualization techniques, such as bar charts, heat-map, emotion graphs, visual examples of action, maps, and star ratings, motivate individuals to perform the recommended activity. In an eCoach recommendation system, visualization [26] aims to reduce the barrier to exploring fundamental visualizations by automatically rendering results for users to search and select rather than manually set. In personalized recommendations, recommendation generation and delivery depend highly on personal preferences. The personal preference data consists of goal settings (e.g., daily, weekly, or monthly), target goal (e.g., medium active or vigorous active), target score, mode of interaction, or recommendation delivery (e.g., text, audio, or graph), and time of recommendation delivery. The preference data must be customizable. An appropriate design method will be helpful to design the data visualization interface in an eCoach recommendation system.

In our designed and developed eCoach recommendation system, we have considered the following eCoach components as identified through the systematic literature review − intervention and recommendation planning, personalization, interaction, co-creation, goal management, automation, and persuasion. The selection of the case study ("Physical Activity eCoaching") helps us to narrow down the research focus from a broad aspect and turn it technically feasible. The concepts used for this study design and the overall research outcomes can be further used for other study cases. The subsequent section identifies research gaps in the existing physical activity eCoach recommendation systems in terms of recommendation generation processes.

3.3 Physical Activity eCoach Recommendation Systems

An appropriate eCoach-based personalized recommendation generation program can help people stay active and achieve their physical activity goals. There can be two types of goals, − short-term goals (e.g., weekly) and long-term goals (e.g., monthly). The accomplishment of the short-term goals (STG) contributes to the achievement of the long-term goals (LTG) where the LTG is the summation of the STGs. In contrast, semantic rules may balance transparency, complexity, and effectiveness of knowledge description and knowledge reasoning, and enhance understandability with a knowledge graph in the personalized lifestyle recommendation generation process following the T-Box (Terminological Box) and A-Box (Assertion Box) components and a knowledge base. Most activity trackers, involving mobile applications and intelligent wearable devices (e.g., smartwatches), predict future activity in terms of "steps" as a point prediction either with time-series forecasting, probabilistic approaches, or specific rules. However, point prediction is a very abstract concept. Therefore, in this context, a probabilistic interval prediction approach may be promising.

We have considered the overall activity eCoaching process in related work by classifying it into a data-driven approach and a rule-based approach. As eCoach design approaches and applications in eHealth are broad, therefore, included search results are mainly focused on technology-driven activity coaching for a healthy lifestyle and personalized feedback or recommendation generation process. Knowledge representation in the eCoach system can be optimized by the ontology model, and the ontology reasoning engine can verify the compatibility and stability of its logic and structure. Improvement of physical activity in combination with wearable activity sensors, digital activity trackers, eCoach features, and machine learning can be promising and motivating to its participants. In this regard, an ontology structure can ensure semantic annotation of raw and processed data collected from heterogeneous sources to make it precise, uniform, meaningful, logical, and queried.

3.3.1 Data-Driven Approach

The literature search reveals that eCoach concepts with machine learning-based tailored recommendation generation are still improving. Few studies have examined the use of actionable and data-driven predictive models [27]. Dijkhuis et al. [28] analyzed personalized physical activity recommendations for sedentary lifestyles using machine learning and deep learning algorithms at Hanze University. They collected daily step count data to train a machine learning classifier, estimated the likelihood of reaching an hourly step count goal, and then used a web-based coaching app to generate feedback. Hansel et al. [29] designed and developed a fully automated web-based tutorial program. They used a pedometer for physical activity or step monitoring to increase activity levels in a randomized group of patients suffering from diabetes type II and obesity. Pessemier et al. [30] used raw accelerometer sensor data for individual activity prediction, accepted personal preferences to schedule activity recommendations, and generated personalized recommendations through a tag-based and rule-based filtering approach.

Amorim et al. [31] and Oliveira et al. [32] performed activity monitoring using a Fitbit Activity Sensor in a randomized study. They performed statistical analysis to find the effectiveness of a multimodal physical activity intervention plan, including supervised exercise, fitness coaching, and activity monitoring of physical activity levels in patients with chronic nonspecific low back pain. Their research shows that physical activity is critical in managing chronic back pain. According to the review results, machine learning (e.g., Support Vector Machine, Decision Tree, K-Nearest Neighbour, Naive Bayes, Logistic Regression, Random Forest, and Linear Discriminant Analysis), deep learning (e.g., Multi-Layer Perception, Convolution Neural Net, Recurrent Neural Net, and LSTM) and statistical (e.g., Auto-Regression, ARIMA, SARIMA, and Kalman filtering) models have been used to classify and/or predict and generate recommendations in health settings.

3.3.2 Rule-based Approach

Rule-based recommendation generation opens up new directions for eCoaching. Petsani et al. [33] designed and developed an eCoach system for older adults to improve their obedience to regular physical activity. They followed electronic coaching guidelines as set by a human therapist or physician or a trusted person chosen by the participant who had access to stored health and wellness data and intervened in the coaching process. They concluded that health eCoaching is a complex process that requires careful planning and collaboration across many scientific fields, including psychology, computer science, and medicine. Braber et al. [34] incorporated the eCoaching concepts into personalized diabetes management, where lifestyle data (e.g., food intake, physical activity, blood glucose values) were recorded and integrated into clinical rules to enable customized coaching for better lifestyle recommendations management.

Chatterjee et al. [24] focused on the design and development of a meaningful, context-specific domain ontology to capture unintuitive and raw insights from human-generated health data (e.g., sensors, interviews, and questionnaires) using semantic models and unstructured observation metadata to create logical abstractions for rule-based health risk prediction in an eCoaching system. Villalonga et al. [35] designed an ontology-based automated reasoning model to generate personalized motivational messages for activity guidance, taking into account behavioral traits. Therefore, ontologies can be a practical choice for rule-based decision-making with powerful design flexibility within the object-oriented design paradigm.

3.4 Formal Knowledge Representation

Knowledge is a fact or understanding of a particular subject. Representation is a symbol or thing representing something else (e.g., refers to, stands for) when we can't use the original like things in the natural world or concepts. Knowledge representation (KR) is an area of artificial intelligence research aimed at representing knowledge in computer-understandable form using meaningful symbols to facilitate inferencing from those knowledge elements, creating new aspects of knowledge [24]. KR aims to solve semantic heterogeneity in data and automated reasoning with the expressive power of intelligent agents' beliefs, intentions, and judgments in a suitable way. Knowledge can be categorized as declarative, structural, procedural, meta, and heuristic [36]. In an intelligent system, knowledge is managed with a database called a knowledge base which provides information to be collected, compact, organized, shared, searched, and inferred. Knowledge engineering informs the system what is accurate with contextual knowledge representation in a computable form, and our designed and developed eCoach system is not an exception.

3.4.1 Forms of Knowledge Representation

There are four universal forms of knowledge representation in an intelligent system to express domain knowledge semantically: semantic networks, rules (if-then), and logic (e.g., predicate, propositional). The logical representation provides a precise semantic interpretation using semantic regulations and networks.

A **semantic network** represents domain knowledge in the graphical format with nodes (or objects) and edges between nodes (to describe the relationship between those objects) [37]. Each node represents a domain concept, and an edge associates two domain concepts with either Is-A relation (inheritance) or Has-A relation (composition). Semantic networks are a natural representation of knowledge and work as an alternative to predicate logic [38]. They are easy to comprehend due to their transparent knowledge representation power. However, they are not intelligent, require more computation time, and suffer from quantifier inadequacy [24, 37, 38]. Figure 3.1 represents a semantic network for personal health status, integrating the concepts of clinical vocabularies, where hasParticipantState, hasClinicalFinding, hasStatus, hasVitalSignFinding, hasHealthRecord, and hasObservables represent the relations between the concepts with cardinal information.

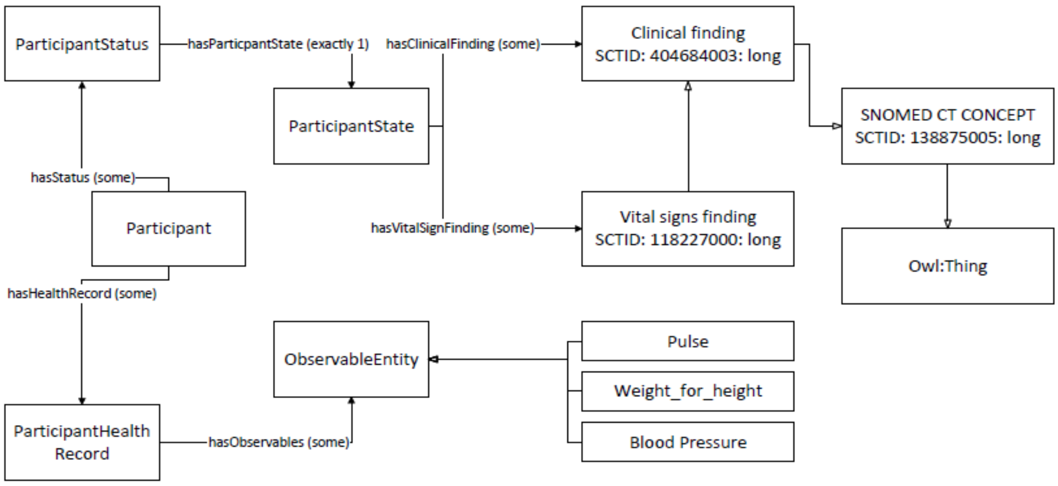

Figure 3.1: A semantic network representation of participant health status.

In the **rule-based** approach, IF-THEN-ELSE constructs are used to represent different kinds of statements. An example is shown as follows for personalized recommendation generation based on daily physical activity level –

- IF $((Steps<5000) \wedge (VPA*2+MPA)*7<90 \wedge LPA \geq 0)) \vee (Steps<5000)$ THEN **hasPhysicalActivityLevel** is 0
- IF **hasPhysicalActivityLevel** is 0 THEN **ActivityLevel** is **Sedentary**
- IF **Sedentary** THEN **Recommendation-1** (e.g., Please continue a light activity (e.g., sports 1-3 days/week, a walking goal of 5,000 to 7,499 steps/day)).

Rule-based knowledge representation follows a binary tree structure where the non-leaf nodes hold the semantic rules (A | A→B) to be executed, the leaf nodes contain the results (B), and the edges keep a decision statement (True or False). Rule sets help to explain the logic behind an action (e.g., recommendation generation in this context). Rule-based systems are modular, intelligible, and easy to manage. If the rules become more complicated, then the performance of the rule-based systems will decrease gradually because of the non-transparent logical interactions within the rules.

A **logic-based** approach gives more detailed semantics to represent knowledge in the form of formal logic using both rules and structural representation. Differently, we can specify rules such as propositional logic, decision tree, relational algebra, and description logic. Description logic is a subset of first-order logic. Propositional logic deals with simple declarative propositions, while description logic additionally covers predicates and quantification. Description logic is the formal knowledge representation of ontology language (e.g., Web Ontology Language (OWL)), which balances transparency, complexity, and effectiveness of knowledge description and knowledge reasoning. Semantic Web Rule Language (SWRL), and SPARQL query protocol, RDF Query Language (SPARQL) are well-accepted languages representing description logics in the domain ontology. The description logic is used to describe classes, objects (or individuals), and properties (object properties and data properties). Description logic has two parts: terminology (TBox) and assertion (ABox). TBox holds controlled vocabularies or concepts (e.g., a set of classes and properties), and ABox are statements about TBox-compliant vocabularies. TBox statements are associated with object-oriented classes, and ABox statements are related to instances of classes mentioned in the TBox. Participant, ParticipantStatus, ParticipantState, and ParticipantHealthRecord are concepts and belong to TBox. In contrast, hasParticipantState, hasHealthRecord, and hasStatus are roles in an ontology and belong to ABox. We can express TBox and ABox relationships as follows −

- **Student** is a kind of **Participant** → **Student** ⊆ **Participant**
- **Participant001** is an instance of **Participant** → **Participant001** ∈ **Participant**
- **Participant** has exactly five health records → Participant $\cap = 5$.hasHealthRecord

A knowledge base [24] is used to store and access logical rules and related messages. It is a database for knowledge management and provides means for information to be collected, organized, shared, searched, and inferred. It comprises two types of statements: asserted and inferred. The inferred statements are logical consequences of asserted statements and logical rules. The knowledge base stores and manipulates knowledge in computer science, interpreting invaluable information. It is often used in artificial intelligence applications and research to better understand a subject in computer-understandable form using appropriate symbols. Generally, a rule set is applied to the systems that involve human-designed or managed rules. It may contain semantic rules with human-understandable symbols and words. Semantic misunderstanding occurs when people assign different meanings to the same word or phrase.

3.4.2 Knowledge Representation with Ontologies

An ontology is a vocabulary to describe the concepts and relationships among the concepts in a particular domain of knowledge representation. It is an abstract entity and a conceptualization specification designed to reuse across different applications, and implementations [8, 24]. It supports an open-world assumption (OWA) knowledge representation style with the following elements: classes, objects, properties, relationships, and axioms [8, 24]. Properties are of two types: Object Properties and Data Properties. Each property has a domain range, restriction rule, restriction filter, and restriction type as Some (existential), Only (Universal), Min (Minimum Cardinality), exact (Exact Cardinality), and Max (Max Cardinality) [8]. A class diagram in an object-oriented paradigm is a visual representation of an ontology. In computer and information science, knowledge is represented with an ontology in a formal way as follows –

1. A hierarchy of concepts within a domain,
2. A shared vocabulary to denote the types, and
3. Properties and interrelationships of these concepts.

An ontology together with a set of individual class instances (or objects) constitutes a knowledge base for an explicit specification of a conceptualization [8, 24]. In reality, the knowledge base begins on a fine borderline where the ontology ends. Ontologies are categorized into the following three types –

1. Upper-level ontology or top-level ontology or foundation ontology to describe the most general concepts that are common across all knowledge domains (e.g., Entity),
2. Domain ontology to represent a certain part of the world, such as medicine, reflects the underlying reality with a theory of domain represented (e.g., SSN, LOINC, SNOMED CT), and
3. Application ontology to design or represent a specific task in a domain.

We have integrated existing ontologies, such as Semantic Sensor Network (SSN) and Systemized Nomenclature of Medicine – Clinical Terms (SNOMED CT) in our eCoach ontology design. The following terminologies are relevant for ontology representation and processing - propositional variable (an atomic name of a truth value that may change from one model to another), constant (the unique propositional variables TRUE and FALSE such that their truth value cannot be changed), operators (the set of logical connectors in each logic. In the case here, we use the following operators: NOT, AND, OR, IMPLIES, and EQUIV), quantifiers (the set of logical quantifiers in a given logic. We can use FOR ALL (for the universal quantifier), EXISTS (for the existential quantifier), quantified clause (a set of propositional variables linked together by Operators and Quantifiers), clause (a Quantified-Clause without any quantifiers), formula (a collection of clauses and quantified-clauses related together by logical operators), and model of the procedure (a group of assignments for each propositional variable, such that when simplified, leads the procession to the constant TRUE). Ontology languages can be divided into the following two categories: traditional syntax ontology languages (e.g., CycL, DOGMA, F-Logic, OCML, OKBC), and markup ontology languages (e.g., RDF, RDF Schema, OWL, OIL, DAML+OIL) [24]. The resource description framework (RDF) describes web resources with a representational power of three or triplets (subject, predicate, and object). A resource in RDF can be documents, physical objects, people, and abstract concepts. RDF descriptions are not designed to be displayed on the web and read by an ordinary human. With XML and RDF, information can easily be exchanged between different types of computers using other operating systems and application languages. RDF uses web identifiers to identify resources and describes resources with properties and property values. RDF Schema (RDFS) is an extension to RDF and provides data-modeling and structured vocabularies for RDF data, as RDF does not provide actual application-specific classes and properties. Types in RDFS are much like classes in object-oriented programming languages. It allows resources to be defined as instances of classes and subclasses of classes. In contrast, Web Ontology Language (OWL) is a vocabulary built on top of the RDF and RDFS vocabularies to provide better expression of objects and relationships, greater machine interpretability, and more restrictions to knowledge representation, a larger vocabulary, and stronger syntax than RDF and RDFS. OWL has three sub-languages: OWL Lite, OWL DL (includes OWL Lite), and OWL Full (includes OWL-DL). OWL Full is the union of OWL syntax and RDF. OWL DL is restricted to the First Order fragment, and the OWL Lite is a simpler subset of OWL DL. OWL ontologies stored in the Terse RDF Triple Language (TTL) format produce better readability. An ontology can be defined as a tuple Ω = Ć, R, where Ć is the set of concepts and R is a set of relations [8]. It follows a directed and acyclic tree-like structure with the following properties −

$L = Levels(O_h)$ = total number of levels in the ontology hierarchy, $0 \leq n \leq L$, where $n \in Z^+$ and $n = 0$ represents the root node.
$C_{n,j}$ = a model classifying ontology at a level n; where, $j \in \{0, 1, \ldots.., |C_n|\}$.
|C| = number of instances classified as class C.
E = Edge ($C_{n,j}$, $C_{n-1,k}$) = edge between node $C_{n,j}$ and its parent node $C_{n-1,k}$.

Note: An ontology uses Internationalized Resource Identifier (IRI) to identify a resource in an ontology. IRI fits well with the concept and features of URI. IRIs help to fetch, insert, and delete an ontology resource without name mangling. The structure of an IRI is: *protocol://host/applicationPath/resourceType/resourceID.*

3.4.2.1 Ontologies in the IoT Domain

Ontology provides a framework for describing sensors. SSN-XG (W3C semantic sensor network incubator group) developed the SSN ontology to model sensor devices, systems, processes, and observations. SSN annotates sensor data with semantic metadata (SSW or semantic sensor web) to increase interoperability among diverse networks, data integration, discovery, and situation awareness. The Sensor Model Language (SensorML) was developed by the Open Geospatial Consortium (OGC), which provides syntactic descriptions using XML to describe sensors, observations, and measurements. While SensorML provides an XML schema for defining sensors, it lacks the repressibility of ontology languages such as OWL [24, 39]. Semantic sensor web (SSW), a combination of sensor and semantic web technologies, helps to annotate spatial, temporal, and thematic semantic metadata for the more artistic representation of sensor data, advanced access, formal analysis of sensor resources, and data standardization. SSN ontology processes sensor devices, sensing, sensor measurement capabilities, observations, process, and systems [24]. SSN allows its network, sensor devices, and data to be installed, structured, managed, queried, and controlled through high-level specifications. Sensors Annotation and Semantic Mapping Language (SASML) offers XML schema to transfer sensor data and sources into the instances of SSN ontology based on a predefined XML-based document (RDF), automatically with sensor data to RDF mapping (SDRM) algorithm [40]. The “M3 Ontology” (machine-to-machine) was developed based on the “SenML” protocol (designed for simple sensor measurement), which is an extension of SSN, to enable the interoperable design of domain-specific or cross-domain specific applications, which are termed as Semantic Web of Things (SWOT) [24]. AeroDAML, KIM, M3 Semantic Annotator, MnM, and SemTag are different available semantic annotators for sensor observations for their corresponding semantic models, such as DAML, KIMO, M3, Kmi, and TAP [40]. Like SSN, there are other IoT-based contextual ontologies, such as IoT-Ontology, IoT-Lite, and IoT-O [41]. SCUPA, CoBrA-Ont, CoDAMoS, PalSPOT, the delivery context ontology, and Fuzzy-Onto are IoT-based ontologies for activity recognition. URI, HTTP, HTML5, REST, SOAP, Web Socket, Web feed, MQTT, CoAP, and AMQP are some standard IoT protocols applicable to the Web of Things (WoT) [42, 43]. In this study, we integrated the concept of SSN ontology to model sensor observations.

3.4.2.2 Ontologies in the Medical Domain

Systematized Nomenclature of Medicine Clinical Terms (SNOMED-CT), International Classification of Diseases (ICD-11), Unified Medical Lexicon System (UMLS semantic network), Foundational Model of Anatomy (FMA), OpenEHR, Gene Ontology (GO), DOLCE, Basic Formal Ontology, Cyc’s upper ontology, Sowa’s top-level ontology, the top level of GALEN, Logical Observation Identifiers Names and Codes (LOINC) are several biomedical ontologies, introduced to deliver semantic interoperability and complete knowledge related to the specific biological and medical domains [43]. Most laboratory and clinical systems send data using the HL7 (V. 2) protocol. In an HL7 message, LOINC codes represent the “question” for a laboratory test or experiment, and the SNOMED-CT code describes the “answer”. In this study, we have reused the SNOMED-CT ontology for modeling the health condition based on health and wellness data and recommendation generation [44]. It is an organized list of various clinical terminology defined with unique codes (ICD). It covers a wide range of medical terminologies for disorders and findings (what was observed!), procedures (what was done!), events (what happened!), substance/medication (what was consumed or administered!), and anything related to medical data. It offers a shared language that enables reliable indexing, storing, reclaiming, and accumulating of clinical data across fields and care sites. It is complete, multilingual clinical terminology that gives clinical content and clarity for clinical documentation and reporting [45]. Integration of SNOMED-CT into FHIR can harness the rich representability (e.g., unambiguity, structured, cohort, easy decision-making) of clinical terminologies for semantic interoperability during the exchange of FHIR resources between systems [14]. The power of FHIR in SNOMED-CT may produce the best health information model [14].

3.4.2.3 Ontology Editors

Protégé, TopBraid Composer, NeOn Toolkit, FOAF editor, WebOnto, OntoEdit, Ontolingua Server, Ontosaurus, and WebODE are some popular ontology editors [24] These ontology editors are open-source ontology development tools with OWL support. Apache

Jena is a Java-based framework used for building semantic web applications. It provides an API to extract data from and write to RDF graphs. A Jena framework includes the following –

- RDF API to parse, create, and search RDF models in XML, N-triple, N3, and Turtle formats. Triples can be stored in memory or database,
- ARQ Engine/SPARQL API is a query engine for querying and updating RDF models using the SPARQL standards,
- TDB Engine as a high-performance RDF store on a single machine,
- Ontology API for handling OWL and RDFS ontologies. and
- Apache Jena Fuseki is the SPARQL server for supporting queries and updates. It is tightly integrated with TDB to deliver a robust, transactional persistent storage layer. The framework has internal reasoners and an OWL API [24].

In this study, we have used Protégé for ontology design, development, and reasoning, and Apache Jena for ontology querying.

3.4.2.4 Ontology Reasoning

A reasoner is a crucial component for working with OWL ontologies. It derives new truths about the concepts being modeled with OWL ontology. Practically, all querying of an OWL ontology (and its import closure) can be done using a reasoner [24]. That is why knowledge in an ontology might not be explicit, and a reasoner is required to deduce implicit knowledge so that the correct query results are obtained. The OWL API includes various interfaces for accessing OWL reasoners. Reasoners can be classified in the following groups [24] – OWL DL (Pellet 2.0, HermiT, FaCT++, RacerPro), OWL EL (CEL, SHER, snorocket, ELLY), OWL RL (OWLIM, Jena, Oracle OWL Reasoner, and OWL QL (Owlgres, QuOnto, Quill).

Protégé is a free, open-source, and popular OWL ontology editor and framework for building intelligent systems. It supports the following reasoners: HermiT, Pellet, Fact++, RacerPro, and KAON2. In this research, we will only discuss the reasoning of description logic. Description logic is created with a focus on controllable reasoning. OWL DL is based on the SHIQ description logic with well-defined semantics, formal representation of properties in terms of complexity and decidability, known reasoning algorithms, and highly optimized implemented systems [24]. Given an assertion box (ABox), we can reason with a terminological box (TBox) about the following –

- Consistency check to ensure individuals in ABox do not contravene descriptions and axioms described by TBox and do not contain any conflicting facts.
- Concept Satisfiability to determine whether an individual or class-instance or object can exist that would be instanced of the concept regarding an ontology (O). In ontology O, for each axiom, $C \subseteq D \in O$, add $\neg C \cup D$ to every node label.

- Concept subsumption to describe if concept C is more general than the description of another concept D.
- Checking of an individual to determine if the individual is an instance of a concept C.
- Classification to develop a tree-like model of the input concept C and followed by, decomposing C syntactically.
- Retrieval of individuals to check if all individuals are instances of a concept C.
- Realization of an individual to check if all concepts to which the individual belongs to, mainly the most specific ones (direct type).

Furthermore, Ontology reasoning can be classified into inductive, deductive, and abductive.

3.4.2.5 Ontology Querying

In relational databases, Structured Query Language (SQL) is used as a standard programming language to manage a database and its data. However, in ontologies, SPARQL and Semantic Query-Enabled Web Rule Language (SQWRL) are used to write rules (premise $\rightarrow$ conclusion) for data retrieval. RDF gives a triple format to represent distributed data, simply with named connections. SPARQL gives a standard way to access RDF data. SPARQL query patterns follow a variation of the Turtle format. SPARQL contains a set of triplets called a basic graph pattern, where the subject, object, and predicate may be variable. SWRL is a Semantic Web Rule Language (SWRL)-based language for querying OWL ontologies. Some statements cannot be expressed in OWL. Therefore, SWRL allows writing rules that can be described in terms of OWL concepts to give more powerful deductive reasoning capabilities than OWL alone. All variables in SWRL are treated as universally quantified ($\forall$) with a scope limited to a given rule. SWRL provides the following seven types of atoms: class, individual property, data-valued property, different individuals, same individual, built-in, and date range.

3.5 Data Processing

The primary learning process is similar to whether the learner is a human or a machine. It can be broken down into the following four interrelated parts – *Data storage* uses observation, memory, and recall to provide a factual basis for further consideration. *Abstraction* involves transforming stored data into more comprehensive representations and concepts. *Generalization* uses abstract data to create knowledge and conclusions that drive action in new contexts. The *assessment* provides a feedback mechanism to measure the usefulness of what has been learned and inform possible improvements.

3.5.1 Statistical Exploration

Statistical methods are mathematical formulas, models, and techniques used for the statistical analysis of raw research data. We have used the following statistical methods in the dissertation.

3.5.1.1 Covariance and Correlation Coefficient

Covariance is a property of a function to retain its form when its variables are linearly transformed. In contrast, the correlation measures the strength of linear relationships between two variables or features[6]. On a scatter plot, each observation is represented as a point with x-coord x_i and y-coord y_i.

Covariance: $Cov(x, y)$

$$cov_{x,y} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{n-1} \tag{3.1}$$

- If x and y are positively associated, then $Cov(x, y)$ will be large and positive
- If x and y are negatively associated, then $Cov(x, y)$ will be large and negative
- If the variables are not positively nor negatively associated, then $Cov(x, y)$ will be small

Correlation Coefficient: r

$$r = \frac{1}{n-1}\sum_{i=1}^{n}(\frac{x_i - \overline{x}}{s_x})(\frac{y_i - \overline{y}}{s_y}) \tag{3.2}$$

where

$$s_x = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n-1}} \tag{3.3}$$

and

$$s_y = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \overline{y})^2}{n-1}} \tag{3.4}$$

Therefore,

$$r = \frac{Cov(x, y)}{s_x s_y} \tag{3.5}$$

- Always falls between -1 and +1
- r value close to +1 or -1 indicates a strong linear association
- r value close to 0 indicates a weak association

[6]https://en.wikipedia.org/wiki/Covariance_and_correlation

3.5.1.2 Weighted Mean

The standard mean[7] of a non-empty finite tuple of data $(x_1, x_2, \ldots, x_n)$ is

$$\mu = \overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i = \frac{1}{n}(x_1 + \cdots + x_n) \tag{3.6}$$

The weighted mean[8] of a non-empty finite tuple of data $(x_1, x_2, \ldots, x_n)$, with corresponding non-negative weights $(w_1, w_2, \ldots, w_n)$ is

$$\mu = \overline{x} = \frac{\sum_{i=1}^{n} x_i.w_i}{\sum_{i=1}^{n} w_i} = \frac{(x_1.w_1 + \cdots + x_n.w_n)}{(w_1 + \cdots + w_n)} \tag{3.7}$$

The extended standard mean calculation with weighted mean calculation to determine personal activity intensity on a weekly basis and thereby use the information in physical activity recommendations (e.g, based on the progress, the activity on Week-2 will likely match the action performed; however, your activity was excellent on Week-3).

3.5.1.3 Standard Deviation

In statistics, the standard deviation (σ)[9] measures the amount of variation or dispersion of a set of values. A low standard deviation indicates that the values tend to be close to the set's mean or expected value, while a high standard deviation indicates that the values are spread out over a broader range.

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{3.8}$$

σ = population standard deviation
N = the size of the population
x_i = each value from the population,
μ = the population mean

The standard deviation can be helpful to determine weekly or monthly deviation in physical activities for personalized recommendation generation.

3.5.1.4 Hypothesis Testing

Hypothesis testing[10] is a statistical process in which analysts test hypotheses about population parameters. Hypothesis testing is used to assess a hypothesis's probability using sample data from a larger population or the data generation process. The null hypothesis claims that there is nothing different or special about the data. It is determined with a p-value and a value of significance (α). If the p-value is greater than α, then the null hypothesis is rejected. In the activity datasets, hypothesis testing is useful to determine

[7] https://en.wikipedia.org/wiki/Mean
[8] https://en.wikipedia.org/wiki/Weighted_arithmetic_mean
[9] https://en.wikipedia.org/wiki/Standard_deviation
[10] https://en.wikipedia.org/wiki/Statistical_hypothesis_testing

whether the data looks Gaussian or not, and the respective methods are Shapiro–Wilk, D'Agostino's Kˆ2, and Anderson–Darling test [7]. The normality test can be performed following the hypothesis testing method with p-value $> \alpha = 0.05$ (i.e., the sample looks like Gaussian) and p-value $\leq \alpha = 0.05$ (i.e., the sample does not look like Gaussian). Furthermore, the Augmented Dicky-Fuller hypothesis test with autolog = 'AIC' and regression = 'CT/C' can be useful to verify stationary in time-series data [46].

H_o: Null hypothesis is a tentative assumption about a population parameter.
H_a: Alternative hypothesis is what the test is attempting to establish.

3.5.1.5 Normal Distribution

The normal distribution[11] is the most common type used in machine learning analysis. The normal distribution, also known as the Gaussian distribution, is a symmetrical probability distribution about the μ, indicating that data close to the mean is more common than data farther away. The normal distribution model is motivated by the Central Limit Theorem. The theory states that the μ calculated from independent, identically distributed random variables is approximately normally distributed, regardless of the type of distribution from which the variable is obtained (assuming it has finite variance).

Random variable X is normally distributed with mean μ and standard deviation σ:

$$X \sim \mathcal{N}(\mu, \sigma^2) \tag{3.9}$$

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2} \tag{3.10}$$

where, P(x) = probability density function

Z is a normal standard distribution with $\mu = 0$ and $\sigma = 1$.

3.5.2 Feature Selection

Feature selection[12] is the method of reducing the input feature space when developing a predictive model. It is desirable to reduce the dimension of input variables to reduce the computational cost of modeling and improve the model's performance. An optimal set of features help to reduce the model overfitting and training time. The followings are the feature selection techniques in AI[13] –

- Statistical approach (a special supervised filter technique): Correlation analysis (e.g, Pearson's or spearman), Analysis of variance (e.g, ANOVA, Kendall), and Univariate selection with statistical method (e.g, SelectKBest with chi-squared)

[11] https://en.wikipedia.org/wiki/Normal_distribution
[12] https://en.wikipedia.org/wiki/Feature_selection
[13] https://scikit-learn.org/stable/modules/feature_selection.html

- Optimal solution approach: Meta-Heuristic (e.g., Genetic algorithm, swarm intelligence, stochastic search)
- Supervised approach: Feature importance approach (e.g., ExtraTreesClassifier), Wrapper (e.g, Recursive feature elimination)
- Unsupervised approach: Machine learning-based variance ratio (e.g, Principal component analysis (PCA)), Deep learning-based (e.g, Deep belief network, auto-encoder)

Deep learning performs automatic feature engineering. An automatic and manual feature selection method can be promising in prediction modeling. Therefore, to better understand the manually selected features, the traditional approaches can better understand feature ranking and feature importance. In this study, we have used methods from statistical, supervised, and unsupervised techniques for feature ranking and manual feature selection from wearable sensor-generated activity data.

3.6 Time-Series Analysis

In mathematics, a time-series[14] is a sequence of discrete-time data points indexed (or listed or graphed) in temporal order. Generally, a time-series is a sequence taken at successive equally spaced points. Time-series are used in statistics, signal processing, pattern recognition, econometrics, mathematical finance, weather forecasting, earthquake prediction, electroencephalography, control engineering, astronomy, communications engineering, and primarily in applied science and engineering, which involves temporal measurements. Time-series analysis [47] comprises methods for analyzing time-series data to extract meaningful statistics and other data characteristics. Time-series forecasting uses a model to predict future values based on previously observed values. Methods for time-series analysis may be divided into two classes: frequency-domain methods and time-domain methods. The former includes spectral and wavelet analysis; the latter includes auto-correlation and cross-correlation analysis.

Additionally, time-series analysis techniques may be divided into parametric and non-parametric methods [47]. The parametric techniques consider that the underlying stationary stochastic process has a particular structure that can be described using several parameters (e.g., an autoregressive (AR) or moving average (MA) model). In such approaches, the task is to evaluate the parameters of the model that describes the stochastic process. By contrast, non-parametric systems explicitly estimate the covariance or the spectrum of the process without assuming that the process has any particular structure. Time-series analysis methods may also be divided into linear and non-linear, univariate, and multivariate. An example of time-series data is daily step count.

Time-series components [47] can be divided into two categories: systematic and non-systematic. A given time series may consist of three systematic components: level, trend, seasonality, and one non-systematic component called noise [48]. Systematic components have consistency or recurrence and can be described and modeled. In contrast, the time-series non-systematic components cannot be directly modeled. Therefore, time-series

[14] https://en.wikipedia.org/wiki/Time_series

data often requires cleaning, scaling, and transformation. Time-series data is strictly sequential; however, highly prone to non-stationary, auto-correlation, trend, and seasonality. Augmented Dicky-Fuller hypothesis test [46] can verify whether a time-series is stationary or not. Seasonal decomposition with model = 'additive' and/or 'multiplicative' can be helpful in analyzing the data's trend, seasonality, and residual components. Non-stationary data can be converted to stationary with the difference transform method to remove trend and seasonality in time-series data. Auto-correlation and partial auto-correlation are helpful for parameter selection in time-series forecasting models. Time-series models are categorized into prediction (or classification) and regression (or forecasting) models.

3.6.1 Multi-Class Classification

For a given a data-set, a classification problem is building a model that associates a new object with the same structure as the others, the probability of belonging to the possible classes, and accordingly to the features of the objects associated with each class. A uni-variate time-series is an ordered set of real values, while a N dimensional multivariate time series consists of N different uni-variate time series with the same length. A time-series classification [49] problem is a problem where the objects of the dataset are univariate or multivariate time-series. Time-series classification methods are: distance-based approaches (e.g., Euclidian, Hamming, Manhattan, and Minkowski), shapelet, model ensembles, dictionary approaches, interval-based approaches with an ensemble of classifiers, and deep neural network (e.g, Multi-layer Perceptron (MLP), Convolutional Neural Net (CNN), Recurrent Neural Net (RNN), Long Short-Term Memory Networks (LSTM), RandOM Convolutional KErnel Transform (Rocket), MiniRocket, and MiniVotingRocket).

With growing time-series physical activity data, deep learning model-based activity level multi-class classification can be useful in personal activity monitoring and recommendation generation for activity eCoaching. In this study, we have used MLP for time-series classification. The MLP is a Fully Connected Neural Net (FCNN) and a basic MLP model looks like it as depicted in Figure 3.2.

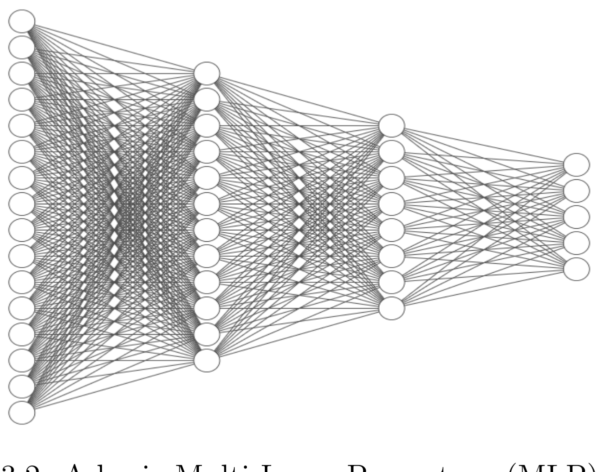

Figure 3.2: A basic Multi-Layer Perceptron (MLP) model.

MLP [50] is a neural network in which the mapping between input and output is non-linear. MLPs have input and output layers and multiple hidden layers with many stacked neurons. In a perceptron, neurons must have an activation function that imposes a threshold, such as ReLU or Sigmoid, whereas neurons in MLP can use any activation function. MLPs fall into the category of feedforward algorithms because the input is combined with the initial weights into a weighted sum and influenced by an activation function, just like a perceptron. The difference, however, is that each linear combination is passed to the next layer. Each layer provides the result of its computation, the internal representation of the data, to the next layer. It goes all the way through the hidden layer to the output layer. Backpropagation [50] is a learning mechanism that allows an MLP to iteratively adjust the weights in the network to minimize the cost function. After the weighted sum is propagated to all layers in each iteration, the mean squared error gradient for all input and output pairs is computed. Then update the weights of the first hidden layer with the gradient values to propagate them back. This process continues until the gradient of each input-output pair converges, which means that the newly computed gradient compared to the previous iteration does not exceed the specified convergence threshold. One iteration of gradient descent in MLP can be represented as follows −

$$\triangle_w(t) = -\epsilon \frac{dE}{d_w(t)} + \alpha \triangle_w(t-1) \tag{3.11}$$

$\triangle_w(t)$ = Gradient current iteration
ϵ = Bias
α = Learning rate
dE = Error
$d_w(t)$ = Weight vector
$\triangle_w(t-1)$ = Gradient previous iteration

3.6.2 Univariate Forecasting and Interval Prediction

Time-series forecasting [46, 51] means predicting the future value over a time period. It entails developing models based on historical data and applying them to make observations and advise on forthcoming strategic decisions. Time-series adds a temporal order dependency between observations. Such dependence is both a constraint and a structure to provide a source of further information. During forecasting, the predictive model may suffer from the following − volume of available data, time duration for the prediction, update frequency of forecasting, and temporal frequency of forecasting. Classical time-series forecasting methods are statistical (e.g, AR, MA, Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving-Average (SARIMA), Seasonal Autoregressive Integrated Moving-Average with Exogenous Regressors (SARIMAX), Simple Exponential Smoothing (SES), and Holt Winter's Exponential Smoothing (HWES)), and deep neural network (e.g, 1-D CNN, LSTM). With growing time-series physical activity data, deep learning model-based uni-variate step prediction can be useful in personal activity monitoring and recommendation generation for activity eCoaching. In this study, we have used 1-D CNN for time-series forecasting. A basic CNN model looks like this, as depicted in Figure 3.3.

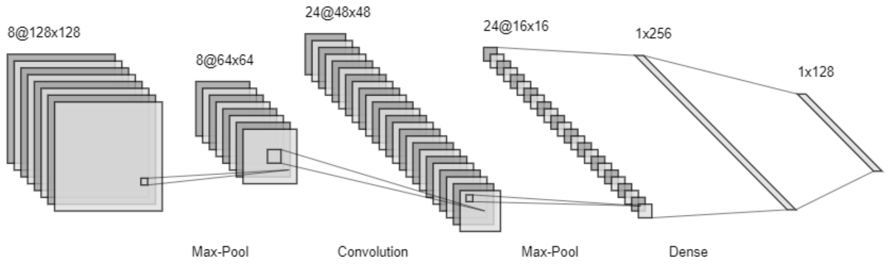

Figure 3.3: A basic Convolutional Neural Net (CNN) model.

CNN is a natural extension to MLP [52]. The input layer of a 1-D CNN takes a fixed-length subsequence of the total time-series and passes it to the convolutional layer [50]. The convolutional and pooling layers smooth the input. Convolution can be considered a "weighted sum of memories" or echoes. Discrete-time convolution generalizes moving averages, so the weights are non-zero and may not sum to 1. Just like a moving average, it smoothes the time-series. A convolutional layer may have multiple filters. The vector (one for each filter) resulting from the inner product of all these weights and all k elements of the original vector is a convolutional layer. Pooling is the process of dividing a vector into non-overlapping equal-sized groups or "pools" and then generating summary statistics for each group. The ReLU layer applies a non-linear ReLU transform to the smoothed subsequence. The output takes a vector-valued result from it and puts it into another activation function, giving class probabilities, continuous-valued responses, counts, or other activation-based selections.

The "step" prediction can be improved with a probabilistic interval prediction approach. Probabilistic methods are a remarkable technique for proving the existence of combined objects with certain properties. It is based on probability theory, but surprisingly, it can be used to prove theorems that have nothing to do with probability. In predictive inference, a prediction interval is an estimate of an interval in which future observations will have some probability of falling, assuming what has already been studied. Prediction intervals are often used in prediction analysis (e.g, step prediction). The prediction interval, which gives the gap to maintain a specific probability value, can be written as −

$$\widehat{Y}_{T+h} \pm c\sigma_h \tag{3.12}$$

c changes with coverage probability. In a one-step interval, prediction c is 1.28 (80% prediction intervals where forecast errors are normally distributed). σ_h is the estimation of the residual standard deviation in the h-step forecast distribution ($h > 0$). Residual standard deviation is used to statistically describe the difference in the standard deviation of observed values versus standard deviations of estimated values.

The value of forecast intervals is that they express uncertainty in the forecast. If we only make point predictions, there is no way to judge the accuracy of the predictions. However, if we also create forecast intervals, it becomes clear how much uncertainty is associated with each forecast. Therefore, point forecasts are of little value without an associated forecast interval[15]. The benchmark methods for prediction interval are –

- Mean forecasts:

$$\widehat{\sigma_h} = \hat{\sigma}\sqrt{1 + \frac{1}{1+T}} \tag{3.13}$$

- Naïve forecasts:

$$\widehat{\sigma_h} = \hat{\sigma}\sqrt{h} \tag{3.14}$$

- Seasonal naïve forecasts:

$$\widehat{\sigma_h} = \hat{\sigma}\sqrt{k+1} \tag{3.15}$$

  k is the integer part of $(h-1)/m$, and m is the seasonal period.

- Drift forecasts:

$$\widehat{\sigma_h} = \hat{\sigma}\sqrt{1 + \frac{h}{T}} \tag{3.16}$$

If $h = 1$ and T are large, then all will produce the same approximate value for $\widehat{\sigma_h}$.

3.6.3 Model Evaluation Metrics

Time-series multi-class classification models can be evaluated against precision, recall, specificity, accuracy score, F1 score, classification report, and confusion matrix. Accuracy tells how close a measured value is to the actual one. Recall or sensitivity suggests the exact number of positive measures. Precision means how relative the measured value is to the actual one. A confusion matrix is a 2-dimensional table (*actual* vs. *predicted*), and both dimensions have $TruePositives(TP)$, $FalsePositives(FP)$, $TrueNegatives(TN)$, and $FalseNegatives(FN)$ [7]. The equations to calculate classification metrics are –

$$Accuracy(A) = \frac{TP+TN}{TP+TN+FP+FN}, 0 \leq \frac{A}{100} \leq 1 \tag{3.17}$$

$$Precision(P) = \frac{TP}{TP+FP} \leq 1 \tag{3.18}$$

$$Recall(R) = Sensitivity = \frac{TP}{TP+FN} \leq 1 \tag{3.19}$$

$$F1 = \frac{2*P*R}{P+R} = \frac{2*TP}{2*TP+FP+FN}, 0 \leq \frac{F1}{100} \leq 1 \tag{3.20}$$

Accuracy and *F1-scores* can be misleading because they do not fully account for the sizes of the four categories of the confusion matrix in the final score calculation. In

[15] https://otexts.com/fpp2/prediction-intervals.html/

comparison, the *MCC* is more informative than the *F1-score* and *Accuracy* because it considers the balanced ratios of the four confusion matrix categories (i.e., *TP, TN, FP*, and *FN*). The *F1-score* depends on which class is defined as a positive class. However, *MCC* does not depend on which class is the positive class, and it has an advantage over the *F1-score* as it avoids incorrect positive classes [53]. The *MCC* is expressed as follows[18].

$$MCC = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{3.21}$$

Time-series forecasting models can be evaluated against mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and forecast bias (FB) [46]. MAE is a measure of errors between paired observations representing the same phenomenon. MSE informs how close the regression line is to a set of points. It calculates "errors" from the points to the regression line and squares them to eliminate negative signs. The squared root of MSE is called RMSE, which gives more weight to a significant difference with no bias. FB can be positive or negative. A non-zero mean prediction error value indicates the tendency of the model to predict too high (negative error) or too low (positive error). Therefore, the mean forecast error is also known as FB. If forecast error = 0, the forecast has no error or perfect skill for that prediction. Overprediction if prediction variance < 0, the model is unbiased if prediction variance ≈ 0. Equations to calculate regression metrics are −

$$MAE = \sum_{i=1}^{D} |x_i - y_i| \tag{3.22}$$

$$MSE = \sum_{i=1}^{D} (x_i - y_i)^2 \tag{3.23}$$

$$RMSE = \sqrt{MSE} \tag{3.24}$$

$$|FB| = \frac{(x_i - y_i)}{|(x_i - y_i)|} \tag{3.25}$$

$$|FB| = \frac{(x_i - y_i)}{|(x_i - y_i)|} \tag{3.26}$$

y_i = predicted value
x_i = actual value

3.6.4 Activation Functions

In artificial neural networks, a node's activation function defines that node's output, given an input or set of information. The popular activation functions are[16]: Sigmoid (logistic), Tanh, ReLU, Leaky ReLU, Softmax, GeLU, and SeLU. This study focuses on ReLU and Softmax non-linear activation functions to model deep neural networks. ReLU [54] is the most commonly used activation function in hidden layers of neural networks. It enables

[16]https://en.wikipedia.org/wiki/Activation_function

faster and more efficient training by mapping non-negative values to zero and keeping positive values. Its main advantage is that it avoids and fixes the vanishing gradient problem and is less computationally expensive than Tanh and Sigmoid. But it also has some drawbacks. Sometimes, some gradients can be fragile and die during training. It causes neurons to die. The ReLU can be represented as −

$$Relu(z) = max(0, z) \tag{3.27}$$

In general, we use a softmax function [54] in the last layer of a neural network, which computes the probability distribution of an event over n different events. The main advantage of this function is the ability to handle multiple classes. Due to construction, the softmax probabilities always add up to 1. A Softmax can be represented as −

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad for\ i = 1, 2, \ldots, K \tag{3.28}$$

3.6.5 Performance Optimizer

In deep learning, model performance optimization is an essential process that optimizes the input weights by comparing the prediction and the loss function. The Adam optimization algorithm [55] extends stochastic gradient descent in deep learning applications. Therefore, Adam can be used instead of the classical stochastic gradient descent method to update the iterative network weights based on training data. Adam realizes the benefits of the Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation (RMSProp) [55]. AdaGrad maintains a per-parameter learning rate that improves performance on problems with sparse gradients. RMSProp maintains per-parameter learning rates adapted based on the average current magnitudes of the gradients for the weight. Instead of adapting the parameter learning rates based on the average first moment as in RMSProp, Adam also uses the average of the second moments of the gradients (or the uncentered variance). We have used the ADAM optimizer in our deep neural network models, as it is computationally efficient and demands less memory. ADAM configuration parameters are α (learning rate), β_1 (exponential decay rate for the first moment estimates), β_2 (exponential decay rate for the second-moment estimates), and ϵ (a tiny number to prevent any division by zero). In Keras, the default ADAM configuration is[17]: α=0.001, β_1=0.9, β_2=0.999, ϵ=1e-08, decay=0.0. The other optimizer as a module, supported by Keras are[18] − Stochastic gradient descent optimizer (SGD), Adadelta, Adamax, and Nadam.

3.6.6 Hyperparameter Tuning and Cross-Validation

Hyperparameter tuning is an important step in building a deep learning model. Examples of hyperparameters in deep learning are learning rate, dropout rate, batch size, number of filters, kernel size, pooling size, number of strides, selection of activation function, number of hidden layers, and number of neurons per layer. The generally used techniques are −

[17] https://www.tensorflow.org/api_docs/python/tf/keras/optimizers/Adam
[18] https://www.tutorialspoint.com/keras/

Grid search, Random search, Bayesian optimization, Evolutionary algorithms, and Automated machine learning (AutoML) tools. Tuning hyperparameters is critical in achieving good performance in deep learning models. The available resources, the nature of the problem, and the algorithms used should be carefully considered. Which method is chosen depends on the size of the hyperparameter space, the time and resources available, and the computational power of the system. In this study, we use the Grid search method for hyperparameter tuning in deep learning classification and forecasting models. Grid search is a brute force method that evaluates the performance of a model using a predefined set of hyperparameter values.

Cross-validation is a general technique used in deep learning to evaluate the performance of a model. Its purpose is to measure how well a trained model generalizes to new, unseen data. In cross-validation, the available dataset is divided into several subsets, usually two or more. One subset is used to train the model and the remaining subset is used for validation. This process is repeated multiple times, and each subset is eventually used for training and validation. The average of the results is calculated from each iteration to get a final performance estimate of each model. The cross-validation techniques are – K-fold, stratified, and leave-one-out. We have used the stratified K-fold cross-validation technique (as the dataset is imbalanced), where we divide activity datasets into k subsets, the deep learning model is trained using k-1 subsets, and the remaining subset is used for validation. This process has been repeated k times, and each subset is used for verification.

3.6.7 Personalized Health Recommendation Generation

Recommendation technology can be defined as a decision-making approach in complex information environments. Health recommendations offer the potential to engage and motivate users to change their behavior by sharing better decision-making and actionable knowledge based on observed user behavior. A Health Recommendation System (HRS) [56] aims to enable people to monitor and improve their health through technology-enabled personalized recommendations. HRS differs from clinical decision support systems, which advise healthcare professionals. In HRS, behavioral advice can be divided into four categories: lifestyle, diet, general health information, and specific health conditions. The main aspects to consider in HRS are the usage context, users, and items. Users are end-users, and items are suggestions that users search for. Recommendations can be generated either at the personal level or at the community level. As vital health signs are personalized and vary from person to person based on conditions and demography, the recommendation models must be very personalized. Personalized recommendations can be turned into behavioral motivations with the adoption of specific techniques, such as reward or credit maximization, emojis, lifestyle goal management, profile ranking, timely notification generation, and meaningful delivery. HRSs are information filtering systems that generate and deliver personalized and contextual recommendations in real-time. Health recommendations generation techniques can be classified among the following four categories [10, 56, 57, 58, 59, 60, 61] –

1. Collaborative filtering: It is the most used and mature technique that compares the

actions of multiple users to generate personalized recommendations. In collaborative filtering, items are filtered out based on the user's choice or reactions by similar users. It searches a large group of people to find a smaller set of users having similar tastes to a particular user. In HRS, patients who convey similar disease profiles/health conditions would have comparable treatments/healthcare services based on the similarity scores and ranking vectors.

2. Content-based filtering: It recommends items similar to other things the specific user prefers. They rely on the features or genre of the objects themselves and are likely to be highly appropriate to a user's interests. In HRS, this technique suggests healthcare services that fit the patient's health condition and are similar to those assigned to them in the past.

3. Knowledge-based filtering: This type of filtering use detailed knowledge about an item, user preferences, and other recommendation measures. Nevertheless, knowledge acquisition can also be dynamic and depends on user feedback. This technique creates recommendations based on knowledge about the items, explicit user preferences, and limitations representing the dependencies between users' preferences and items' properties.

4. Hybrid (rule-based + data-driven) filtering: It combines rule-based and data-driven filtering techniques to increase the accuracy of recommendation generation. Solely data-driven recommendation technology with machine learning and deep learning algorithms suffer from insufficient data, high computing power, lack of interpretability, re-training for new cases, personalization, and cold-start problem. In data-driven filtering, models are more explicit, and in rule-based filtering, models are interpretable as logic is detailed. In contrast, a rule-based recommendation technology uses binary logic in a symbolic form to present knowledge in IF-THEN or IF-ELSE-THEN rules and infer new knowledge with reasoning. A hybrid technique can effectively overcome the failings of both data-driven and rule-based recommendation technologies. The majority of HRSs use hybrid recommendation techniques.

This study focuses on the personalized hybrid recommendation generation technique in activity eCoaching. The data-driven approach includes AI, statistical and probabilistic methods. The rule-based approach utilizes ontology reasoning and querying features.

3.7 Chapter Summary

In this chapter, we have discussed different aspects of integrating interdisciplinary concepts required to design and develop a health eCoach recommendation system. The health intervention discusses related methods for a healthy lifestyle. Afterward, we reviewed existing human coaching methods applicable in eCoaching as behavioral intervention. The related work part identifies existing studies related to recommendation generation processes in activity eCoaching. Furthermore, this part introduces our recommendation generation approach to address the shortcomings of existing literature and make the state-of-the-art balanced. In the semantics part, we have discussed formal knowledge representation techniques to exploit data semantics. We have presented data integration techniques with ontologies to give a semantic annotation to unstructured data to create a compact, intelligible abstraction. Restful Web services describe the management of resources over the web. In the data processing part, we have discussed different deep learning, statistical and probabilistic methods to process personal physical activity time-series datasets for health state monitoring. In the recommendation part, we discuss other health recommendation generation techniques and their delivery methods. In the design part, we briefly describe the human-centered design approach. In this work, we have selected an ontology-based data integration approach to solve data integration issues in personal and person-generated health data collection and personalized recommendation presentation. Furthermore, we have used an iterative UCD approach to design and develop an eCoach system for physical activity, effectively integrating the offline human coaching components. Moreover, a hybrid recommendation generation model has been conceptualized inside our eCoach system.

Chapter 4

Objectives and Requirements

The aim of this research project is to design, develop, and technically evaluate the performance of an intelligent eCoach system for health and wellness observation, assessment, person-generated data collection, and governance, and for the generation and provisioning of personalized and automatic recommendation generation. It requires proper planning to make it successful. This chapter explains the strategies for further study design based on the outcome of UCD workshops to run the experiments.

4.1 Objectives

Our research focus is on health prevention with the reinforcement of positive habits using effective lifestyle recommendation generation and does not include the treatment or health intervention of any type of diagnosed state of illnesses. The overall objective is to carry out a technical PoC study, rather than a clinical research study of health outcomes. This research project does not aim at knowledge about the treatment of health and illness, nor does it deliver and evaluate any medical software applications that aim at the treatment of any state of illness, or at any such health interventions. As the health eCoaching's application area in self-management is broad, we select activity eCoaching as a study case for this research based on the input from end-users and experts involved in the UCD workshops. A goal is a specific outcome or purpose that a project expects. Project goals determine what is to be achieved throughout the project and should be directly related to the problem and vision. Goals are achieved through project objectives and activities. Objectives are the specific steps that lead to the successful completion of a project objective. The achievement of objectives produces specific, measurable, achievable, relevant, and time-bound (SMART) [62] results that directly contribute to the achievement of project goals. Based on the UCD workshops, we list the objectives to plan the steps to meet the eCoach prototype design and development requirements.

- *What data to collect?* The activity eCoach system will collect heterogeneous data from external sources, and turn them into meaningful information,
- *What data to share?* The activity eCoach system will have a proper data sharing plan following the GDPR guidelines,

- *What recommendations to generate?* The activity eCoach system will generate automatic and personalized physical activity recommendations,
- *What information to present in recommendations?* The activity eCoach mobile application will visualize continuous and discrete data, personalized recommendations, and activity goals in a meaningful way.

4.2 Requirements

This section describes the collection, filtering, and documenting process of user requirements from the UCD workshops and the selection of specific requirements to meet the research objectives. We have also shown a direction to categorize the selected software requirements.

4.2.1 Requirement Collection and Filtering

Software requirements can be either functional or non-functional. Functional requirements give specifications for each atomic operation or functionality and the non-functional requirements strictly focus on visualization, usability, security, maintainability, interoperability, scalability, compatibility, operational, performance, compliance, and cultural requirements. We consider requirements that are specific, measurable, achievable, relevant, and time-bound (SMART), and should reflect the needs and expectations of the users for this technological verification study. We avoid voice recognition, language processing, image processing, random controlled trials, cultural aspects, social traits, group-based recommendation generation, medical parameters, such as BMI, weight reduction, calories, nutrition, habit (tobacco and alcohol consumption), sentiment, stress, sleep, historical data, cholesterol levels, blood pressure, heart rate, and medical status for clinical evaluation. We turn the adopted requirements into a granular level for the preparation of test cases to technically evaluate our activity eCoach prototype.

4.2.2 Documenting User Requirements

The UCD Workshop 1 helps to collect high-level functional and non-functional requirements on the opportunities of having an eCoach system and its importance on the self-management of physical activity, data collection approach, data governance method, personalization and goal-settings criteria on recommendation generation, and feedback generation to motivate self-management. We turn "SMART" requirements from high-level design requirements into low-level detailed design requirements by breaking down the overall design into smaller, more specific components and defining their implementation details. We prepare a low-fidelity activity eCoach prototype based on the documented user requirements from Workshop 1 as a stepping stone for UCD Workshop 2 and improve it further based on the end-user feedback. In Table 4.1 and Table 4.2, we document all the relevant and considered requirements (REQS-ID), corresponding use case (NEEDS-ID), requirement description, rationale, the fit criterion for the eCoach prototyping. For all the requirements, we have considered the standard Volere satisfaction/dissatisfaction scale (1-5).

4.2.3 Mapping Requirements with Objectives

The UCD approach has given us an understanding of end-users' requirements to design and develop our activity eCoach app. The foremost requirements for the eCoach app design and development as derived from the UCD approach are described in this section to meet the objectives. We describe the requirements to meet the objectives by connecting "What" with "How" (see Table 4.3).

4.2.3.1 How to collect required data?

Data serves as input for the activity eCoaching session. Therefore, according to the context, appropriate selection of data, data collection methods, and defined data collection frequency are essential in eCoaching. Our study aims to collect personal data, personal preferences, and person-generated behavioral data (e.g., physical activity) and contextual data (e.g., external weather) to meet the project objective.

- The personal dataset comprises height, weight, age (date of birth), gender (male, female, or others), contact details (address with postcode, mobile, and email), education, designation, and medical history (illness, hospitalization) of last one year and severe chronic health issues (e.g., high BP, high diabetes, high cholesterol, high BMI and similar).

- The preferences are following three types: activity goal setting type (e.g., nature of goals, direct vs. motivational goals, and generic vs. personalized goals), response type (e.g., way to communicate extended health state, health state prediction, and customized recommendation generation for activity coaching), and type of interaction with the eCoach system (e.g., interaction mode, frequency, and medium). Therefore, the personal preference data may consist of goal-setting types (e.g., daily, weekly, or monthly), target goal (e.g., medium active or vigorous active), target score, mode of interaction, or recommendation message delivery (e.g., text, audio, or graph), and time of recommendation message delivery. The generic goals in activity coaching correspond to the activity guidelines set by the World Health Organization (WHO). Participants are allowed to view and update their preference information over time through the eCoach app. Preference data are important for recommendation generation planning and recommendation message delivery.

- The physical activity data are processed signal data with the following features - the intensity of physical activity (IMA), sedentary bouts, step count, levels of physical activities (e.g., low physical activity or LPA, medium physical activity or MPA, vigorous physical activity or VPA), and postures.

- The contextual parameters associated with weather forecast data are - minimum and maximum temperature, weather status (e.g., sunny, rain, cloudy, snow, or windy), humidity, real feel, wind speed, visibility, and location information in latitude and longitude.

For the objective of the project, targeted personal, personal preference, and person-generated behavioral data will be collected via secure medical-grade (CE-approved) wearable sensors, weather sensors, and form-based questionnaires over time. We will keep the questionnaire short, easy to understand, and easy to answer and submit. Data collected from heterogeneous sources are raw, massive, and unstructured. Therefore, the concept of semantic ontology can turn them into meaningful information.

4.2.3.2 How to share data?

The design of the eCoach solution shall enforce a secure, ethical, and authorized handling of the data. In Norway, the Norwegian Center for Research Data (NSD)[1] and the Regional Committees for Medical and Health Research Ethics (REK)[2] are two authorities responsible for the security and privacy enforcement of personal data give ethical approval for healthcare research, and for the ethical approval, respectively. Our project has received approval from NSD (approval number: 797208) and REK (approval number: 53224). Written informed consent has been obtained from all participants. All data (i.e., video, audio, text) collected in this research are stored following the privacy protection guidelines without personal identity disclosure. For the objectives of this project, no studies of human interventions are required.

After collecting personal and person-generated health and wellness data from the participants, their privacy and security need to be ensured, based on strict access control rules. Collected data will be fed to AI models for generating meaningful information. Generated information will be required for the analysis of wellness trends, risk prediction, and the generation of corresponding recommendations. In line with the participant's consent or request, information about the participants will be anonymized (by removing personal identifiers, such as mobile number, email address, user ID, and postcode). It will be deleted at the latest after the project has ended. Participants will be given a secure user-id and modifiable password to authenticate themselves in the system. Participants will have read-only permission to view their personal and processed health data in the system. We have planned to impose access control rules and de-identification techniques for individual data access. The data collection process will be completely secure and without any risk of information leakage. We plan to use Transport Layer Security (TLS) and Virtual Private Network (VPN) technologies to secure data transmission. Collected data will be stored on a dedicated platform for collecting, storing, analyzing, and sharing sensitive data in compliance with the Norwegian privacy regulation established at UiA or in the TSD-System provided by UiO. Linking between unique user-id and personal identifiers (email/phone/postcode) will be stored in a secure environment, and there will be no clue to perform any cross-identification. Data management in the TSD system is

[1]https://www.nsd.no/en
[2]https://www.forskningsetikk.no/om-oss/komiteer-og-utvalg/rek/

Table 4.1: Documented functional requirements in ReqView software with Volere Requirements Specification Template.

REQS-ID	Use Case	Description	Rationale	Fit Criterion
REQS-1	NEEDS-1: User Login to the eCoach system	The eCoach system will accept valid user credentials and access tokens to allow legitimate users in the system	To allow legitimate users in system	A legitimate user is one who has valid authentication and authorization information
REQS-2	NEEDS-2: Connection to the activity sensor	The eCoach app. will establish a connection to the activity sensor over BLE	Individual activity data is required for predictive analysis	The eCoach app will connect to the activity sensor and collect temporal activity data
REQS-3	NEEDS-3: User interaction with the self-reported forms	Participant will upload their preference data, and activity goals in the form of a questionnaire	The preference and goal data will help to generate and present personalized recommendations	A legitimate participant can fill and submit form
REQS-4	NEEDS-3: User interaction with the self-reported forms	Participant will change their preference data and activity goals in the form of a questionnaire	The preference and goal data will help to generate and present personalized recommendations	A legitimate participant can change personal preference data and goal information
REQS-5	NEEDS-4: User interaction with eCoach UI	Participant will receive a pop-up notification in the eCoach app, based on pre-set time as preference data	Notification generation is a form of personalized recommendation message delivery to provide on-time alert	An active participant can receive pop-up notification
REQS-6	NEEDS-4: User interaction with eCoach UI	Participant will access their personal data, preference data, activity performance, notifications, and rewards over eCoach UI	To access personalized information and visual reflection of achieved performance	Active participants can only access their information
REQS-7	NEEDS-4: User interaction with eCoach UI	eCoach system will update individual activity performance in eCoach UI over time	To reflect the change in individual activity performance as graphical recommendation	Active participants can only visualize their change in activity performance

Table 4.2: Documented non-functional requirements in ReqView software with Volere Requirements Specification Template.

REQS-ID	Use Case	Description	Rationale	Fit Criterion
REQS-8	NEEDS-5: User interaction with eCoach GUI	The eCoach GUI must be designed with proper layout, content, icon, and color	A well-designed GUI can increase user engagement, reduce frustration, and ultimately lead to a more successful and effective eCoaching experience	A legitimate user can only access the eCoach GUI
REQS-9	NEEDS-5: User interaction with eCoach GUI	The eCoach app. should provide easy navigation between pages	Easy navigation is essential for creating a positive user experience and ensuring that users can access the information or functionality quickly and efficiently	A legitimate user can only navigate pages in the eCoach app.
REQS-10	NEEDS-5: User interaction with eCoach GUI	The eCoach GUI must be designed with proper layout for the visualization of daily, weekly, and monthly activity patterns	Visualization layout can help promote user engagement, satisfaction, and ultimately, better health outcomes	Active participants can only visualize their activity performance
REQS-11	NEEDS-6: User interaction with eCoach API	eCoach API must be protected from external attacks	protecting the eCoach API from external attacks, eCoach can provide a secure and reliable platform for eCoaching services	API security includes the security and integrity of the data being transmitted
REQS-12	NEEDS-6: User interaction with eCoach API	eCoach system must be designed and implemented in a way that allows for easy scalability to meet increased demand	Scalability is essential to handle a growing user base or increased transaction volume	The system must be designed using scalable architecture patterns, such as micro-services
REQS-13	NEEDS-6: User interaction with eCoach API	eCoach system must be designed and implemented in a way that allows semantic and structural interoperability	Semantic and structural interoperability ensures that eCoaching services can operate effectively and efficiently, with seamless communication between different systems, applications, and data sources	The system must be designed using appropriate protocols, such as HL7 FHIR, SNOMED, LOINC

Table 4.3: Mapping between Objectives and Requirements.

Objective(s)	Requirement(s)
What data to collect?	How to collect the required data?
What data to share?	How to share data?
What recommendations to generate?	How to generate personalized recommendations?
What information to present in recommendations?	How to present personalized recommendations?

General Data Protection Regulation (GDPR)[3] and NORMEN[4] compliant.

4.2.3.3 How to generate personalized recommendations?

In health eCoaching, the generation of personalized recommendations is essential for goal management and self-motivation. The recommendation generation module in the eCoach system should continuously monitor individual health states and generate contextual and meaningful recommendations. The recommendation generation can be data-driven or rule-based, or hybrid. An intelligent eCoach recommender can generate effective and meaningful recommendations when the below requirements are sorted − data required to build a recommender, data type to be used to build a recommender, filtering type (or rules) to be used in recommendation generation, algorithm to be used to build a recommender, technology to be used to automate the recommendation generation process, and mitigation of cold-start problem during the recruitment of new participants.

We use a hybrid approach (data-driven and rule-based) with deep learning algorithms and OWL ontology to generate personalized activity recommendations in our activity eCoach system, as detailed in the next chapter. Furthermore, we automate the recommendation generation process, integrate contextual data to make the customized recommendation generation process effective, and adopt an approach to mitigate the cold-start problem, and the same is elaborated in the following two chapters.

4.2.3.4 How to present personalized recommendations?

Besides, generating automatic, personalized, contextual recommendations, timely delivery, and meaningful presentation are essential to motivate eCoach participants. To visualize continuous and discrete data, customized recommendations, and activity goals in an eCoaching application for physical activity requires the following considerations on personal preference settings −

- Goal-settings (e.g., Nature of goals, Direct vs Motivational, and Generic vs Personalized)
- Response type (e.g., Direct vs Indirect)

[3]https://gdpr-info.eu/
[4]https://www.ehelse.no/normen

- Interaction type (e.g., Mode (style, graph), Frequency (e.g, hourly, quarterly, once, twice), and Medium (e.g., audio, voice, text))

The recommendation presentation must be on-time, short, understandable, simple, and positive. In the subsequent chapter, we have detailed the recommendation presentation (or visualization) approaches in terms of a simplified graph, notification, and reward maximization for our activity eCoach prototype system.

4.2.4 Requirement Categorization

We have categorized the documented requirements into the following groups based on the mapping between the objectives and requirements (see Table 4.4) − Data collection (DC), Data sharing (DS), Recommendation generation (RG), and Recommendation presentation (RP). It helps to create potential test cases for technological verification of our designed and developed activity eCoach prototype in laboratory settings. Some of the requirements will be evaluated theoretically and others will be evaluated experimentally. In the end, we plan to address all the documented requirements in our activity eCoach design and development.

Table 4.4: The categorization of documented requirements for eCoach prototyping.

REQS-ID	DC	DS	RG	RP
REQS-1	-	✓	-	-
REQS-2	✓	-	-	-
REQS-3	✓	✓	-	-
REQS-4	✓	✓	-	-
REQS-5	-	-	✓	✓
REQS-6	-	✓	-	-
REQS-7	-	✓	-	✓
REQS-8	-	✓	-	✓
REQS-9	-	✓	-	✓
REQS-10	-	✓	-	✓
REQS-11	-	✓	-	-
REQS-12	✓	-	-	-
REQS-13	-	✓	-	-

From the workshops, we identified many other technical and non-technical requirements for evaluation (e.g., usability, clinical effectiveness, reliability, adequacy, trustworthiness, and scalability of recommendation generation model); however, we plan to include them in the future scope (see Sub-Section 1.2.2 of Chapter 1) to maintain the focus of our study with time-constraint. Moreover, in Sub-Section 4.2.1, we have added how the requirements have been filtered for our eCoach prototype design and implementation!

4.3 Chapter Summary

In this chapter, We have turned objectives and requirements into technical requirements using the "Volere Requirements Specification Template" as a basis for the activity eCoach prototype design and development as a PoC, described in the subsequent chapter.

Chapter 5

Design and Development

In Workshop 1, we focused on identifying end-users, understanding the user's context, specifying user requirements, and designing and developing an initial low-fidelity eCoach prototype. In Workshop 2, we focused on maturing the low-fidelity solution design. This chapter explains the adopted approach to design and develops a working prototype of an activity eCoach system that meets the identified end-user requirements and expectations towards an evidence-based, adaptive, and personalized recommendation generation and its meaningful presentation. The overall design and its implementation address the objectives and requirements as stated in the previous chapter.

5.1 Design

The design phase has been critical in eCoach solution design, as it sets the foundation for the development of a working eCoach prototype of an activity eCoach system. During this phase, the user's requirements gathered in the UCD workshops have been translated into a detailed system design to guide the development team in building the eCoach prototype.

5.1.1 eCoach Solution Design

In this study, our focus on eCoaching has been physical activity coaching. Our eCoach mobile app design follows the standard Figma open-source software with "Google Material Design" guidelines and a modular design pattern. Figma[1] is a collaborative web application for interface design with additional offline capabilities enabled by desktop and mobile applications for Mac-OS, Android, and Windows. Figma and Google Material Design offer some useful benefits for UX designers. Figma's real-time collaboration, prototyping, vector-based, and cloud-based approach can increase efficiency and productivity. The Google Material Design provides usable themes, material guidelines, system icons, and color palettes to craft an intuitive eCoach app and ensure consistency, accessibility, and flexibility to create a more seamless user experience. In contrast, a modular system design can lead to more efficient, flexible, reusable, fault-tolerant, and reliable systems that are easier to develop and maintain.

[1]https://www.figma.com/

The software architecture of the activity eCoach solution design is depicted in Figure 5.1. The eCoach solution consists of two parts: *eCoach app part* - which is responsible for rendering the view, user interaction, and data collection to the end user device, and *eCoach back-end part* – which is the server hosted in the infrastructure and where the business logic (e.g., data processing, data persistence, and recommendation generation) is deployed. Figure 5.1 represents different functionalities supported by the eCoach app and eCoach back-end. We have followed the Model-View-Controller (MVC) architectural pattern to separate the eCoach system into three main logical components: the model, the view, and the controller. The Model component represents all the data-related logic at the eCoach back-end. It can handle data that is being transferred between the View and Controller components. The View component is used for all the UI logic of our eCoach application at the eCoach mobile app. The Controllers interface between the Model and the View to process all the business logic and incoming requests, data manipulation using the Model component, and communication with the Views to render the final output. eCoach controllers follow a Restful Microservice Architecture to expose their endpoints as RESTful Web APIs. Therefore, the eCoach app communicates with the eCoach back-end with HTTP methods, such as GET, POST, PUT, and DELETE, over a secure VPN channel ("EduVPN") to access resources. Only legitimate users are allowed to log in to the eCoach mobile app and edit to update their personal preference data with authentication and authorization (OAuth 2.0).

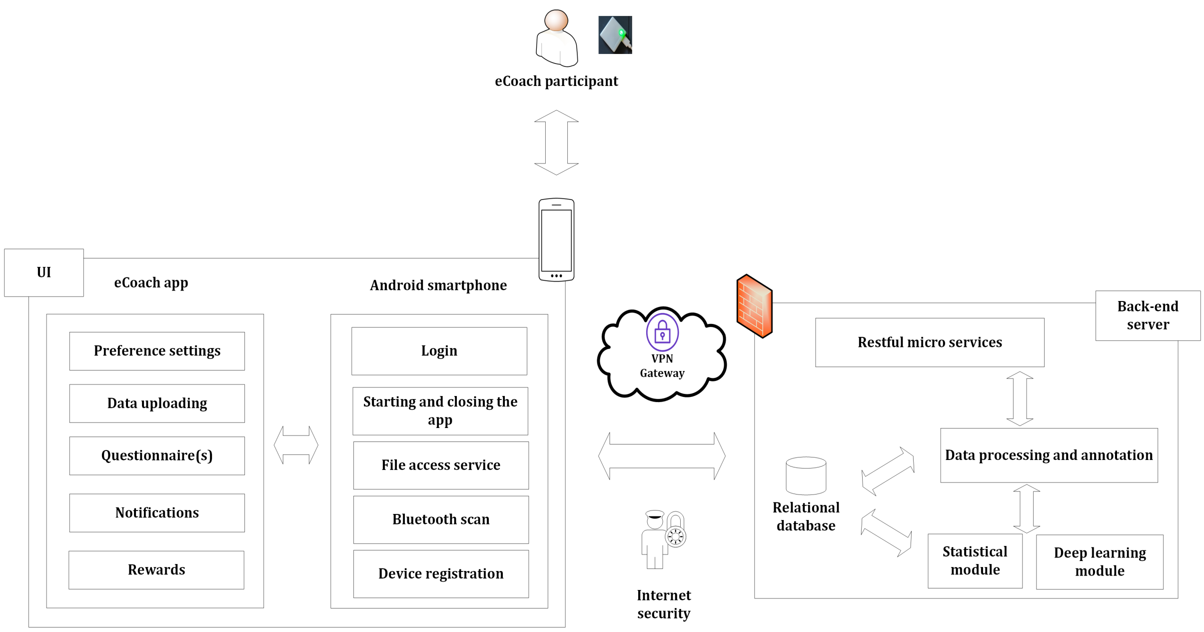

Figure 5.1: The software architecture with functional components of the activity eCoaching solution.

For data integration from heterogeneous sources and the semantic annotation of collected data and processed information, we have used the concept of domain Ontology. We have used HL7 FHIR for a uniform representation of personal and person-generated health data in JSON format based on different FHIR resource profiles [14]. The semantic vocabularies and SCTIDs of SNOMED-CT medical Ontology have been used in the FHIR resource profiles [14]. To measure the data loss and unreliable performances during the data fetching from the eCoach system's backend to the frontend over RESTful microservices (HTTP GET), we derive two metrics [14] – Loss% (a ratio between the number of bytes not received and the total number of bytes), and the probability of the unreliable performances (a ratio between the number of failing cases and the total number of cases under consideration). In Table 5.1, we have mapped the documented eCoach design requirements (see Table 4.4) with the functional components of the activity eCoaching solution's UI (see Figure 5.1) for enhanced understandability on how the design and development have been carried out! Moreover, in-depth elaborations on REQS-11, REQS-12, and REQS-13 are not in the scope of this dissertation.

Table 5.1: Mapping of documented requirements with functional components of activity eCoaching solution's UI.

REQS-ID	Functional Components
REQS-1	Login
REQS-2	Bluetooth scan and Data uploading
REQS-3	Preference settings and Questionnaire(s)
REQS-4	Preference settings and Questionnaire(s)
REQS-5	Notifications
REQS-6	Preference settings, Notifications, and Rewards
REQS-7	Preference settings, Notifications, and Rewards
REQS-8	Login, Device registration, Preference settings, Data uploading, Questionnaire(s), Notifications, and Rewards
REQS-9	Login, Device registration, Preference settings, Data uploading, Questionnaire(s), Notifications, and Rewards
REQS-10	Login, Device registration, Preference settings, Data uploading, Questionnaire(s), Notifications, and Rewards
REQS-11	Login, Device registration, Preference settings, Data uploading, Questionnaire(s), Notifications, and Rewards
REQS-12	Login, Preference settings, Data uploading, and Questionnaire(s)
REQS-13	Preference settings, Data uploading, Questionnaire(s), Notifications, and Rewards

5.1.2 Semantic Ontology Design

We have proposed an OWL-based ontology model (OntoReco) to integrate and annotate personal, preference, physiological, behavioral, and contextual data from heterogeneous sources (such as sensors, questionnaires, feedback, and interviews), followed by structuring and standardizing diverse descriptions to generate meaningful, personalized, and contextualized lifestyle recommendations based on the defined semantic rules in the knowledge base. The data and knowledge representation results using the OntoReco Ontology are elaborated in *Paper-D (P-D)*. Furthermore, we have extended the OntoReco ontology design for the semantic representation of processed activity data (e.g., prediction and classification outcomes and statistical computation results). The proposed OntoeCoach ontology in *Paper-E (P-E)* follows the following knowledge representation phases − abstraction or lexicon phase (L) for mapping rules, abduction phase (B) for hypothesis generation rule, deduction phase (C) for the operator-reduction rule, and induction phase (D) for the generalization rule. The resultant recommendation generation tree (T) follows a binary structure, and T syntactic knowledge representation helps address the understandability problem in personalized lifestyle recommendation generation. We have represented our OntoeCoach ontology (O) with four tuples −

$$O = \{C_a, R, I, A\} \tag{5.1}$$

$C_a : C_{a1}, C_{a2}, \ldots.., C_{an}$ represents "n" concepts or classes and each C_{ai} has a set of "j" attributes or properties $A_i = a_1, a_2, \ldots\ldots.., a_j$ provided n, i, j $\in Z^+$.
R: A set of binary relations between the elements of C_a.
I: Represents a knowledge base with a set of object instances.
A: Represents a set of axioms to model O. "A" includes domain-specific constraints to model ontology O with C_a, R, and I.

The knowledge (K) in the ontology has been expressed with two tuples −

$$K = \{Onto_{ActivityReco}, Rules_{ActivityReco}\} \tag{5.2}$$

The elements of $Onto_{ActivityReco}$ and $Rules_{ActivityReco}$ are −

$$Onto_{ActivityReco} = \{K_L, K_B, K_C, K_D\} \tag{5.3}$$

$$Rules_{ActivityReco} = \{R_L, R_B, R_C, R_D\} \tag{5.4}$$

K_L, K_B, K_C, K_D are the knowledge bases of the personalized physical activity recommendation generation's lexicon or abstraction, abduction, deduction, and induction interfaces. In contrast, R_L, R_B, R_C, R_D are a set of rules to match with the abstraction, abduction, deduction, and induction interfaces, respectively. Rule sets help to explain the logic behind recommendation generation. The following terms are related to OntoeCoach representation and processing − *Propositional variables* (the atomic name of the truth value can be changed from one model to another), *Constants* (the only propositional variables are TRUE and FALSE; thus, their truth values cannot be changed), and *Operators* (it is a set of logical connectors in each logic).

We have used operators, such as NOT, AND, OR, IMPLIES, EQUIV, and quantifiers (a set of logical quantifiers in a given logic) to represent complex relationships and constraints among concepts in our ontology. In this study, we have used FORALL as a universal quantifier and EXISTS as an existential quantifier to define the scope of relationships across concepts. Quantified clauses (sets of propositional variables connected by an operator and a quantifier) and clauses (quantified clauses without a quantifier) enable the representation of intricate logical statements. Furthermore, formulas, which link clauses and quantified clauses together by logical operators, and the process model (a set of assignments to each propositional variable such that the process yields the constant TRUE when simplified) facilitate the reasoning process within the ontology. In this research, the following are the steps used for OWL Ontology design and development −

- Domain identification to define the scope of Ontology (O) and model the concepts and relationships.
- Knowledge gathering on the domain, including relevant literature, expert opinions, and existing ontologies to identify concepts and relationships.
- Defining Ontology structure with classes, properties, and relationships that will be used to represent the concepts and their interrelationships.
- Ontology development with Ontology editors or other software tools. This involves creating the classes, attributes, and relationships defined in the previous step and adding instances to the ontology to illustrate the concepts.
- Checking structural consistency of the Ontology with reasoners.
- Validation of an ontology to ensure that it accurately represents the domain and can be used for its intended purpose. This may involve using ontologies to perform tasks such as classification, retrieval, or inference.
- Refine and update the Ontology with new knowledge. It is important to maintain the Ontology updated and useful.

Overall, Ontology development is an iterative process, involving refinement and improvement over time-based on feedback from domain experts and participants. In this research, Ontology has played a crucial role in personalized recommendation generation in eCoaching with its querying and reasoning capabilities, together with personal preferences, physical activity prediction, and forecasting outcomes.

5.1.3 Design for Recommendation Generation Algorithm

In the activity eCoaching, by default, we plan to generate recommendations to maximize weekly individual physical activity levels and minimize sedentary time. However, the maximization problem is user preference-based. The maximization problem focuses on maintaining a moderate activity level for an entire week (i.e., $\sum$ Days $\in$ (1, 2...n) $\forall\, n = 7$. We consider multiple expression for the activity maximization problem. We maximize the four parameters – 1) $\sum$ Moderate$_{Activitytime} > 150$, 2) $\sum$ GoalScore$_{daily} \geq 21$, 3) $0 \leq \sum \mu_S \leq 32$, and 4) SimilarityScore$_{weekly} \geq 0$. These parameters are maximized subject to the multiple conditions such as – 1) Moderate$_{Activitytime} \geq 21.45$, 2) GoalScore$_{daily} \geq 3$, 3) $0 \leq$ PerformanceScore$_{daily} \leq 32$, 4) $C_V \rightarrow P$, 5) $P \rightarrow R$, 6) $\sum P = 1$, and 7) ModerateActivitytime = 2 * VigorousActivitytime.

Activity goals can be system-defined (i.e., generic goals defined by WHO) or user-defined, as athletes may have different goal plans than ordinary people. According to the World Health Organization, adults (ages: 18-64) should complete at least 150-300 minutes

(2.5-5 hours) of moderate-intensity aerobic activity (MPA); or at least 75-150 minutes of vigorous Vigorous aerobic activity (VPA) or equivalent moderate- and vigorous-intensity exercise to stay active. To calculate each week's individual goal achievement scores, we have added the daily activity scores (see Table 5.2). Activity eCoach is designed to maximize target scores through continuous activity monitoring and personalized recommendation generation. For validation, we used rule-based personalized activity recommendation generation and *SPARQL* queries to motivate eCoach participants to stay active by reducing their sedentary time. Ontologies annotate recommendation messages to describe their attributes, metadata, and content information outside the static text form. Recommendation messages can be both formal and informal. The rule base helps explain the logic behind recommendation generation through logical *AND*, *OR*, and *NOT* operations.

Table 5.2: The "Activity Level" classification rules following the WHO guidelines.

Level (score)	Rule(s)[a]
Sedentary (0)	((step $<$5000) $\wedge$ (VPA*2 + MPA) *7 $<$90 $\wedge$ LPA $\geq$ 0)) $\vee$ (step $<$5000)
Low physical active (1)	((step $>$4999) $\wedge$ (VPA*2 + MPA) *7 $\geq$ 90 $\wedge$ (VPA*2 + MPA) *7 $<$210) $\vee$ (step $>$4999 $\wedge$ step $<$7500)
Active (2)	((step $>$4999) $\wedge$ (VPA*2 + MPA) *7 $\geq$ 210 $\wedge$ (VPA*2 + MPA) *7 $<$300) $\vee$ (step $>$7499 $\wedge$ step $<$10000)
Medium physical active (3)	((step $>$4999) $\wedge$ (VPA*2 + MPA) *7 $\geq$ 300 $\wedge$ (VPA*2 + MPA) *7 $<$360)) $\vee$ (step $>$9999 $\wedge$ step $<$12500)
High physical active (4)	((step $>$4999) $\wedge$ (VPA*2 + MPA) *7 $\geq$ 360) $\vee$ (step $>$12499)
*[a] $MPA = 2\,VPA$	

Paper-E (P-E) elaborates on a set of recommended messages for OntoeCoach ontology validation based on the used dataset. The integrated semantic concepts and Ontology rules as elaborated in *Paper-E (P-E)* are easy to follow and apply. Custom recommendations are generated using the structure ((rule) IMPLIES (suggestion variable) $\rightarrow$ recommendation message). Measurable parameters related to the activity of a particular participant in a timestamp can be obtained at preference-based intervals based on SPARQL queries. We have verified using Ontology Reasoner that the correct recommendation message is triggered for a particular situation. However, it is essential to ensure that no variable patterns would make the entire rule unsatisfactory. We've made sure that only one message is active at a time. Here we have a formal guarantee that neither two "once a day" messages can be active at the same time, nor can there be a model with a reasoner output each time for every possible combination of variables. All rule execution in the Ontology structure internally follows a binary tree structure, where the non-leaf nodes contain the semantic rules to be executed ($X \mid X \rightarrow Y$), and the leaf nodes have the results (X or recommendation message). Edges have decision statements (true or false).

In this way, satisfiability and understandability (or explainability) issues are addressed in the custom recommendation generation in our Activity eCoach system. The proposed automatic and personalized hybrid recommendation generation approach is described in Algorithm 1. The presentation and delivery of the recommendations are strictly personal preference based. The adopted high-level approach of automatic, personalized, and hybrid activity recommendation generation and its asynchronous delivery are depicted in Figure 5.2.

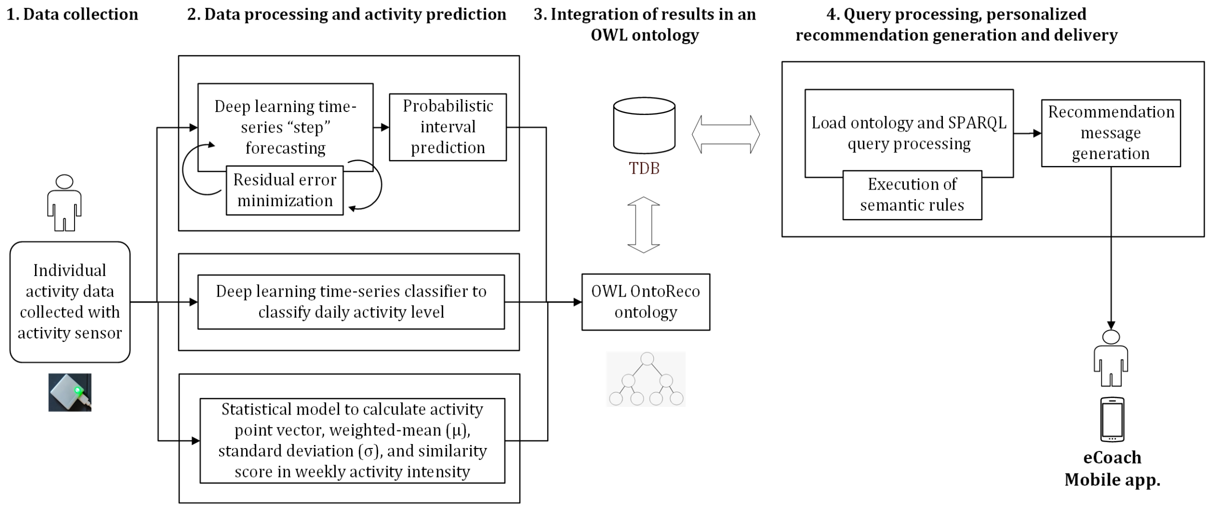

Figure 5.2: The adopted approach for hybrid personalized recommendation generation in eCoach prototype system. Data collected from individuals are stored in TDB following a semantic annotation after getting processed. SPARQL query periodically accesses ontological data from TDB for personalized recommendation generation.

5.2 eCoach Prototype Development

The eCoach app supports the following functionalities: updating personal preference information, submission of questionnaire data, uploading activity sensor data, and viewing notifications and rewards as a part of recommendations and goal management. After installing the eCoach app on the Android smartphone, the end-users can start or close the app, can access files, and can register the device and personal encrypted identifier. The collected data can be divided into the following categories: measurable vs non-measurable (or categorical), and time-variant vs time-invariant. Height, weight, and sensor data (e.g., activity and outdoor weather) are measurable and time-variant. The data are collected through the eCoach app and sent to the backend server for integration, semantic annotation, and persistence. Then, all the collected data are processed in the eCoach backend server based on the logic to generate personalized activity recommendations. The recommendations are sent to the eCoach app for visualization as a part of self-motivation. Personalized recommendation generation can be either data-driven or rule-based.

The security solution implementation (e.g., authentication, authorization, access rules) with TSD (Services for Sensitive Data) as Infrastructure-as-a-Service (IaaS), eCoach infrastructure, and service deployments in the infrastructure using Docker platform are

Algorithm 1 Hybrid recommendation generation with the person-based heuristic approach.

Input: Individual daily activity data *D(t)*;
Knowledge base set $S = \{$*semantic rules, activity variables*$\}$;
Recommendation message set $R = \{$*proposition variables, message bodies*$\}$;
Preference set $P = \{$*Goal setting, target goal, target activity score, mode of interaction, recommendation delivery time*$\}$;
Ontology model *ontologyO*;
Duration of eCoaching *DeCo*

Output: Personalized recommendation message set $L \subseteq R$

Days $\leftarrow$ 0
while (Days < *DeCo*) **do**
D(t-1) $\leftarrow$ load (previous day's individual daily activity data)
pre-process *D(t-1)* and split it into set $XY = \{x_{train}, x_{test}, y_{train}, y_{test}\}$
initialize list{L} = ϕ
$select_C \leftarrow$ predict configuration for the time-series classifier model *(C)* with set XY
$select_F \leftarrow$ predict the best configuration for the time-series forecast model *(F)* with set XY
ontologyO $\leftarrow \Delta_1, \Delta_2, \Delta_3, \Delta_4, \Delta_5, \Delta_6, \Delta_7$
$\Delta_1 = \sum_{k=1}^{n} \alpha$ {*D(t-1)*} where α is activity pattern vector for different weeks {k = 1...n}
$\Delta_2 = \sum_{k=1}^{n} \beta$ {*D(t-1)*} where β is activity score vector for different weeks {k = 1...n}
$\Delta_3 = \sum_{k=1}^{n} \gamma$ {*D(t-1)*} where γ is mean for different weeks {k = 1...n}
$\Delta_4 = \sum_{k=1}^{n} \delta$ {*D(t-1)*} where δ is standard deviation for different weeks {k = 1...n}
$\Delta_5 = \sum_{k=1}^{n} \theta$ {*D(t-1)*} where θ is activity similarity score for different weeks {k = 1...n}
$\Delta_6 = \sum_{k=1}^{n} \eta$ {*D(t-1)*} where η is daily activity level for different weeks {k = 1...n}
$\Delta_7 = \sum_{k=1}^{n} \zeta$ {*D(t-1)*} where ζ is step interval prediction for different weeks {k = 1...n}
result *(ontologyO)* $\leftarrow$ execute SPARQL queries on *ontologyO*
activity variables $\leftarrow$ result *(ontologyO)*
formed *proposition variables* based on the results of *activity variables*
update list{L}
Generate and deliver L based on P
Days $\leftarrow$ Days + 1

described in [14, 16, 15]. In [14], we have shown a direction to use HL7 FHIR with SNOMED-CT for semantic and structural interoperability in eCoaching. Our activity eCoach system follows a modular design pattern and consists of the following modules –

- Data sharing,
- Data collection and integration,
- Preferences,
- Recommendation generation and visualization,
- Notifications, and
- Rewards

5.2.1 Data Sharing

This module deals with user log-in and personalized configuration for activity sensors. We maintain the login as simple and secure as possible. We plan to collect person-related and activity data without personal identity disclosure. Only authorized users are allowed to access the eCoach system. Each participant receives a unique user identifier (UUID), and they can access the system with a personal email-id and modifiable password. The system is further protected with the "eduVPN" network. Activity data are only allowed to be shared with the researchers to create meaningful information out of raw data. Sharing data through social media or any other means is prohibited according to the GDPR regulations. The data-sharing plans follow the NSD guidelines. For this study, informed or signed consent have been obtained from all the participants. We have not disclosed any identifiable data of the participants using text, numbers, or figures.

5.2.2 Data Collection and Integration

This module is responsible for collecting sensor data, contextual data, and questionnaire data from different sources. Data collected from the eCoach app side are sent to the eCoach back-end using REST services for semantic annotation with OWL ontology, persistence, and processing. We have integrated two existing ontologies in our ontology design, such as SSN and SNOMED-CT, in our ontology model for a meaningful knowledge representation. All annotated data are stored in semantic triplet form (subject, predicate, and object) in a tuple database (TDB). The ontological representation of data (e.g., personal, sensor, context, recommendations, and questionnaire) has been depicted in *Paper-C (P-C)* and *Paper-D (P-D)* using Protégé. We divide data types and their collection method into the following four parts –

1. Activity data collection with wearable Bluetooth enabled (BLE) low-energy activity device,
2. Questionnaire for daily self-reporting, feedback (or survey), and the reporting of technical problems during the study in progress,

3. Personal preference settings (goal settings, response, and interaction), and

4. Contextual external weather data collection with Open Weather REST API against API Key validation.

5.2.2.1 Selection of Wearable Activity Device

We have used the MOX2-5 medical-grade (CE certified) accelerometer-based low-energy activity sensor for continuous monitoring[2]. The device flawlessly measures and transfers high-resolution activity data, such as activity intensity, weight-bearing, sedentary, standing, low physical activity (LPA), medium physical activity (MPA), and vigorous physical activity (VPA), and steps for every minute. The collected data is well suited for physical activity classification (LPA, MPA, VPA) and posture detection (sedentary (such as sitting or lying), standing, and weight-bearing). The wearable activity monitor must be connected to a personal smartphone via Bluetooth. The recommended wear locations of the device are thigh, hip, arm, or sacrum. The MOX2-5 activity sensor is a 3-dimensional accelerometer with a 25-100 Hertz sample rate (dimensions 35 x 35 x 10 mm). Its sensitivity is 4 mg/LSB. Maastricht Instruments had developed it. It is dustproof, waterproof, gives a battery backup for seven days, and is built with a rechargeable "Lithium Ion125 mAh". The current version of the MOX2-5 activity sensor is not suitable for classifying activities into the following detailed activity classes: cycling, swimming, rowing, and skiing. Therefore, participants must report them manually as questionnaire data.

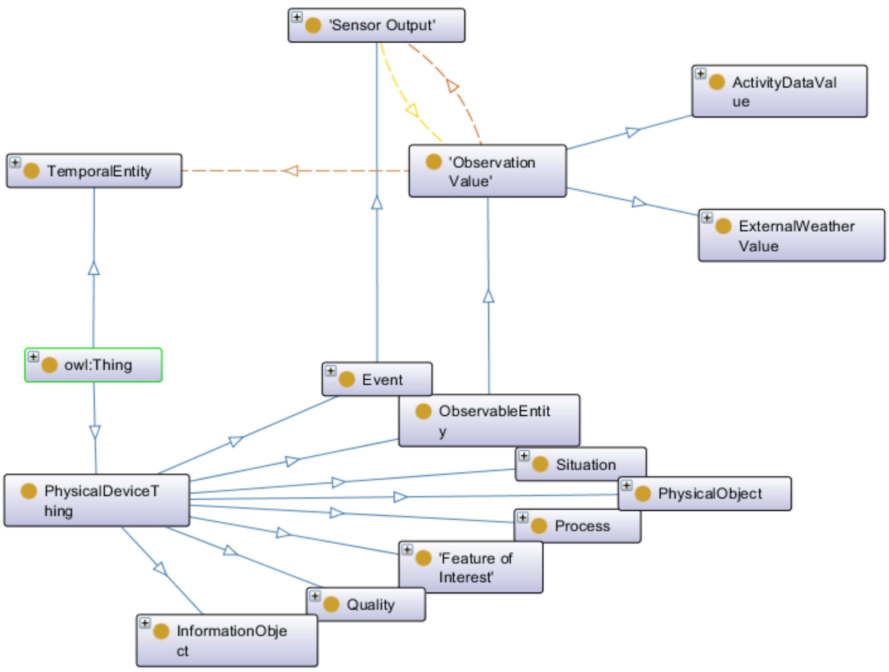

Figure 5.3: High-level graphical representation of observable sensor data.

[2]https://www.accelerometry.eu/products/wearable-sensors/mox2/

5.2.2.2 Data Integration and Semantic Annotation

We have used the SSN ontology in our proposed ontology to describe sensors, such as wearable activity and external weather sensors, their observations, and methods for sensing individual activities and context [24]. Observation data related to activity and external weather are annotated with SSN ontology concepts and object properties (see Figure 5.3) and the semantic results are described in *Paper-D (P-D)*.

We have used concepts from SNOMED-CT in our proposed ontology model to define how information about the participant's state is to be structured and processed [24]. The SNOMED-CT ontology combines hierarchical "IS-A" relationships and other related relationships to describe clinical attributes for vital signs, processes, body measurements, and observations. The semantic representation results are elaborated in *Paper-C (P-C)* and depicted in Figure 5.4. We have collected personal preference data at the beginning of personal eCoaching [8]. The participants' preference data are divided into three categories (see Figure 5.5): (1) activity goal setting, (2) eCoach response type, and (3) interaction type. Current intelligent coaching strategies are mostly based on handcrafted string messages that rarely individualize each user's needs, context, and preferences. Therefore, more realistic, flexible, practical, sophisticated, and engaging strategies are needed to model personalized recommendations. Furthermore, we have extended the ontology design for the semantic representation of processed information, such as deep learning prediction and classification outcomes, and statistical calculations (see Figure 5.6).

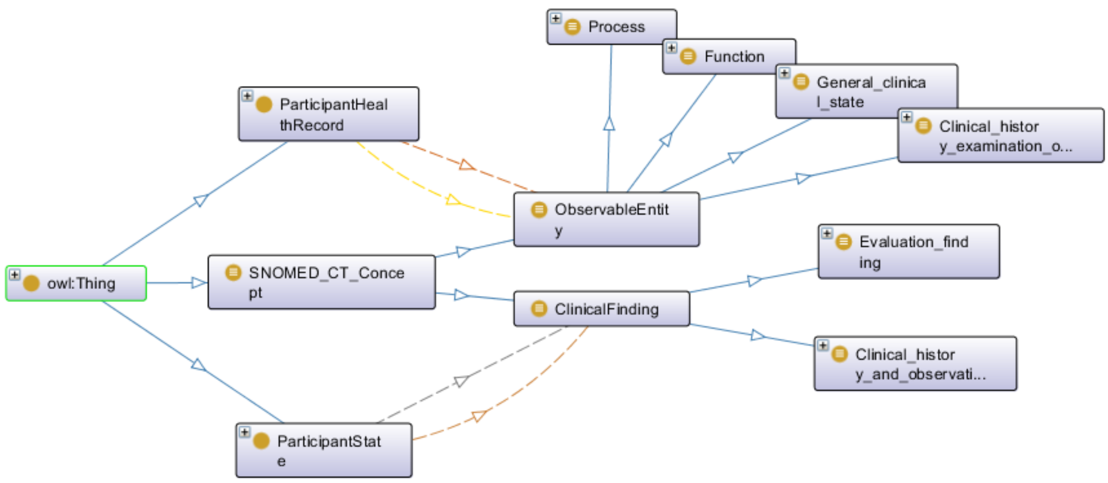

Figure 5.4: High-level graphical representation of SNOMED-CT concept.

5.2.3 Preferences

This module is responsible for collecting user preferences and storing them for goal management and personalized recommendation generation planning. Preferences have been classified into the following categories: Goal setting, Response type, and Interaction type. In our eCoach app, we have considered the following options under preference settings to run the PoC –

- Goal Type: Generic or Personalized

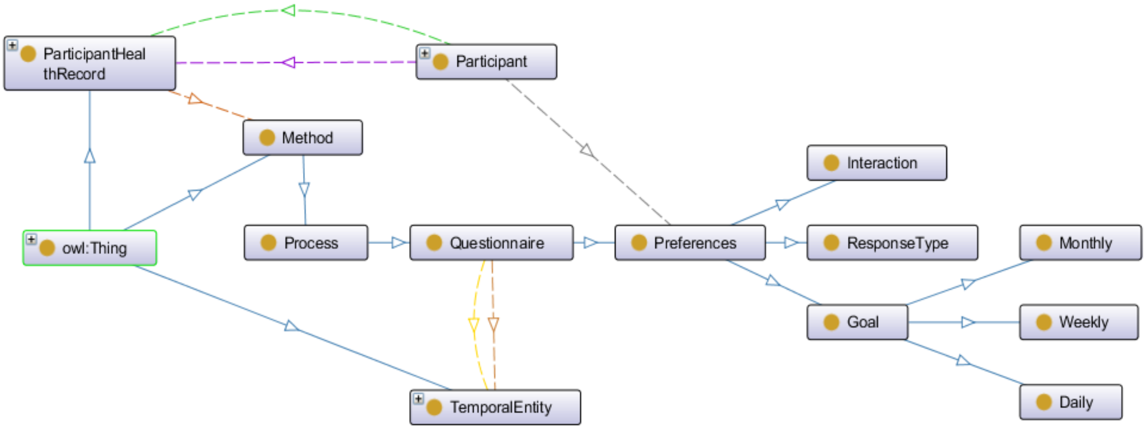

Figure 5.5: High-level graphical representation of preference information.

- Goal Period: 4 weeks
- Response Type: Representation of steps, VPA, MPA, LPA, sedentary bouts, future step prediction, and interval prediction value
- Interaction Mode: Graph, Text, Audio
- Interaction Frequency: Regular interval, Daily, Weekly
- Interaction Medium: Text (e.g., push notification), Audio

The duration of the goal period can be set to 4-12 weeks or more based on personal preferences. Users can set long-term (e.g., bi-weekly, monthly) or short-term (e.g., daily, weekly) physical activity goals, or the system can suggest them for a system-defined goal set. Users can update their goals when they wish. The level of goals gradually increases with the progress of individual activity performance.

5.2.4 Recommendation Generation and Visualization

This module is responsible for processing individual activity data and then assessing individual health states and comparing it with pre-set user preferences to generate personalized recommendations. This module also monitors contextual weather data that helps in contextual recommendation generation. This module consists of five submodules at the eCoach back-end server – feature selection, data labeling for classification, prediction, forecasting, and statistical analysis (SA), and one submodule in the eCoach app side for the recommendation presentation. The classification submodule classifies daily time-series activity data into different activity levels. The prediction submodule is responsible for forecasting daily steps for the next 7-days based on the temporal pattern in individual step data. To understand the weekly activity intensity, the SA submodule calculates the weighted mean, activity pattern, and similarity score between the weekly achieved activity score and weekly goal score. All the outcomes of the data processing module are semantically annotated in our ontology model and followed by stored in the TDB as explained in *Paper-E (P-E)*.

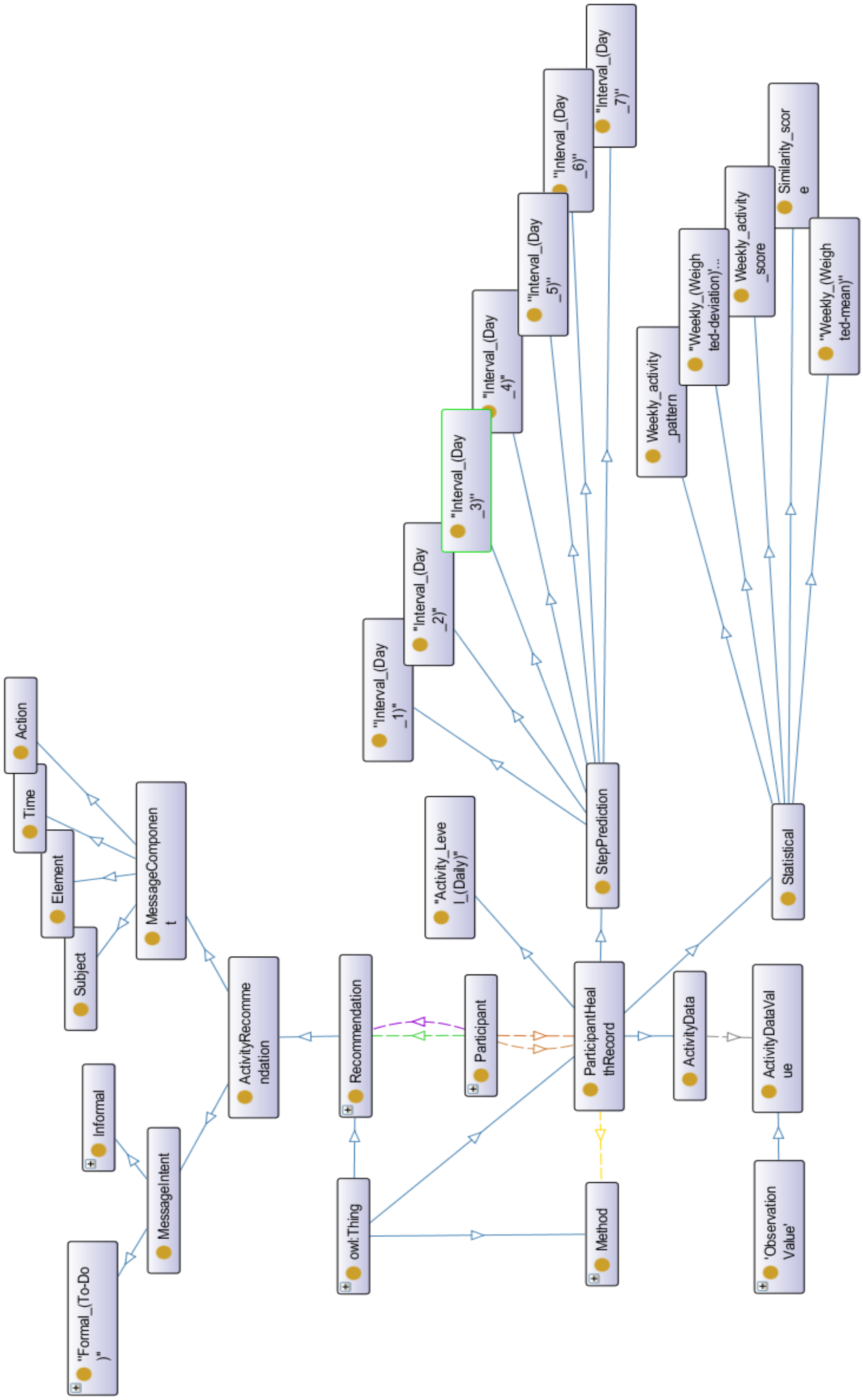

Figure 5.6: Ontology model to represent recommendation messages and processed activity information.

5.2.4.1 Initial Data Collection for Model Training

We have used one public PMData activity dataset of 16 adults [63] and one private MOX2-5 activity dataset to use data in the algorithm of automatic personalized recommendation generation for verification. Public datasets are freely available and do not require legal approval. The collection and handling of real-time private activity datasets are legally compliant. We recruited 16 healthy participants (including males and females) in the initial data collection phase with wearable activity sensors for 4–8 weeks, following a convenience sampling technique and the inclusion criteria as mentioned in Chapter 2. Features, such as age, gender, and weight are not in the scope of this study. Both public and personal datasets used for this study are described in *Paper-E (P-E)* with the class distribution. Moreover, P-E describes demographic characteristics and the relation between activity intensity and activity level classification.

5.2.4.2 Feature Selection

We use Augmented Dicky-Fuller (ADF) hypothesis testing to verify the stationery of the time-series data. We use seasonal decomposition to analyze the trend, seasonality, and residual components in data. We convert the non-stationary data to stationary with the difference transform method, which helped to remove trend and seasonality in time-series data. The normality test reveals that the activity data samples did not look like "Gaussian". For the feature selection, we use correlation analysis to calculate the correlation coefficient (r). Moreover, feature ranking and feature importance methods (e.g., SelectKBest with Chi-square, ExtraTreesClassifier, and Principal component analysis (PCA)) help in the selection of strong features in both datasets.

5.2.4.3 Data Labelling for Classification

The "Activity Level" feature represents the following five classes (see Table 5.2) – sedentary (0), low active (1), active (2), medium active (3), and highly active (4). The rule for "Activity Level" feature class creation is defined in *Paper-E (P-E)*.

5.2.4.4 Activity Level Classification

We develop a deep learning time-series classifier model inspired by the conventional, well-known MLP architectures based on the Fully-Connected-Neural-Network (FCNN) style. We consider a decent number of neurons in each layer based on the common heuristics (e.g., validation loss, hidden units are a fraction of the input) as our datasets were small. The complete structure of our designed and developed model for the used datasets has been depicted in Figure 5.7. The designed and developed MLP classifier is described in *Paper-E (P-E)*.

5.2.4.5 Daily Step Forecasting

The conventional, well-known CNN architectures have inspired our developed uni-variate time-series forecasting model. We retain a reasonable number of neurons in each layer

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 32)                192
_________________________________________________________________
dense_1 (Dense)              (None, 32)                1056
_________________________________________________________________
dense_2 (Dense)              (None, 16)                528
_________________________________________________________________
dense_3 (Dense)              (None, 16)                272
_________________________________________________________________
dense_4 (Dense)              (None, 16)                272
_________________________________________________________________
dense_5 (Dense)              (None, 5)                 85
=================================================================
Total params: 2,405
Trainable params: 2,405
Non-trainable params: 0
```

Figure 5.7: Our MLP model for time-series classification.

based on the common heuristics (e.g., validation loss, hidden units are a fraction of the input) as our datasets were small. The comprehensive structure of our designed and developed model for the used datasets has been depicted in Figure 5.8. The designed and developed 1-D CNN model is elaborated in *Paper-E (P-E)*.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d (Conv1D)              (None, 5, 256)            1024
_________________________________________________________________
conv1d_1 (Conv1D)            (None, 3, 256)            196864
_________________________________________________________________
max_pooling1d (MaxPooling1D) (None, 1, 256)            0
_________________________________________________________________
flatten (Flatten)            (None, 256)               0
_________________________________________________________________
dense (Dense)                (None, 1)                 257
=================================================================
Total params: 198,145
Trainable params: 198,145
Non-trainable params: 0
```

Figure 5.8: Our 1-D CNN model for uni-variate time-series forecasting.

5.2.4.6 Statistical Analysis

We developed the following new four statistical metrics beyond the existing ones –

- *Activity pattern vector (APV)*: it is a weekly activity pattern vector of length 7 that contains the activity level scores for a given week. Therefore, it can be termed an activity level vector (ALV).

- *Similarity score (SC)*: a weekly similarity score is a difference between the summation of the weekly activity pattern vector and the weekly goal vector. If SC ≥ 0, then it signifies that the participant has achieved the weekly goal.

- *Weighted mean (μ_S)*: it is the extended version of standard mean calculation with weights to the numbers to determine personal activity intensity on a weekly basis and thereby use the information in activity recommendation generation. We have calculated a weighted mean on an individual weekly activity dataset to calculate weekly activity progression with a defined non-negative weight point set: $\{0, 2, 4, 6, 8\}$ that represents sedentary, low active, active, medium active, high active. Therefore, in a week a person can achieve an activity point P $\in$ 0, 32.

- *Standard deviation (σ)*: It uses weighted mean values to calculate deviations in weekly activity intensities.

The following steps for statistical analysis are defined as follows −

1. Load individual activity datasets for the last few weeks,

2. calculates the weekly mean of the following activity features F: Sedentary time, LPA, MPA, VPA, Steps,

3. Calculate weekly activity level score based on the activity level classification results, APV,

4. SC = Σ APV (W_i) - Σ GoalScore (W_i), where W_i signifies a week,

5. calculates performance score against APV with the following rule: Score (S) = activity level on day-n * P,

6. μ = Calculate mean of S on weekly basis (= S/7),

7. calculate activity intensity of the corresponding week based on µ score and prepare a weightedMeanList, and

8. Calculate deviation in between weekly activities and prepare a deviationList.

The explanation and evaluation criteria for these metrics are elaborated in *Paper-F (P-F)*.

5.2.4.7 Automatic Recommendation Generation

According to WHO, adults (ages: 18-64) should complete at least 150–300 minutes (2.5-5 hours) of moderate-intensity aerobic exercise (MPA); or at least 75–150 minutes in a week of vigorous-intensity aerobic exercise (VPA) or an equivalent combination of moderate- and vigorous-intensity exercise to stay active. Activity goals can be system-defined (i.e., WHO-defined generic goals) or user-defined, as athletes may have different goal plans than normal individuals. We aggregated daily activity scores to determine weekly individual goal achievement scores. Activity eCoaching strives to maximize target scores by constantly monitoring activity and generating recommendations. We plan to generate personalized lifestyle recommendations based on health state monitoring results (e.g., prediction, forecasting, and statistical data), preference information, and a ruleset. The recommendation generation module runs a scheduler periodically to query and process individual activity prediction results from the TDB database with a SPARQL query engine and a knowledge base. The knowledge base stores the rules for recommendation generation. Furthermore, we have designed a pipeline to automate the process of data collection, data processing, deep learning model training on an incremental basis, decision-making, and personalized recommendation generation. An incremental learning approach helps to keep the deep learning time-series classification and forecasting models updated with real-time growing activity data. This module is built with Python (V.3.8.5) programming language and exposed with PyFlask for inter-modular accesses.

Temporal analysis of data helps to analyze the pattern in human activities and generate evidence-based personalized recommendations to motivate participants. We have made the recommendations contextual, with the inclusion of external weather information (e.g., tomorrow morning, the weather is sunny, and the temperature is between 20 and 23 degrees Celcius (C). Therefore, you can plan to run for 1 h or perform similar activities). *Paper P-C* and *Paper P-D* focuses on rule-based personalized recommendation generation. In its extended form, the entire process of personalized and hybrid recommendation generation is described in *Paper P-E*, in an algorithmic structure. Furthermore, *Paper-E (P-E)* validates the proposed algorithm against defined preference data, modifiable semantic rules, customizable semantic messages, statistical metrics, and defined public and private activity datasets.

5.2.4.8 Recommendation Presentation

This module periodically accesses TDB for personal preference data and generates individual recommendation data to send personalized feedback based on personal preferences. Moreover, it displays a reflection of activity in progress with continuous and discrete personal health data, notifications, rewards, and recommendation messages in a meaningful way to motivate participants. For this PoC, based on the end-users' feedback, we have designed our eCoach app to generate numerical feedback on the activity performed using simplified graphs. Recommendations are of two types to motivate participants − indirect visual feedback (e.g., graphs, charts) and direct (e.g., textual pop-up notification generation). The participant receives daily and cumulative feedback to view their progress toward the goal. Our activity eCoach app keeps track of an individual number of daily steps, duration of activity levels (in minutes per day), and sedentary bouts (in minutes per day) until the monitoring period gets ended. Participants can actively track the number of exercises they have performed over the day or week based on their preferences. Moreover, for estimating future activity in terms of "steps" based on time-series forecasting, we have focused on probabilistic interval prediction with a Naive-based approach rather than abstract point prediction. A prediction interval gives a meaningful interval within which we expect to remain with a specified probability. In the eCoach app, they can also browse their historical performances. At the end of the eCoaching session, they can report their satisfaction level in terms of a self-reporting form using the eCoach app. *Paper-F (P-F)* elaborates interval prediction and personalized recommendation presentation with simplified graphs.

5.2.5 Notifications

This module is responsible for generating personalized reminders adaptively based on the context, preferences, and health state. It can be an audio notification or a push notification with precise and dynamic content. We have chosen to push notifications with precise and dynamic text content. Notifications are direct recommendation messages to the users. Instant notifications can contain two types of messages: formal To-Do (for instance, "You need to complete another 2500 steps in the next one hour to reach your daily step goal") and (b.) informal motivational notifications (e.g., "Good work, keep going! You have achieved targeted activity level."). The participants can select the notification frequency as a part of the app preferences. We have designed notifications to be precise, understandable, and positive. *Paper-F (P-F)* elaborates on notification generation and presentation in our eCoach app.

5.2.6 Rewards

This module classifies the user's progress to reach a personalized goal at the end of a preset period into three groups with standard emojis and credit points: well done (10 credit points), up-to-the-mark (5 credit points), must be improved (0 credit point). All the credit points can be reimbursed against "Food bank", as "Reward" means that the user can eat a bit more if he/she has trained more. *Paper-F (P-F)* elaborates on personalized reward generation and presentation in our eCoach app.

5.3 Chapter Summary

In this chapter, we have discussed the design and development of our activity eCoach prototype as a part of PoC, based on the design inputs received from UCD Workshop 1 and Workshop 2. Workshop 1 has given a high-level design idea to develop a low-fidelity eCoach prototype. The design ideas and feedback in Workshop 2 have helped to narrow down the design focus with a scope to develop a fundamental activity eCoach working prototype. We have described our eCoach design criteria, software development architecture, data collection, and integrated approach with a proposed OWL ontology model, workflow for data processing and predictive analysis, strategy for hybrid and automatic personalized recommendation generation, and its meaningful presentation to keep participants motivated. Moreover, the eCoach app design directs to an innovative approach with the adoption of the following concepts – eCoach design strategies, ontology-based data annotation, hybrid recommendation technology, interval prediction, and the incorporation of medical-grade activity sensors.

Chapter 6

Experimental Evaluation, Results, and Discussion

This chapter presents the outcome of a systematic literature review to identify the human coaching methods applicable for eCoaching, experimental setup, and evaluation of the deep learning time-series models, proposed ontology model, algorithm, and the basic functionality of the eCoach prototype system. The evaluation process is divided into experimental setup, quantitative and qualitative evaluations.

6.1 Human Coaching Methods for eCoaching

From the systematic literature review [5], the identified eCoaching methods following a top-down ranking are personalization, interaction, co-creation, behavior change with technology, goal-setting and evaluation, persuasion, automation, and promotion of a healthy lifestyle. Methods such as personalization, persuasion, goal setting and assessment, interaction, and co-creation are borrowed in eCoaching from traditional offline human coaching.

In eCoaching, persuasion is developed by relying on self-reporting or automation using sensors to observe human behavior, followed by health risk prediction using pattern recognition algorithms [5]. Personalized recommendations are required for an intervention plan to be effective. Automation is related to providing participants with automated behavioral recommendations to promote a healthy lifestyle. It helps give the users automatic behavioral suggestions to maintain a healthy lifestyle. Recent advances in ICT have improved personal healthcare. The healthcare sector is still looking for an interactive, easy-to-use, simplified, cost-effective, and safe behavioral intervention eCoach system to promote healthy lifestyles. The design should be able to normalize personalized data in different formats through proper ontology research to ensure data confidentiality. It should use AI algorithms based on ethical principles to analyze human psychology, monitor human behavior, and guide participants accordingly. Technology can support eCoach by supporting coaching types, process management, human-computer interaction, remote communication, data collection and storage, data privacy, data analysis, recommendation generation, assessment, and self-tracking.

6.2 Experimental Setup

We have used Python programming language (V.3.8.5) and Anaconda distribution for data processing with statistical and AI libraries (e.g., pandas (v. 1.1.3), NumPy (v. 1.21.2), SciPy (v. 1.5.2), Matplotlib (v. 3.3.2), Seaborn (v. 0.11.0), Plotly (v. 5.2.1), scikit-learn, or sklearn (v. 0.24.2), Keras (v. 2.6.0), and Graph Viz (v. 2.49.1)), as detailed in *Paper-E (P-E)* with the system information. We have used Jupyter Notebook (v. 6.4.5) for the deep learning model development, model analysis, and data visualization.

All the eCoach modules follow a microservice architecture. The exposed eCoach interfaces are protected with multifactor authentication and authorization (OAuth2) to allow legitimate users only [14, 15, 16]. eCoach services are deployed in Apache Tomcat (V.9.x) using Docker. The eCoach codebase is maintained in the GitHub repository. For the eCoach app design and development, the Figma open-source design framework and Kotlin programming language are used. Protégé (V. 5.x) has been used for OWL ontology design, development, reasoning, querying, and verification. Protégé supports different reasoners, such as HermiT, Pellet, Fact++, RacerPro, and KAON2. The open-source Apache libraries (e.g., Jena, Jena Fuseki) are used for ontology querying and verification.

For the functional evaluation of our activity eCoach prototype, we have used its functional demonstration to the end-users and thereby, feedback-receiving approaches against a defined set of test cases; however, it is not a usability and acceptability evaluation under the lab settings. To measure the scalability, data loss, and unreliable performances, the Apache open-source software JMeter (V 5.4.1) has been used to generate HTTP requests and capture the outcomes. Moreover, we have used the Postman open-source software (V 10.x) for REST API testing. Overall, we have used GitHub for code management, Figshare for data management, jMonitor and JProfiler to identify Java memory leaks and overcome performance issues, Cobertura and SonarQube for static code coverage analysis as Jenkins-plugin during the auto-deployment via Jenkins, Logstash for log management, Graphana open-source analytics for interactive performance visualization, and JIRA for issue tracking; however, their results are not in the scope of this dissertation.

6.3 Quantitative Evaluation

This section describes the quantitative evaluation of the deep learning models, statistical computation, and the OntoReco ontology model as a part of experimental evaluation. The quantitative evaluation contributes to partially achieving REQS-5 in recommendation generation, REQS-6 in data analysis for reward generation, and REQS-7 in exploratory data analysis for effective presentation of activity performance.

6.3.1 Correlation Analysis and Feature Selection

The correlation matrices for the PMData and MOX2-5 datasets are explained in *Paper-E (P-E)*. The value of the correlation coefficient helps to understand the strong association between the features, followed by preparing the final feature set to run the entire experiment. The feature rankings are presented in 6.1 for both datasets against the used methods. Table 6.1 has revealed “Step” as an essential feature in the activity datasets. We have prepared a final feature set from the overall feature analysis with the most relevant features, such as Steps, sedentary, LPA, VPA, and MPA.

Table 6.1: The feature ranking in the used datasets and corresponding methods.

Method	Dataset	Ranking
SelectKBest	PMData	steps, sedentary, LPA, VPA, MPA
SelectKBest	MOX2-5	steps, sedentary, LPA, VPA, MPA
PCA	PMData	steps, VPA, MPA, LPA, sedentary
PCA	MOx2-5	steps, VPA, MPA, LPA, sedentary
ExtraTreesClassifier	PMData	steps, VPA, sedentary, LPA, MPA
ExtraTreesClassifier	MOx2-5	steps, LPA, MPA, VPA, sedentary

6.3.2 Time-Series Classification

A comparative analysis between our developed MLP classifier and other state-of-the-art time-series classifiers, such as Rocket, MiniRocket, and MiniRocketVoting has been captured in Table 6.2 and Table 6.3 for PMData, and MOX2-5 data-sets, respectively. The proposed MLP classifier has outclassed its nearest best-performing MiniRocket classifier with $\approx$ 46% and 27.5% accuracy improvement for PMData and MOX2-5 datasets, respectively.

Table 6.2: The multi-class classification outcomes on the PMData datasets.

Models	Precision	Recall	F1-score	Accuracy	MCC
Our MLP model	97.7	97.0	97.0	97.0	94.0
Rocket	51.0	56.0	52.0	56.0	54.0
MiniRocket	66.0	52.0	58.2	58.2	54.2
MiniRocketVoting	45.0	52.0	48.5	49.0	46.0

Table 6.3: The multi-class classification outcomes on the MOX2-5 datasets.

Models	Precision	Recall	F1-score	Accuracy	MCC
Our MLP model	74.0	71.0	72.5	71.0	69.0
Rocket	56.0	42.0	48.0	48.0	45.0
MiniRocket	58.0	45.0	50.5	51.0	49.0
MiniRocketVoting	39.0	44.0	41.3	42.0	41.0

Moreover, we have compared the “Model Loss” on training and test sets over epochs for both the used datasets are explained in *Paper-E (P-E)*. Furthermore, we have used confusion matrices to describe the weighted average precision, recall, F1-score, and accuracy score for the datasets against our developed MLP multi-class classifier, and the same is depicted in *Paper-E (P-E)*. Similar precision and recall scores signify that FP = FN, and their similarity with accuracy states that the model is balanced. According to the classification results in Table 6.2 and Table 6.3, the outcomes may vary from case to case and data-set to data-set. Deep learning models improve their learning gradually with an increased volume of data.

6.3.3 Time-Series Forecasting

The mean performance analysis against forecasting matrices between our 1D-CNN-based univariate "Step" forecasting model and other existing deep learning time-series forecasting models has been compared in Table 6.4 and Table 6.5 for both data-sets. The model evaluation process is elaborated *Paper-E (P-E)*. Moreover, we have used an Auto Regressor (AR) time-series baseline model with residual error minimization (REM) technique to check how our model addresses traditional REM problems in the time-series step data. For the same, the data preparation steps are described in *Paper-E (P-E)*. Table 6.4 and Table 6.5 reveal that 1D-CNN outperforms other baseline models against adopted evaluation matrices, and its close competitors are bidirectional LSTM and bidirectional GRU models. According to the results, CNN, LSTM, and GRU have effectively managed the residual errors to produce better results than AR with a residual error minimization approach.

Table 6.4: The step-forecasting outcomes on PMData datasets.

Models	RMSE	|FB|	RSD	ET (sec)
Our 1D-CNN	1520.9	222.54	1534.0	88.0
AR with REM	5936.5	223.4	1475.6	144.0
Vanilla LSTM	4537.3	234.0	4574.7	149.2
Stacked LSTM	4541.7	244.0	4580.4	232.6
Bidirectional LSTM	4369.7	369.0	4411.0	211.8
Vanilla GRU	4488.3	223.5	4526.6	146.8
Stacked GRU	4518.6	125.0	4515.0	234.2
Bidirectional GRU	4367.4	224.6	4434.3	219.3

Table 6.5: The step-forecasting outcomes on MOX2-5 data-sets.

Models	RMSE	|FB|	RSD	ET (sec)
Our 1D-CNN	1742.7	246.3	1796.3	88.0
AR with REM	3753.1	150.0	3956.4	143.0
Vanilla LSTM	3831.5	128.4	3951.0	157.3
Stacked LSTM	3788.7	111.0	3907.2	199.3
Bidirectional LSTM	3687.9	138.0	3801.7	192.0
Vanilla GRU	3930.9	104.8	4052.9	152.0
Stacked GRU	3877.1	185.3	4007.1	205.5
Bidirectional GRU	3703.9	117.5	3819.4	209.3

1D-CNN has outperformed other forecast models and produced high-speed output for both datasets. We have tried to improve the model's efficiency with more hidden layers, neurons, variations in filters, and dropout layers; however, we could not succeed because of the limited volume of datasets. We have witnessed that CNN, LSTM, and GRU models have different hyperparameters in terms of filter dimension, the number of filters, and hidden state dimension, and they internally work differently. However, 1D-CNN manipulates the spatial correlation in data and serves well when apprehending the neighborhood information.

6.3.4 Statistical Analysis and Interval Prediction

Based on the proposed weighted mean calculation method, we have shown the weekly activity score (S), similarity score (SC), and standard deviation (SD) calculation for participant-1 or P-1 from the MOX2-5 datasets in *Paper-E (P-E)*. For example, we have considered the activity data of P-1 for the last four weeks. We can use the same method for other participant data. The mean sedentary, LPA, MPA, and LPA times are measured in seconds. SC signifies that P-1 has failed to achieve weekly goals for the last three consecutive weeks and therefore needs proper recommendation planning to stay motivated in the following weeks. The S and SD values tell that the activity performance has significantly dropped after Week-1.

Table 6.6: Step and interval prediction for Week-X for P-1 in MOX2-5 datasets.

Week-x	Predicted step points (SP)	80% interval step prediction with c = 1.28, σ_h = 1271.0
Day-1	3520.0	[1893, 5147]
Day-2	5171.0	[3544, 6798]
Day-3	4855.0	[3228, 6482]
Day-4	4979.0	[3353, 6605]
Day-5	5071.0	[3445, 6697]
Day-6	4508.0	[2882, 6134]
Day-7	3928.0	[2302, 5554]

Future step prediction for individuals combined with the estimated S-value for the previous weeks can be a good direction for generating personalized recommendations. Furthermore, *Paper-E (P-E)* describes the analysis of interval prediction on top of the univariate step prediction and meaningful activity state representation. we have used our 1D-CNN model for the next seven days' step forecast for P-1 based on its temporal step data analysis. We have calculated the residual standard deviation (RSD) value $\approx$ 1271.0 for the step data of P-1. Using the Naïve-based interval prediction method, we have shown a direction to calculate the 1-step interval prediction of activity steps on top of the point prediction (see Table 6.6). The mean predicted steps for the following week (Week-X) have produced a value of 4576.0 ($\approx$ (3520.0 + 5171.0 + 4855.0 + 4979.0 +

5071.0 + 4508.0 + 3928.0)/7) which tells that the upcoming week (or Week-X) can be a match with Week-3. Therefore, the daily activity performance must be improved.

6.3.5 Ontology Evaluation, Query Processing, and Recommendation Generation

Protégé supports a list of reasoners, such as HermiT, Pellet, Fact++, RacerPro, and KAON2, to check ontologies' logical and structural consistencies. The HermiT reasoner performed the best without any inconsistencies. We have compared mean reasoning time and selected the best reasoner for our OntoReco ontology as described in Table 6.7. We have loaded the ontology file in "TTL" format into the Jena Fuseki server for cross-verification in SPARQL query execution time. We have used Jena Framework to query each class, predicate, subject, and object.

We have used the "*OWL_MEM_MICRO_RULE_INF*" specification (OWL full) to step through the ontology in Jena in "TTL" format and approximated read times to 1.0-1.5 seconds. Furthermore, we have used "in-memory" storage, "optimized rule-based inference engine OWL rules", and the Jena framework to query the ontology class, ontology, predicate, subject, and object of each sentence in <1.0 seconds, <2.0 seconds or <2.0 seconds, respectively. Our proposed ontology model is associated with a document manager (default: "OntDocumentManager") to support the processing of ontology documents. All classes that represent ontology values in the Ontology API have "OntResource" as a common superclass. We have implemented the RDF interface provided by Jena to persist modeled ontologies and their instances in TDB and reloaded them for further processing. Jena Fuseki is tightly integrated with TDB to offer a robust transactional persistent storage layer. The average SPARQL queries' execution time has been captured between 0.1 and 0.4 seconds (sec). The TDB database has acted as a knowledge base. As explained in *Paper-E (P-E)*, we have maintained a list of customizable semantic rules and probable recommendation messages in the knowledge base. In *Paper-E (P-E)*, we have shown a direction to generate personalized activity recommendations as a part of ontology verification. We have executed the semantic rules and used the Jena ARQ engine to run relevant SPARQL queries on the used datasets. Query results have been combined to create personalized recommendations to meet the criteria for automatic recommendation generation in eCoaching. The rule-based binary reasoning (If $\rightarrow$ 1, else $\rightarrow$ 0) has helped to interpret the formation of a personal activity recommendation message. Therefore, a prediction modeling followed by an annotated rule set added more value to personalized health recommendation generations.

A complete data-driven approach to personalized recommendation generation in healthcare is critical due to false-positive scenarios. To solve the cold-start problem in recommendation generation, we have recorded data for an initial two weeks to identify the activity patterns in an individual before starting data processing and followed by a recommendation generation. We have followed the algorithmic steps proposed in *Paper-E (P-E)* for hybrid recommendation generation with person-based heuristic configuration. As described in the previous chapter, the designed machine learning pipeline with an incremental learning approach has helped to automate our eCoach system's recommendation generation. The incorporation of external weather information in recommendation generation has made it contextual. As an extended work, a transfer learning approach to improve the machine learning model training and its performance, and an incremental learning approach to handle daily growing data and fit them into the machine learning models are captured in [18].

Table 6.7: Performance analysis of different reasoners available in Protégé.

Reasoner(s)	Average reasoning time (sec.)
HermiT	1-2 sec.
Pellet	2-4 sec.
Fact++	3-4 sec.
RacerPro	2-3 sec.
KAON2	3-4 sec.

6.4 Qualitative Evaluation

The qualitative evaluation consists of the technical evaluation of the identified and documented basic functional (REQS-1 − REQS-7) and certain non-functional (REQS-8 − REQS-13) requirements on the working version of the activity eCoach prototype system. For some requirement evaluation (REQS-1 − REQS-10), we considered user inputs, and for other requirements (REQS-11 − REQS-13), we adopted a simulated environment under lab settings. The low-fidelity eCoach activity monitoring prototype as a result of Workshop 1 was presented to the end-user group in Workshop 2 for their valuable feedback. Feedback includes three options − Pass (5), fail (0), and further scope of improvements (3). We demonstrated the prototype to evaluate the following requirements of the prototype − REQS-1, REQS-2, REQS-3, REQS-4, REQS-5, REQS-6, REQS-7, REQS-8, REQS-9, and REQS-10. We improved the low-fidelity eCoach prototype based on the input from the UCD Workshop 2. We used Figma app view, simple web view, and Microsoft PowerPoint to present the eCoach prototype. We received feedback on the followings − logging in based on email IDs instead of long unique user IDs or UUIDs, uploading different types of data from activity sensors, improving the questionnaire set and its design, feedback presentation, unifying the layout design, and choosing an appropriate icon for all eCoach default color views and concepts and an integrated circular layout to visualize activity patterns over time. Overall, our average rating was 3.0 out of 5.0 for the low-fidelity version of the eCoach prototype. Any feedback or comments are incorporated into eCoach's first working prototype app. All the feedback or comments were addressed in the initial eCoach working prototype app.

Following Workshop 2, we invited a similar sub-set of end-users to evaluate the functional design and working of the initial eCoach prototype with a heuristic approach and provide feedback. We handed over the prototype to each group to do hands-on basic functionality testing under our lab settings, and the outcomes are noted in *Paper-F (P-F)*. The feedback consisted of three choices – passed (5), failed (0), and further scope of improvement (3). We received a rating of ≈ 4.1 out of 5.0 with different improvement scopes in layout design to give the app a sophisticated view. However, this is not a usability evaluation. Our eCoach app supports Android version 11 and onward, due to development constraints on periodic data uploading from the local mobile storage to the remote eCoach server. Therefore, it created a version incompatibility problem for Android smartphone users with an Android version < 11. At the end of Workshop 2, we received an average (Volere) satisfaction score of 4.0 for the REQS-1 $-$ REQS-10 on their design and basic functionality. The Figma eCoach UI design and its Bootstrap (open-source HTML, CSS, and JavaScript library) implementation helped to make the eCoach UI compatible across smartphones, tablets, and desktops. We have added arguments for achieving the non-functional requirements REQS-11, REQS-12, and REQS-13 without in-depth elaborations as they are not in the scope of this dissertation $-$

- REQS-11: In [15], we have devised a hybrid security strategy to safeguard the collection and management of personal health information, this strategy was implemented using the Spring Framework (SF) and the Services for Sensitive Data (TSD) as a platform for the service, and HTTP security methods as a means of protection. The solution chosen (SFTSDH = SF + TSD + H) has the following security features $-$ identity brokering, OAuth2, multifactor authentication, and access control to safeguard the Microservices APIs, following the GDPR. We were able to successfully defend the eCoach APIs from external vulnerabilities, including cross-site scripting, clickjacking, and content sniffing. Moreover, in [15] and [16], we have shown a direction to achieve protection against the brute force attack.

- REQS-12: The prototype of the eCoach with the SFTSDH solution in [15] sustained a load of (approximately) 1000 concurrent users in the digital healthcare infrastructure. To execute scalability testing in JMeter, we considered the "Thread Group" feature of the program, concurrent threads or loads (X) were assigned three different ramp-up times (Y) and a loop count of five (Z). At each iteration, X*Z loads were created in order to capture the mean throughput and mean latency. Additionally, we proposed a code that is pseudo-implemented for scalability testing.

- REQS-13: In [14], we have shown a direction to combine HL7 FHIR and SNOMED-CT vocabularies to exchange personal health data in eCoach system, using a structured JavaScript object notion (JSON) format. This study investigated and analyzed an attempt to create and implement a structurally and logically compatible tethered PHR (eCoach) that allows bidirectional communication with an EHR (data storage at TSD [15]) following the PHR-S FM functions as an interoperability standard. We recorded 0% data loss and 0% unreliable performance during the transfer of data between PHR and EHR.

6.5 Answer to the Research Questions

In this section, we revisit our research questions and research problem. Overall, the well-established DSRM method helps to design and develop an activity eCoach prototype as explained in Chapter 2, thereby answering the research questions to address the identified research problem.

Research Question RQ-1

Human coaching is a complex process. Coaching as human behavioral intervention is a personalized, planned process designed to reward and reinforce the positive behavior of human beings. Each behavioral intervention differs from others based on the participants, who are the primary targets of the intervention, where psychology and context play crucial roles. It involves different methods to understand psychology, behavioral science, philosophy, and essential coaching processes for effective coaching. Integrating the human coaching methods in eCoaching for healthy lifestyle management using ICT is another challenging task. This can be explored with different methods, such as interviewing, workshops, and systematic literature reviews.

In this study, we have performed a systematic literature review to search the scientific databases using the PRISMA framework for the evidence-based systematic review and meta-analysis. The literature review helps to address RQ-1 and in detail, elaborated in *Paper-B (P-B).* We have found knowledge, coaching skills, observation, interaction, ethics, trust, effectiveness research, coaching experience, pragmatism, intervention, goal setting, and coaching process assessment relevant to eCoaching. The most appropriate methods for human coaching are behavior, methodology, psychology, and mentoring. In contrast, persuasive eCoaching methods are personalization, interaction and co-creation, technology adoption for behavior change, goal setting and evaluation, persuasion, automation, and lifestyle change. The obtained knowledge through the literature review has helped to integrate offline human coaching methods and processes into our designed and developed real-time activity eCoach prototype.

Research Question RQ-2

Appropriate selection of data is crucial in eCoaching to plan personalized recommendation generation. Such an eCoach system must collect and transform distributed and heterogeneous personal preferences, and health and wellness data into meaningful information. A semantic annotation can help in this regard to convert heterogeneous data into meaningful information for enhanced knowledge representation and reasoning. A semantic annotation can be achieved by different modeling techniques and semantic models [24].

As a part of the study design prerequisites, we have initially created a set of personal, physiological, behavioral, and contextual data from heterogeneous sources (e.g., sensors, questionnaires, feedback, and interview). Furthermore, we have refined our selection based on the inputs from experts and end-users in the UCD workshops. This study develops an OWL-based domain ontology to annotate a selected set of personal, physiological, behavioral, and contextual data to generate meaningful, practical, personalized, and contextual lifestyle recommendations based on the defined rules in a knowledge base. Moreover, we have extended the ontology design to annotate personalized recommendation message intent, components (e.g., suggestions, feedback, argument, and follow-ups), and contents (such as spatial and temporal context and objects relevant to performing the recommended activities). A reasoning technique has helped to discover implied knowledge from the proposed ontology. We have integrated the well-established concepts from the SSN and SNOMED-CT ontologies into our ontology design. The idea of semantic knowledge representation with ontology help to address RQ-2.

Research Question RQ-3

The generation of automatic and personalized recommendations in an eCoach system is an existing research problem to be addressed. According to the literature survey, recommendation generation in eCoaching is in the nascent stage. The recommendation generation can be either rule-based or data-driven. A rule-based recommendation generation follows an IF-ELSE binary decision-tree structure, where each branch defines a rule, and the leaf node represents the action to be executed. In contrast, a data-driven approach follows an intelligent optimization technique (e.g., machine learning and deep learning algorithms) to make data-based decisions. A data-driven approach requires more data than a rule-based approach. A hybrid approach may overcome the shortcomings of data-driven and rule-based recommendation technologies, which have been addressed in this study.

This study proposes an algorithm for an automatic, hybrid, and personalized recommendation generation with deep learning and OWL ontology, and its integration into an activity eCoach recommendation system. We have designed and developed an eCoach prototype that can – collect activity data from actual participants with wearable activity sensors; process collected data with deep learning models to forecast step count; classify individual activity levels; calculate and compare activity intensity across different weeks with statistical methods; combine the results in an ontology for semantic knowledge representation and thereby generate personalized recommendations with SPARQL query engine against a rule base. The novel contributions are –

1. Design and development of an ontology model (OntoeCoach) for semantic representation of personal and personalized activity data,

2. Propose a novel algorithm that combines the OntoeCoach model with deep learning for hybrid recommendation generation with person-based heuristic configuration, and

3. Evaluation of the performance of time-series prediction, classification, and ontology models on both public (i.e., PMData) and private (i.e., MOX2-5 activity) datasets.

Therefore, deep learning models, OntoeCoach ontology, and a hybrid personalized recommendation generation algorithm help to address RQ-3.

Research Question RQ-4

Besides automatic and personalized recommendation generation, its effective representation in eCoaching to motivate individuals is challenging. It involves human psychology, technical readiness, cultural diversity, quality of life, and human values. As a prerequisite for the prototype design of such a helpful eCoach system, it is essential to involve the end-users and subject-matter experts throughout the iterative design process. Different design methods are available in the Software Engineering discipline, such as UCD, Usage-Centered-Design, Self-Design, Genius Design, and Activity-Focused Design. However, based on the evidence from scientific design and development studies, the UCD approach has been widespread. It can be achieved in either an iterative process or a non-iterative process.

In this study, we have used an iterative UCD approach to understand the context of use and to collect qualitative data to develop a roadmap for self-management with eCoaching. We have involved researchers, non-technical and technical people, health professionals, subject-matter experts, and potential end-users in the design process. We have designed and developed the eCoach prototype in two stages, adopting different phases of the iterative design process. In Design Workshop 1, we focused on identifying end-users, understanding the user's context, specifying user requirements, and designing and developing an initial low-fidelity eCoach prototype. In Design Workshop 2, we focused on maturing the low-fidelity eCoach prototype. Therefore, the iterative UCD approach helps to address RQ-4.

Arguments to Address the Research Problem with Answering to the RQs

A research problem is a statement that addresses a knowledge gap, challenge, or contradiction. Research problems can be of different types, such as theoretical, applied, and action-based. Different researchers address a research problem in different ways depending on the research approach, planning, context, and interests. We have used a bottom-up approach to address our applied research problem - ***How to generate automatic personalized recommendations in eCoaching?***

First, we create a research problem. *Second*, we defined scope and limitations. *third*, we prepare four potential research questions (RQ-1 to RQ-4) to address the research problem. We select the most suitable method from potential alternatives to answer each research question. *Forth*, our paper-based contributions (Paper-A to Paper-F) help to answer the research questions. Identified research questions are contextually linked, as the answer to one research question is an entry point to answer the following research question. *Fifth*, we combine the answers to research questions to show a direction to address our identified research problem.

The RQ-1 serves as a theoretical backbone to identify and integrate offline human coaching methods and processes into our designed and developed activity eCoach system. The inputs from experts and end-users in the UCD workshops help us to prepare a set of data (e.g., personal, activity, contextual, preferences) to be used in the design and development of our activity eCoach system. Therefore, we plan to collect data from heterogeneous sources. The RQ-2 contributes toward the semantic representation of heterogeneous data with OWL ontology. Collected data has served as input for the activity eCoaching session, as they are essential to building a recommendation model in the eCoach system. The RQ-3 contributes toward a theoretical concept of hybrid personalized recommendation generation in eCoaching with deep learning algorithms, OWL ontology, SPARQL, ruleset, and personal preferences. We have verified our proposed recommendation algorithm with public and private activity datasets. We integrate the machine learning pipeline with an incremental learning approach in our recommendation generation to automate the process in our eCoach system. Besides the generation of personalized recommendations, its effective presentation is essential to motivate eCoach participants.

Therefore, in RQ-4, we have shown a direction to present personalized activity recommendations in a meaningful way based on the inputs from experts and end-users in the UCD workshops.

Therefore, the answers to the research questions have added knowledge to address the identified research problem using a Design Science Research Methodology. As an alternative, the identified problem can be approached with the technology-oriented education methodology as explained in [64]. However, both methods are on the foundation of Design Science Principles. As an alternative, in the prediction and forecasting model, we can use different standard machine learning classification algorithms and statistical time-series forecasting algorithms; however, with growing data, deep learning algorithms are very relevant. In this regard, AutoML can also be effective. As an alternative, in ontology querying, we can use Jena Expression Rules; however, SPARQL and SWRL give a robust vocabulary to process ontological data as compared to other Expression rules. If we could have used the alternative approaches, we would not have been far off in addressing our research problem using our current approaches.

6.6 Discussion

In this section, we compare our study with existing literature, qualitatively, discuss novelty, evaluate the technological readiness level (TRL) of our designed and developed activity eCoach prototype system, add arguments to use MOX2-5 wearable activity device, and generalize the research outcomes.

6.6.1 Comparison with Existing Literature

eCoach features [5] such as intervention, personalization, interaction, co-creation, goal management, automation, persuasion, and recommendation generation with a combination of wearable activity sensors have the potential in improving physical activity. In Table 6.8, we have carried out a qualitative comparison between our activity eCoach prototype and commercial activity tracking smartphone apps (e.g., Fitbit, Actigraph, MOX2-5, Pedometer, Garmin, and smartwatches (e.g. Apple, Samsung, Huawei) regarding eCoach components identified in the systematic literature search [5]. Traditional activity-tracking smartphone apps focus more on data collection and representation; however, they suffer from the UCD approach, adequate data, semantic annotation of data for knowledge representation, data governance, data consistency, proper documentation, guidelines, and ethical approvals. From the literature search, the eCoaching concept in healthcare is still in its infancy stage. Real-time analysis of data to generate personalized recommendations on time is crucial in eCoaching. The feasibility analysis of deep learning and machine learning models in physical activity recognition has been proven to design a pipeline. However, this study describes their application one step ahead by applying deep learning models, statistical methods, and OWL ontology in real-time activity coaching to improve sedentary lifestyles with goal management capabilities. Our study is novel, and no similar work has been published, as found in the existing literature. The eCoaching concept with AI-based personalized recommendation generation is still improving. Therefore, a qualitative comparison between our study and the related activity coaching studies has been performed instead of a quantitative evaluation in Table 6.9. The study mentioned by Pessemier et al. [30] focused on recommendation generation at the "Community" level, whereas this work targets activity coaching and recommendation generation at the "Personal" level.

Table 6.8: A qualitative comparison with the commercial lifestyle management apps and smartwatches regarding the generic eCoaching components.

eCoach components	Commercial apps and smartwatches	Our eCoach prototype
Intervention	×	✓
Personalization	×	✓
Interaction	✓	✓
Co-creation	×	✓
Goal management	×	✓
Automation	×	✓
Persuasion	×	✓
Recommendations	×	✓

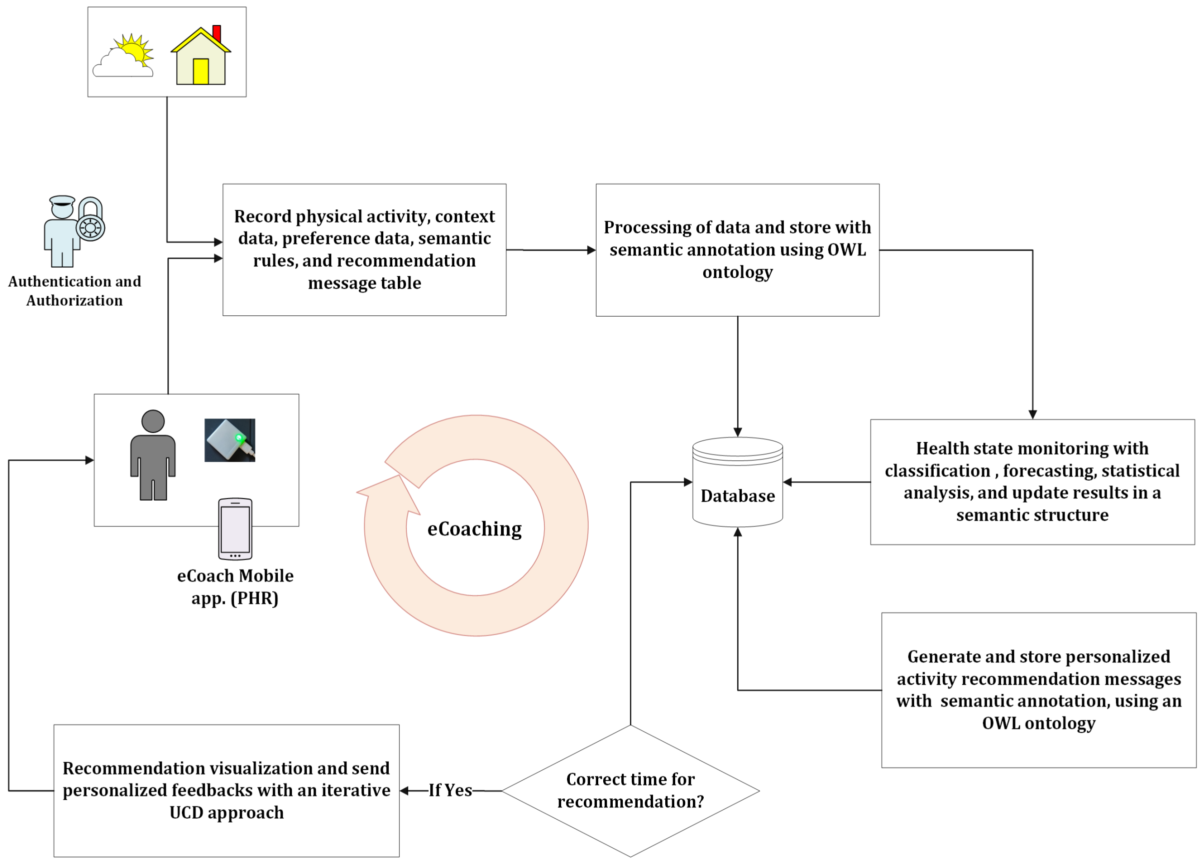

Figure 6.1: Overall concept of automatic and personalized recommendation generation in our activity eCoach system.

Table 6.9: A qualitative comparison with the existing studies.

Study	Hybrid recommendation generation	Semantic modeling with ontology and ontology tree in decision-making	Interval prediction	Observation with activity sensor	Incorporation of preference data	Logical recommendation generation
Our work	✓	✓	✓	✓	✓	✓
A Dijkhuis et al.[28]	×	×	×	✓	×	×
B Hansel et al. [29]	×	×	×	✓	×	×
TD Pessemier et al. [30]	✓	×	×	✓	✓	×
AB Amorim et al. [31]	×	×	×	✓	×	×
CB Oliveira et al. [32]	×	×	×	✓	×	×
D Petsani et al. [33]	×	×	×	×	×	×
NB Den et al. [34]	×	×	×	✓	×	×
A Chatterjee et al. [24]	×	✓	×	×	×	×
C Villalonga et al. [35]	×	✓	×	×	×	×

6.6.2 Novelty

This novel research demonstrates the feasibility of analysis of deep learning time-series classifiers and prediction models to design a pipeline for automatic and personalized recommendation generation in a physical activity eCoaching system. However, this study shows its application one step ahead by applying predictive data analysis, statistical methods, and OWL ontology in real-time activity recommendation generation to improve sedentary lifestyles through goal management skills. In particular, this study has theoretically developed a hybrid activity recommendation generation concept in activity coaching with – 1) a deep learning model to classify individual daily physical activity into multiple levels such as sedentary, low physically active (LPA), medium physically active (MPA), and vigorous physically active (VPA), 2) a deep learning model for univariate "step" forecasting, 3) state-of-the-art statistical methods to calculate weekly activity intensity, 4) mapping the time-series point prediction to a probabilistic interval prediction, and 5) the creation of an OWL ontology for semantic modeling of personal preferences, activity predictions, and the generation of personalized recommendations with SPARQL against a rule base.

To verify the mentioned objectives, we have used time-series sensor data (in a processed form) for individual activity prediction and forecasting. To explain the study's relevance, we have proposed an algorithm to annotate the activity prediction outcomes in an ontology for personalized recommendation generation. Semantic annotation can more easily identify causal relationships between data inputs and recommendation results. To the best of our knowledge, no similar work on recommendation generation in eCoaching has been published or made available online. Moreover, our recommendation generation technique follows a logical binary tree structure, which helps to **interpret** the recommendation generation (see Figure 6.2). It turns the generated automatic and personalized recommendations in eCoaching **appropriate** and **trustworthy**.

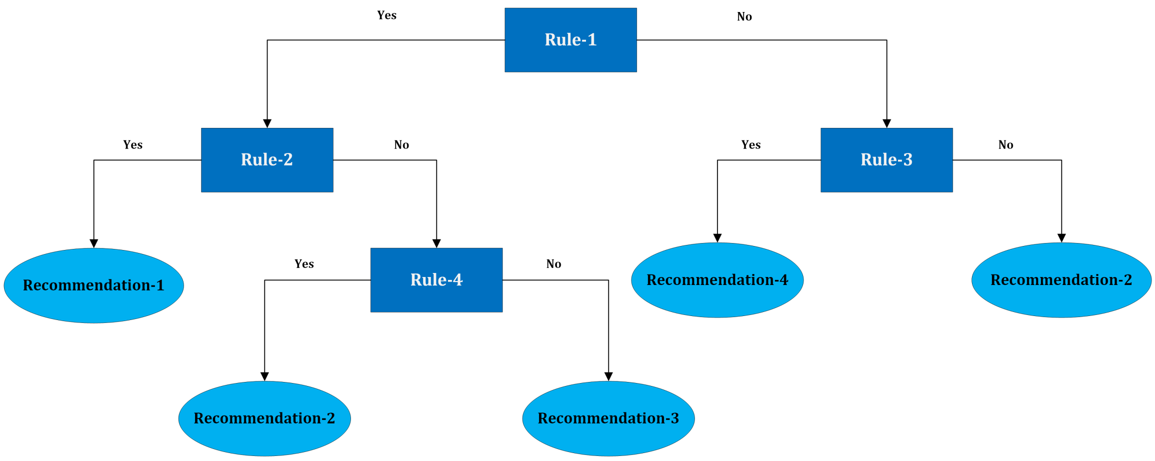

Figure 6.2: The structure of the recommendation generation binary tree. "Recommendations" on leaf nodes are maintained in a knowledge base. "Rules" on the branch nodes are semantic rules, and variables in each rule are derived from the SPARQL query execution over the Ontology model.

Overall, this research study has been successful in contributing towards automatic and personalized recommendation technology enabling part in a physical activity eCoach recommendation system with Ontology, Deep Learning, Statistical Exploration, and Software Engineering. Moreover, the quantitative (Section 6.3) and qualitative (Section 6.4) evaluation outcomes have successfully captured the evaluation of recommendation generation technology, rather than the content and quality of the recommendations. The outcomes of this research can further be extended for other study cases, in a broader perspective.

6.6.3 Technology Readiness Level

Our activity eCoach prototype system aims to increase individual participants' physical activities and motivation with monitoring and automatic recommendation generation, and to trigger participants to engage in physical activities at the right time by leveraging self-maintained persuasive strategies. We have collected design requirements from the end-users to design and develop our activity eCoach prototype that can generate an automatic and effective personalized recommendation for a sedentary lifestyle and turn it into a behavioral motivation for an effective human-eCoach-interaction.

Table 6.10: Achieved TRLs in our eCoach prototype system as compared to work in [1].

TRLs	Work in [1]	Our work
1: Basic principles observed	✓	✓
2: Technology concept formulated	✓	✓
3: Experimental proof of concept	×	✓
4: Technology validated in lab	×	✓
5: Technology validated in relevant environment	×	×
6: Technology demonstrated in relevant environment	×	×
7: System prototype demonstration	×	×

In the eCoach system, converting distributed, heterogeneous health and wellness data (e.g., sensor, questionnaire) into meaningful information with semantic ontology is inventive. The concept of hybrid recommendation technology, processing of medical-grade sensor data, and probabilistic interval prediction for motivational recommendation visualization make the solution pioneering. Furthermore, adopting persuasive strategies in the design phase has made the eCoaching idea innovative. The overall concept of automatic and personalized recommendation generation in our activity eCoach system has been depicted in Figure 6.1. Our eCoaching concept has been an improvisation of [1] towards generating automatic and personalized recommendations in eCoaching. Therefore, Table 6.10 describes a comparison of technology readiness levels (TRLs) of our activity eCoach prototype with the study performed in [1], against standard levels set by the EU.

6.6.4 Arguments to Select MOX2-5 Activity Device

Questions may arise about using the MOX2 device for activity monitoring as there are different activity monitoring mechanisms in the market, such as Apple, Samsung, and other consumer devices (e.g., Fitbit, Actigraph). MOX2 activity monitoring device is CE certified. Maastricht Instruments, a spin-off company of the Maastricht Hospital, and supplier of the MOX-2 activity monitoring device has informed the following −

- Apple, Samsung, or similar service providers utilizes the sensors in the smartphone. People do not wear the smartphone at the same body location all day, so this poses difficulty in accurately assessing physical activity. An actigraph is in the same category of devices as the MOX; however, MOX2-5 is cheaper to use.
- Maastricht Instruments validated Fitbit and the like in elderly populations, and they saw a high variability. Furthermore, it is never known when the manufacturer replaces the algorithms or sensors in the device, so it is tricky to do clinical trials with such devices (over longer durations).
- Most consumer devices are not suitable for use in medical applications. Maastricht Instruments has proven the performance of their MOX2 device in several published studies on higher-level activity.

6.6.5 Generalization

In this dissertation, we have discussed eCoaching for physical activity monitoring with automatic and personalized recommendation generation, self-monitoring, motivation, and goal management as a PoC study. However, eCoaching can broadly control other behavioral changes, such as habit, nutrition, depression, chronic pain, and cognitive decline. Therefore, the eCoaching concept can be promising in self-monitoring of chronic illnesses, such as diabetes type II, obesity and overweight, mental health, and cardiovascular rehabilitation.

The RQ-1 helps to identify and integrate offline human coaching methods and processes into eCoach systems in a broader perspective. The contribution of RQ-2 toward the semantic representation of heterogeneous data with OWL ontology can be extended for other study cases. The proposed automatic and personalized recommendation generation algorithm with heuristic configuration as an outcome of RQ-3, can be further expanded and customized to support eCoaching for other case studies. The interactive interface design with iterative UCD workshops is a general and well-established approach. The idea and approach of recommendation presentation in a meaningful way based on the inputs from experts and end-users in the UCD workshops, as obtained from RQ-4, can further be applied for other case-specific eCoach design and development. Therefore, the research questions not only address the research problem but also their research outcomes can be extended for other case-specific eCoaching in a broader perspective.

6.7 Chapter Summary

In this chapter, we explain different human coaching methods applicable to eCoaching and elaborate on the experimental setup to run the overall experiment. We have divided our experimental evaluations into quantitative evaluations and qualitative evaluations. Quantitative evaluation discusses feature engineering on PMData and MOX2-5 datasets, performance evaluation of our designed and developed time-series prediction and forecasting models, and ontology evaluation for the personalized and hybrid recommendation generation following a logical structure. In contrast, the qualitative assessment discusses the functionality testing of our eCoach prototype app, the novelty of the prototype as compared with existing studies, and the technology readiness level against standard levels set by the EU. We explain the research outcome to answer the identified research questions to address the identified research problem using a bottom-up manner. Furthermore, we have informed the alternative approaches to answer the research questions and address the research problem.

Chapter 7

Conclusion and Future Scope

This chapter elaborates our conclusive summary of the contributions and is followed by identified limitations to overcome as a part of the future research scope.

7.1 Summary of Contributions

The objective of this thesis has been to conceptualize and technically verify the concept of automatic and personalized recommendation generation in eCoaching. To proof-the-concept, we have designed and developed an intelligent activity eCoach prototype to generate intuitive, meaningful, evidence-based, and customized lifestyle recommendations to achieve personal lifestyle goals. Furthermore, this study presents a detailed overview of rationale, characteristics, iterative user-centered design, and the development process of a health eCoach app for the self-management of physical activity to stay active (or reduce sedentary time). Our original contributions to knowledge are summarized as follows. The layout of the contributions is depicted in Figure 7.1.

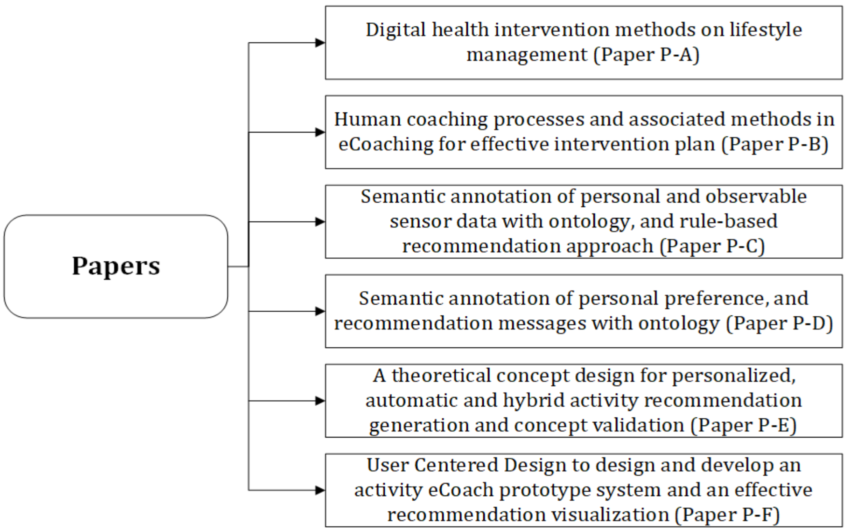

Figure 7.1: The layout of the included papers.

- **P-A**: This paper has helped to contribute to State-of-The-Art. In this contribution, we evaluated the impact of digital interventions on weight management in maintaining a healthy lifestyle (e.g., regular physical activity, healthy habits, and proper dietary patterns). The results help us understand how digital interventions influence lifestyle management and overcome existing shortcomings. It serves as a basis for further research focusing on designing, developing, testing, and evaluating the generation of personalized lifestyle recommendations as a part of digital health interventions.

- **P-B**: This paper has helped to address RQ-1 and contribute to State-of-The-Art. In this contribution, we identified coaching and eCoaching processes as behavioral interventions and the methods behind these processes. Here, we mainly looked at processes (and corresponding models that describe coaching as specific processes) and the methods used within the different processes. The identified methods of coaching point toward integrating human psychology in eCoaching to develop effective intervention plans for healthy lifestyle management and overcome the existing limitations of human coaching.

- **P-C**: This paper has helped to address RQ-2. This contribution developed an OWL-based ontology (UiA eHealth Ontology/UiAeHo) model to annotate personal, physiological, behavioral, and contextual data from heterogeneous sources (sensor, questionnaire, and interview), followed by structuring and standardizing diverse descriptions to generate meaningful, practical, personalized, and contextual lifestyle recommendations based on the defined rules.

- **P-D**: This paper has helped to address RQ-2. In this contribution, we designed and developed an ontology to model personalized recommendation message intent, components (such as suggestion, feedback, argument, and follow-ups), and contents (such as spatial and temporal context and objects relevant to perform the recommended activities).

- **P-E**: This paper has helped to address RQ-3. This contribution proposed a hybrid personalized recommendation generation method in eCoaching. We considered "Physical Activity" as a study case. This contribution found a mixed activity prediction approach with the following methods: time-series prediction, time-series activity level classification, and statistical approaches (e.g., weighted mean, standard deviation, activity pattern, and similarity score). We used Naïve-based probabilistic interval prediction with residual standard deviation to make point prediction meaningful in the recommendation presentation. We integrated the processed outcomes on activity datasets in an ontology (OntoeCoach) for semantic representation and reasoning. We used SPARQL to generate personalized recommendations in an understandable format.

- **P-F**: This paper has helped to address RQ-4. This contribution designed and implemented the process of an activity eCoach monitoring and personalized recommendation generation app for the preparation of a mobile health (mHealth) intervention to encourage the self-management of physical activity. It demonstrated a

UCD process's consideration to make it suitable for end-user, technology, healthcare professionals, engineers, and researchers.

7.2 Future Outlook

We plan to overcome certain limitations of this study in our future work. The restrictions are summarized as follows –

- We have presented the design and development of an eCoach prototype for activity coaching. However, we have not performed its usability and acceptability testing for the heuristic evaluation of the eCoach prototype.
- In the physical activity monitoring, the scope can be extended to sleep monitoring rather than only step prediction and visualization along with daily step count and total minutes of VPA, MPA, and sedentary bouts.
- Clinical evaluation (medical efficiency and improvements of the health and wellness) of eCoaching on different cases in the direction of adequacy, reliability, and effectiveness of the automatically generated/delivered recommendations in controlled or uncontrolled trials.
- This study has not evaluated recommendation generation's credibility, reliability, effectiveness, and presentation (direct and indirect) towards motivational and behavioral change. Following usability evaluation, we will recruit participants of similar interests in efficacy evaluation of the recommendation generation.
- Constraints, such as poor internet connectivity, android version constraints, battery lifetime due to background processing, budget, time plan, and technological limitations should be overcome.
- The used version of the MOX2-5 activity sensor cannot distinguish the type of activity, such as swimming, skiing, or cycling. Therefore, a questionnaire should be designed to overcome its reporting.
- The scope of recommendation generation and turning it into a behavioral motivation is extensive. Here, we have not evaluated concepts, such as what is a good goal? How do we generate effective feedback for behavioral motivation? Future studies can compare actual participants' feedback and activity trends to modify goal settings and gradually tailor them. Likewise, recommendations can be presented to participants in different ways, such as visual (e.g., graph, chart), audio, text (e.g., pop-up notification or on-screen messages), or any combination. In our future study, we can recruit different people to compare the conceptual basis of effective recommendation presentation for behavioral motivation.
- Besides only activity monitoring and recommendation generation, incorporating nutrition assessment and tracking habits can allow the eCoach app to change behavior for a healthy lifestyle in obesity cases.

- Improvement in AI prediction to classify meaningful (effective) and bad (inefficient) recommendations with continuous learning from individual data and performance trends, and following, personalized recommendation generation with obtained knowledge.

- Recommendations in an eCoach system can be rule-based, data-driven, or hybrid. An appropriate selection of recommendation generation methods is essential in eCoaching to generate contextual and meaningful personalized and group-level recommendations. Adopting explanation methods in recommendation generation will make eCoaching more attractive and trustworthy to its participants.

- Improvement of automatic recommendation generation in eCoaching with the concepts, such as clustering, similarity score, reward maximization, fuzzy logic, entropy, and community-based heuristic approaches,

- Behavior is a slow but gradual change. To evaluate the practical efficacy of eCoaching toward behavior change, self-management, credibility, and motivation, a proper longitudinal study plan is necessary for two groups (one group without eCoaching and one group with eCoaching) of controlled trials with a minimum group size of 50 participants following inclusion and exclusion criteria, to compare the outcomes with statistical methods. Furthermore, future work focuses on understanding the importance of socio-demographic characteristics such as age, gender, ethnicity, and education level of the enrolled individuals to achieve a high level of generalized findings. It also helps to categorize individuals into different subgroups to obtain adequate support to control their lifestyle and behaviors for more generalized purposes.

- Collaborative filtering is a popular recommendation generation technique to filter out items based on the reactions of similar users. Collaborative filtering is a searching problem where a large group of users is being searched to find a smaller set of users with tastes like a particular user. It helps to create a ranked recommendation. This research proposes a model-based personalized recommendation algorithm based on a hybrid approach where the deep learning classification and forecasting results are combined with semantic ontology to generate rule-based customized recommendations. Activity recommendations are filtered out based on personal preferences and goal achievements. The ontology tree structure explains the logic or rules behind a particular recommendation generation. The process is very personalized and, therefore, does not include the concept of group similarity in recommendation generation. In the future, we will extend this study with a group-based meta-heuristic approach by combining the idea of collaborative filtering. We will analyze further the applicability of density-based spatial clustering, session, and criteria in our future group-based lifestyle recommendation generation.

- We will adopt different synthetic data generation methods to generate a high volume of training, validation, and testing data to evaluate the robustness of the AI models.

- Anomaly is a generic problem associated with sensor-based time-series observations. We will adopt different anomaly detection and correction methods to increase time-series forecasting and prediction efficiency.

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Paper A

Digital Interventions on Healthy Lifestyle Management: Systematic Review

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Digital Interventions on Healthy Lifestyle Management: Systematic Review

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Abstract – **Background**: Digital interventions have tremendous potential to improve well-being and health care conveyance by improving adequacy, proficiency, availability, and personalization. They have gained acknowledgment in interventions for the management of a healthy lifestyle. Therefore, we are reviewing existing conceptual frameworks, digital intervention approaches, and associated methods to identify the impact of digital intervention on adopting a healthier lifestyle. **Objective**: This study aims to evaluate the impact of digital interventions on weight management in maintaining a healthy lifestyle (eg, regular physical activity, healthy habits, and proper dietary patterns). **Methods**: We conducted a systematic literature review to search the scientific databases (Nature, SpringerLink, Elsevier, IEEE Xplore, and PubMed) that included digital interventions on healthy lifestyle, focusing on preventing obesity and being overweight as a prime objective. Peer-reviewed articles published between 2015 and 2020 were included. We used the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines and a framework for an evidence-based systematic review. Furthermore, we improved the review process by adopting the Rayyan tool and the Scale for the Assessment of Narrative Review Articles. **Results**: Our initial searches identified 780 potential studies through electronic and manual searches; however, 107 articles in the final stage were cited following the specified inclusion and exclusion criteria. The identified methods for a successful digital intervention to promote a healthy lifestyle are self-monitoring, self-motivation, goal setting, personalized feedback, participant engagement, psychological empowerment, persuasion, digital literacy, efficacy, and credibility. In this study, we identified existing conceptual frameworks for digital interventions, different approaches to provide digital interventions, associated methods, and execution challenges and their impact on the promotion of healthy lifestyle management. **Conclusions**: This systematic literature review selected intervention principles (rules), theories, design features, ways to determine efficient interventions, and weaknesses in healthy lifestyle management from established digital intervention approaches. The results help us understand how digital interventions influence lifestyle management and overcome the existing shortcomings. It serves as a basis for further research with a focus on designing, developing, testing, and evaluating the generation of personalized lifestyle recommendations as a part of digital health interventions.

Introduction

Overview

Deaths caused by lifestyle diseases are increasing rapidly compared with deaths caused by infectious disease [1][2][3][4]. Most lifestyle diseases arise from unhealthy and sedentary lifestyles, low nutritional propensities, and poor living conditions, affecting individuals from different financial backgrounds, beyond age and gender biases [1][2][3]. Lifestyle diseases are a monetary burden to individuals, families, businesses, and governments. They cause 41 million deaths each year, equivalent to 71% of all deaths worldwide [1][2][3][4][5][6]. Every year, 15 million people die from lifestyle diseases between the ages of 30 and 69 years, and more than 85% of these premature deaths occur in low- and middle-income countries [1][2][3][4][5][6]. The fundamental risk factors [7][8][9][10][11][12][13] behind lifestyle diseases are excessive alcohol and tobacco consumption, improper food plan, and physical inactivity, resulting in excess weight gain (obesity), increased blood glucose, hypertension, high blood cholesterol, and social detachment [1][2][3][4][5][6]. The fundamental risk factors [7][8][9][10][11][12][13]. Obesity is a primary lifestyle disease that leads to other lifestyle diseases, such as cardiovascular diseases (CVDs), clinical obstructive pulmonary disease, cancer, type 2 diabetes, hypertension, and depression [1][2][3][4][5][6]. The fundamental risk factors [7][8][9][10][11][12][13]. In 2016, more than 1.9 billion adults age $\geq$18 years were overweight. Of these, over 650 million were obese [2][3][4]. In 2016, 39% of adults aged $\geq$ 18 years were overweight, and 13% were obese [2][3][4]. In 2019, an estimated 38.2 million children aged $\leq$ 5 years were overweight or obese [2][3][4]. Once considered a problem in high-income countries, overweight and obesity are now rising in low- and middle-income countries (especially in urban environments) [2][3][4]. Since 2000, the number of overweight children aged $\leq$ 5 years has increased by nearly 24% in Africa [2][3][4][8]. In 2019, almost half of the children aged $\leq$5 years who were overweight or obese lived in Asia [2][3][4][8]. Thus, control plans need to include detection, screening, treatment, and prevention methods. Digital interventions may provide viable and hypothetically cost-effective models to improve well-being. They provide widely distributed, trusted, and personalized well-being information and services to fulfill individualized needs to maintain a healthy lifestyle [14][15][16][17][18][19].

Digital interventions for changing negative health behaviors to advance a healthy lifestyle are instigated by persuasion studies. The World Health Organization (WHO) has classified digital health interventions into the following 4 categories: clients, health care providers, health system managers, and data services, where digital and mobile technologies are being used to help well-being system needs and achieve health objectives [20][21][22][23][24][25][26]. Digital intervention methods include conceptualization, intervention strategies, policy design, understanding of the environment, motivation, behavioral determinants and psychology, persuasion, self-determination theory, self-regulation, participation (engagement), decision-making and feedback generation, goal setting and evaluation, incorporation of digital technologies (eg, smartphones, computers, and wearable sensors), and digital recommendation generation. Its success depends on credibility, satisfaction, privacy, digital literacy, proper connectivity, cocreation, and efficacy evaluation [20][21][22][23][24][25][26]. According to the WHO, harnessing the power of digital technology is critical to achieving universal health coverage, and digital technologies are not an end in themselves; they are essential tools for promoting health, maintaining world security, and serving the disadvantaged [18][19][20][21][22][23][24]. Digital interventions have been carried out effectively for well-being advancement and psychological well-being, and for enabling self-administration of enduring conditions [18][19][20][21][22][23][24]. None theless, their capability is restricted by low use rates, with noncommitment being a significant challenge. The use of digital technology provides new opportunities to improve health [18][19][20][21][22][23][24]. However, the evidence also highlights the challenges posed by certain interventions. If digital technologies are to be maintained and integrated into health systems, they must be able to demonstrate long-term improvements compared with traditional methods of providing health services [23][24].

Limitations

Digital intervention depends heavily on the context and ensures the proper design, including the structural issues in the environment in which they are used, the available infrastructure, the health needs they are addressing, and the ease of use of technology [1][15][16]. Consequently, it is important to discover successful procedures for expanding individual engagement with digital interventions. Digital interventions can also support health workers to give them more opportunities to clinical protocols around, for example, decision support mechanisms or telemedicine consultation [15][16]. Digital interventions should supplement and enhance the functions of the health system by accelerating information exchange and other mechanisms but cannot substitute the essential components required by the health system, such as the health workforce, funding, leadership and governance, and access to critical medicines. However, digital interventions in health care have tremendous potential as scalable tools to enhance well-being and health care service conveyance by improving viability, proficiency, openness, and personalization [1][15][16]. The WHO is working hard to ensure that it can be used as efficiently as possible, which means adding value to medical staff and individuals who use these technologies, considering the limitations of the infrastructure, and making appropriate coordination [22][23][24]. Although digital intervention's application area is broad, we have focused only on digital behavioral intervention for healthy lifestyle studies in this paper.

Study Aim

Efficiency, acceptability, and compliance are 3 necessary indicators of digital behavioral interventions, as they are prerequisites for positively affecting health or healthy behavior. Efficacy refers to the effect of using technology in behavioral interventions. Acceptability means that users are satisfied with the technology. Compliance refers to the degree to which technology is used, as expected. This systematic literature review addresses the following research questions (RQs):

RQ1: what are the existing conceptual frameworks for digital interventions for healthy

lifestyle management?
RQ2: what are the different approaches to provide digital interventions for healthy lifestyle, and what are the essential methods?
RQ3: what is the importance of digital intervention in promoting healthy lifestyles, targeting obesity and overweight?

Methods

Overview

We used a systematic literature review method to obtain a broad overview of the current literature on the subject in a reproducible and understandable manner. A systematic review is a study of the evidence of a clearly expressed problem. It uses systematic and transparent strategies to understand, select, and strictly evaluate related basic research and extract and explore facts from the research covered in the evaluation. Systematic reviews represent scientific synthesis of evidence. We used the PRISMA [27] and Rayyan [28] evidence-based frameworks for systematic literature reviews. Subsequently, for article selection, we used the Scale for the Assessment of Narrative Review Articles (SANRA) scaling [29]. We conducted our systematic literature review following the Wendler [30] proposals to search scientific databases, as explained in *Strategy* subsection.

Strategy

The system's search strategy was designed using a combination of thesaurus, Oxford Dictionary, and free terms covering the following terms: eCoach, e-Coach, eHealth, e-Health, electronic coaching, online, automatic, persuasion, persuasive technology, mHealth, mobile health, digital health, mobile, digital intervention, smartphone, smart-phone, application, app, prevention, healthy behaviour, healthy behavior, behaviour change, behavior change, exercise, activity, walk, step, fitness, sitting, inactive, screen time, sport, leisure activity, nutrition, nutritional, diet, dietary, healthy eating, salad, vegetables, fruit, discretionary food, snack, sweet beverage, carbonated beverage, soft drink, habit, tobacco, alcohol, computer, sedentary, lifestyle, intervention, lifestyle recommendation, digital recommendation, behavioral recommendation, program, programme, conceptual model, health promotion, prevention, obesity, overweight, weight-gain, weight gain, weight change, engagement, effectiveness, efficiency, credibility, trust, motivation, regulation, challenges, preferences, sample, and study duration. We filtered our search with the following search string: ((eCoach OR *Coach OR *coaching OR automatic OR online OR eHealth OR e-Health OR persuasion OR persuasive* OR mHealth OR mobile* OR digital health) AND (digital intervention OR smartphone OR smart-phone OR computer OR app* OR prevention OR *recommendation) AND (*behavior* OR *behaviour* OR sedentary* OR lifestyle OR exercise OR *activity OR walk OR step OR fitness OR inactive OR screen time OR sport OR nutrition* OR diet* OR healthy eating OR salad OR veg* OR fruit OR discretionary* OR snack OR *beverage OR soft drink OR habit OR tobacco OR alcohol) AND (engagement OR persuasion OR effectiveness OR efficacy OR efficiency

OR *motivation OR *regulation OR challenge* OR limitation* OR credibility OR trust OR preferences OR program OR programme OR conceptual* OR sample OR *duration) AND (obesity OR *weight*)). We conducted the search in collaboration with the library of the University of Agder in Norway on the following 5 electronic databases, Nature, SpringerLink, Elsevier, IEEE Xplore, and PubMed, as they produced the maximum number of scientific sources related to digital intervention studies for healthy behavior targeting on the prevention of obesity and overweight as a primary objective. Related search keywords were identified using Medical Subject Headings terms, keywords from relevant articles, synonyms, and self-established search terms. EndNote (V.9.x), DOAJ, SHERPA/RoMEO, and Microsoft Excel (Office 365, 2019) were used to search, collect, and select related articles effectively.

Textbox A.1: Inclusion criteria for systematic literature review.

Inclusion criteria

- Peer-reviewed, full-length articles written in English
- Digital intervention on healthy lifestyle articles published in the selected databases between 2015 and 2020
- Articles indexed in Google Scholar and (SCOPUS or SCI or SCIE)
- Journal papers, conference papers, or books
- Both qualitative (primary and secondary research) and quantitative studies
- Open access and accessible through the university library
- Studies associated with behavior change prevention rather than treatment and management of health conditions

Studies on digital intervention are promising and have an enormous scope in the health care domain with information and communication technologies. A systematic literature review produced related older studies, but they are primarily in the theoretical phase, and its practical implementation is very young. Therefore, to keep our systematic literature review focused, articles related to digital interventions for healthy lifestyle management were included when published between January 1, 2015, and December 15, 2020. The search was limited to English literature, humans, digital health intervention methods, and research focused on improving healthy lifestyles. We aim to include peer-reviewed articles that describe digital intervention methodologies, conceptual models, theories, key challenges, lifestyle recommendations, and research related to healthy lifestyle management focusing on preventing obesity and being overweight with digital means. Articles are classified into the following groups: quantitative, qualitative, both quantitative and qualitative, and short papers, such as posters, editorials, and commentaries. Quantitative analysis is the factual examination of information gathered by the framework to test explicit speculations. Qualitative analysis centers around words and implications to investigate thoughts and encounters inside and out. The selection criteria (or specific parameters) for the quantitative and qualitative articles were (1) articles associated with a healthy lifestyle, with the main goal of preventing obesity and being overweight using digital interventions (or recommendations); (2) methods, theories, and strategies associated with digital interventions; and (3) challenges of digital interventions for lifestyle change.

Textbox A.2: Exclusion criteria for systematic literature review.

Exclusion criteria

- Article not written in English
- Incomplete, non–peer-reviewed articles
- Non-experimental studies
- Poster, editorial, and commentary papers
- Articles published outside the selected time frame (<2015 and >2020)
- Articles not indexed in Google Scholar and (SCOPUS or SCI or SCIE)
- Studies related to offline human behavior interventions
- Papers having a considerable amount of analogous content or exact duplicate articles
- Economic, investment, and policymaking articles related to digital interventions
- Articles related to impacts from social interactions on behavior changes
- Articles related to traditional nutritional and physical activity assessment without any adoption of digital intervention methodologies
- Articles related to behavioral impacts on other lifestyle diseases apart from obesity such as cancer, mental health, chronic obstructive pulmonary disease, cardiovascular disease, dysglycemia, type 2 diabetes, loneliness, and hypertension
- Articles related to the treatment and management of health conditions rather than prevention of lifestyle disease (obesity and overweight in context)
- Articles related to cultural adaptation, nutrition policy, pregnancy, and genetics
- Articles related to worksite wellness, remote patient monitoring, hospital care, osteoporosis prevention for older adults, and web-based intervention for victims of cyberbullying

We aim to adopt the explicit inclusion and exclusion criteria, as described in Textbox A.1 and Textbox A.2 and divide and distribute the articles among authors to complete the screening using the Rayyan collaboration and research tool. After individual screening, the results will be verified by other authors to resolve discrepancies between the reviewers. Subsequently, eligible peer-reviewed articles will be identified by manual search, quality score, and manual assessment of reference lists of related papers. Initially, titles, keywords, abstracts, and conclusions will be screened for inclusion. Then, we review the screened articles independently and check for individual eligibility for final inclusion.

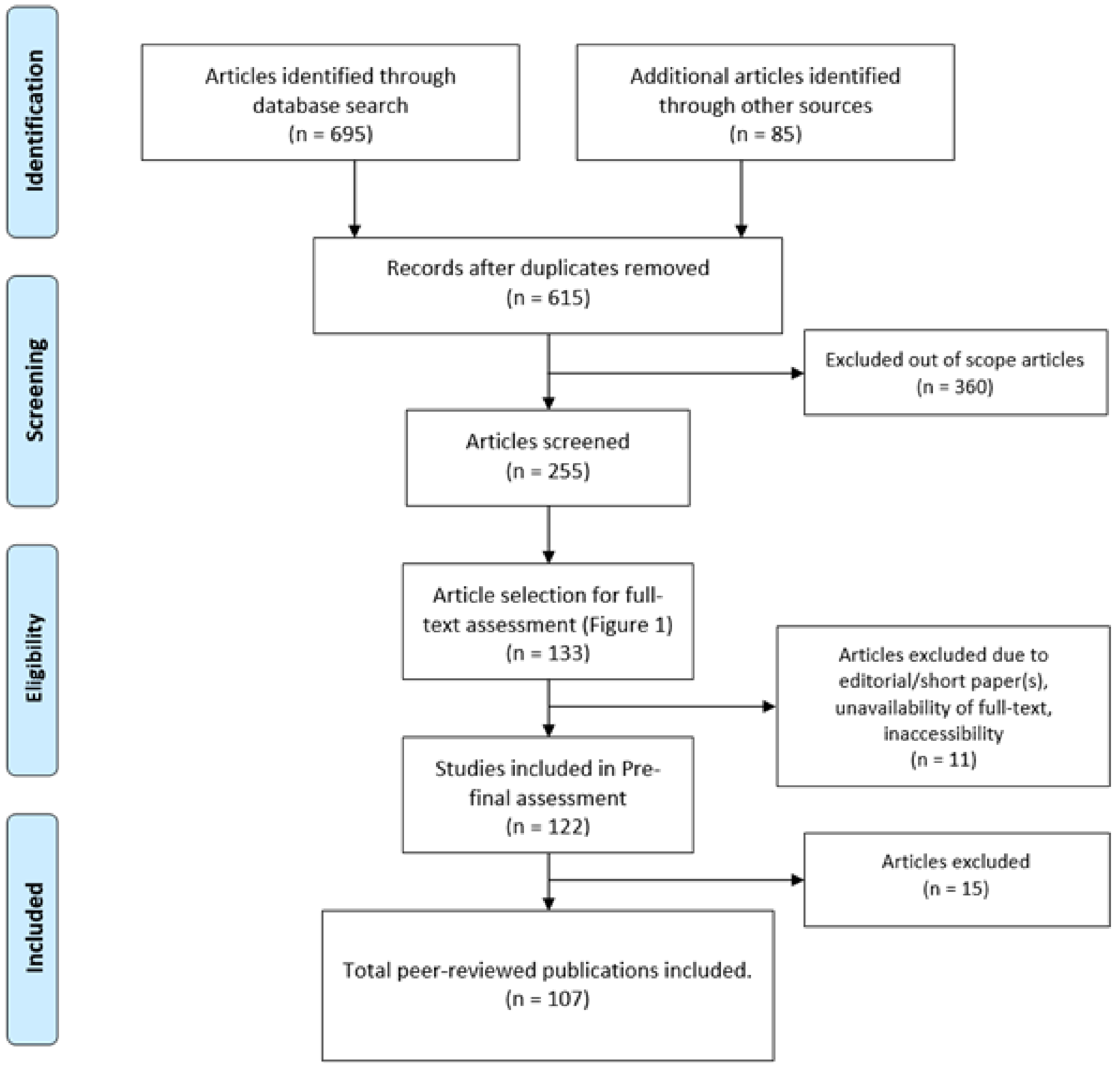

Figure A.1: PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart for article selection process.

The search results from the databases for full-text assessment are as follows: IEEE Xplore (n=2), Nature (n=4), Elsevier (n=28), PubMed (n=40), and SpringerLink (n=59); "n" signifies total number articles screened for full-text assessment. We then excluded short research articles (1-2 pages) from the previous search list (Figure A.1). In the prefinal assessment, for data extraction, we maintained an Excel spreadsheet with the following fields: title, reference in the American Medical Association format, author, population size, study duration, target group (children, adolescents, adults, and older adults), nature of the paper (review, conceptual or methodology, survey, and implementation), year, country of research, key terms, keywords, intervention type, publication channel, technology use, peer-reviewed, key findings (outcome, measures, intervention methods, theory, intervention components, effectiveness, and results), nature of assessment (qualitative, quantitative, or both), key challenges, and quality score based on SANRA. The primary outcome indicators extracted from the preliminary research results were digital intervention methods, nutritional intake, physical exercise, and healthy habits (consumption of tobacco and alcohol). The quality of the included articles was assessed using the SANRA 0-2-point scale. We graded individual papers based on the 6 quality parameters, as defined in Textbox A.3. Individual quality parameters were subcategorized into a 0-2–point scale. Finally, we calculated the mean score of the 6 quality parameters. The number of studies included in the prefinal assessment was 122 with a SANRA score >1.90. Out of 122 studies, 15 had a SANRA score between 1.9 and 2.0. Therefore, we selected 107 articles that scored scale 2 based on the SANRA scale (Textbox A.3).

Textbox A.3: Searched article scaling based on quality parameters.

Quality parameters

- Justification of the article's importance for readership
- Statement of concrete or specific aims or formulation of questions
- Conference and journal papers to describe the overview of this study
- Referencing
- Scientific reasoning
- Appropriate presentation of data

In the final stage, we had articles with grade 2 and cited them as references (Textbox A.4). In addition, we added 30 articles to the reference list (Textbox A.4), including websites (accessed URLs), conference and journal papers to describe the overview of this study, risks of lifestyle diseases, and healthy behavior plans.

Textbox A.4: Nature of studies in the reference list.

Nature of studies

- Articles and web resources (URLs) to describe the overview of this study, risks of lifestyle diseases, and healthy behavior plan [2]-[31]
- Included studies with the Scale for the Assessment of Narrative Review Articles scale 2 (107 articles) [1][32][33][34][35][36][37][38][39][40][41][42][43][44][45][46][47][48][49][50][51][52][53][54][55][56][57][58][59][60][61][62][63][64][65][66][67][68][69][70][71][72][73][74][75][76][77][78][79][80][81][82][83][84][85][86][87][88][89][90][91][92][93][94][95][96][97][98][99][100][101][102][103][104][105][106][107][108][109][110][111][112][113][114][115][116][117][118][119][120][121] [122][119][123][124][125][126][127][128][129][130][131][132][133][134][135][136]

The complete process of choosing the source for this study is shown in the flowchart in Figure A.1. The article selection process consists of 4 stages—identification, screening, eligibility, and inclusion. Instead of depicting all the included studies as separate tables, we have presented significant findings from the respective studies.

Results

Study Selection and Study Characteristics

The searches (electronic database and manual databases) resulted in 780 papers (695 in electronic databases and 85 manually), of which 165 were duplicates. A total of 360 articles were excluded from the study following the exclusion criteria, and 255 articles were screened by reading abstracts, keywords, and conclusion sections. We selected 133 articles for full-text reading. We decided on 122 articles after a full-text review and checked the paper's length and the full-text availability in the pre-final stage. The final search produced 107 core peer-reviewed articles eligible for citation (4 from Nature, 49 from Springer, 23 from Elsevier, 1 from IEEE, and 30 from PubMed) related to digital intervention for healthy lifestyle management. Of the 107 papers, 72 (67.3%) were qualitative, 29 (27.1%) were quantitative, and the remaining 6 were both qualitative and quantitative. The final 107 papers were selected from the following 4 continents: Asia, Europe, North America, and Oceania with the subsequent detailed search results as indicated by "n": Europe (n=56), North America (n=32), Oceania (n=16), Asia (n=2), Asia and North America (n=1), North America and Europe (n=1), Oceania and North America (n=1).

The selected studies were clustered among the following 4 study groups that helped to answer our RQs: review (n=38), implementation (n=37), conceptual or methodology (n=23), and survey (n=9) studies related to digital interventions for healthy lifestyle management. Here, n signifies the total distribution of studies in the 4 study groups. The findings related to the identified RQs are elaborated as follows.

RQ1: What Are the Existing Conceptual Frameworks for Digital Interventions for Healthy Lifestyle Management?

Mummah et al. [32] proposed the concept of a conceptual framework with the following 10 phases: empathize with target users, define the target behavior, the basics of behavioral theory, come up with implementation strategies, potential prototype products, gather user feedback, build a real minimum product, a pilot test to evaluate potential efficacy and utility, evaluation of effectiveness in randomized controlled trials, and sharing of interventions and results. These phases are grouped into 4 overarching categories: integration, design, evaluation, and sharing. Muench et al. [33] proposed an overarching framework to perform digital triggering (text messages, emails, and push alerts) focusing on individual goals with the following 5 components: who (sender), how (stimulus type, delivery medium, and heterogeneity), when (delivered), how much (frequency and intensity), and what (trigger target, trigger structure, and trigger narrative). They showed how user characteristics, conceptual models, and clinical aims help to plan digital interventions and initiate tailoring with product features and user states. Lewis et al. [34] provided an idea to understand human behavior technology engagement to measure digital behavior change interventions (DBCIs) using a proposed framework. The proposed framework conceptualizes the 2 basic categories of commitment measured in digital behavior interventions (DBIs). The types are committed to health behaviors known as Big E and involvement of DBI known as Small E. DBI engagement has been further broken down into 2 subclasses: user interactions with intervention features designed to encourage frequent use, such as simple log-in, games, and social interactions and make the user experience attractive, and interactions of the user with the components of a behavior change intervention (ie, behavior change techniques) that influence determinants of health behaviors and then affect health behaviors. Wang et al. [35] proposed a holistic TUDER (Targeting, Understanding, Designing, Evaluating, and Refining) framework to integrate taxonomies into the theory-based digital health behavior intervention model. They showed how digital health behavior intervention is guided and influenced by theoretical concepts, such as behavior theories, behavior change technologies, and persuasive technology.

Lubans et al. [36] proposed a framework for designing and delivering organized physical activity (PA) sessions for children and adolescents for effective dissemination. Recommended strategies include creating partnerships, presentations, intervention dissemination, scaling up research, and embedding evidence-based interventions. According to Morgan et al. [37], the limitations of digital health intervention programs include the lack of attention to critical sociocultural factors that affect participation and interventions on research results. Their research provides a conceptual model that illustrates the design and implementation of social and cultural interventions. Hekler et al. [38] proposed models and theories for DBCI based on international experts' discussions (including behavioral, computer, and health scientists and engineers) and provided suggestions for developing models and theories that can be learned from DBCI and can provide references. The proposed framework provides state-space representations to define when, where, for whom, and for the person in which the intervention will have a targeted effect. State refers to an individual's state based on various variables, which define the space in which an action mechanism may affect. The state-space representation can be used to help guide theorization and determine interdisciplinary methodological strategies to improve measurement, experimental design, and analysis so that DBCI can match the complexity of real-world behavior changes.

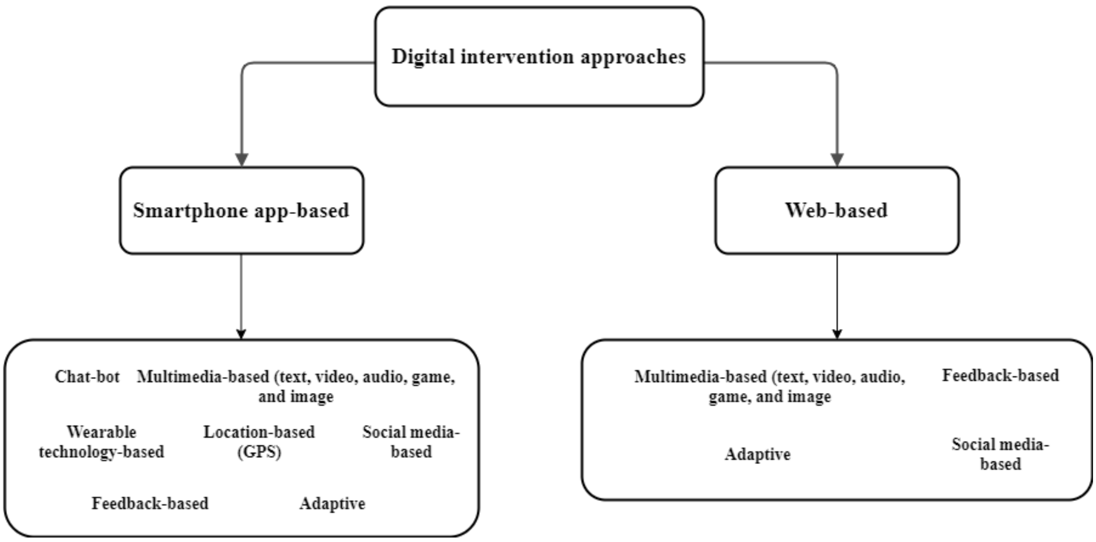

Figure A.2: Structuring of digital intervention approaches for a healthy lifestyle.

RQ2: What Are the Different Approaches to Provide Digital Interventions for Healthy Lifestyle, and What Are the Essential Methods?

In this systematic literature review, we identified the following 2 digital intervention approaches for a healthy lifestyle, and they are further structured in Figure A.2: smartphone app–based intervention (health monitoring and personalized recommendation generation) [33][39][40][41][42][43][44][45][46][47][48][49][50][51][52][53][54][55][56][57][58][59][60] and web-based intervention (web-based monitoring and self-management or self-reporting program) [1][61][62][63][64][65][66][67][68][69][70][71][72][73][74][75][76][77][78][79]. Further details on smartphone app–based intervention are elaborated in [80][81][82][83][84][85][86][87][88][89][90][91][92][93][94][95][96][97][98][99][100][101][102][103][104][105][106] and on web-based intervention are elaborated in [97][98][99][100][101][102]. In this systematic literature review, 35 studies targeted app-based interventions, 18 targeted web-based interventions, and 19 targeted both app-based and web-based interventions. The essential methods associated with both types of intervention approaches are listed in Textbox A.5.

Textbox A.5: Essential methods associated with digital interventions for healthy lifestyle.

Study and key methods associated with digital interventions

- Lindwall et al [107]: motivation, satisfaction, self-determination, human-centered design, psychological needs (competence, autonomy, and relationship), and exercise-related behavior in selected motivational profiles
- Nicklas et al [108]: motivation and self-determination
- Yu et al [109]: self-monitoring for dietary intake—pen and paper documentation, self-check, and PDAs
- Karppinen et al [110]: motivation, persuasion with persuasive technologies, self-monitoring, goal setting, and evaluation
- Nouri et al [111]: user-centered design, observation, persuasive prompts, and feedback generation
- Sharpe et al [112]: efficacy evaluation, encouragement, and engagement
- O'Connor et al [113]: complexity analysis and identification of challenges
- Yardley et al [114]: feasibility study, usability study, beliefs, attitudes, needs, and conditions of people
- Fischer et al [105]: behavior change techniques, personal coaching, regular prompting, and efficacy evaluation
- Mitchell et al [53]: engagement, goal setting, incentives, and goal evaluation

RQ3: What Is the Importance of a Digital Intervention to Promote a Healthy Lifestyle Targeting Obesity and Overweight?

In recent years, an increasing number of digital intervention approaches have been implemented to promote a healthy lifestyle in different age groups. This RQ found modest evidence for effective digital interventions to improve PA, diet, and habits to prevent obesity and overweight. In individuals who are overweight and obese, therapeutic weight control approaches contribute to clinically significant weight losses; however, due to limited access, expense, and/or time constraints, many people cannot engage in these face-to-face treatments. The advancement of several digital weight loss services has resulted in technological advances, such as universal access to the internet, expanded use of smartphones, and newer behavioral self-monitoring tools. Verjans-Janssen et al [99] recognized the importance of implementing a long-term, locally relevant, holistic approach to promoting healthy weight status, stimulating the PA levels of children, and preventing them from wasting unnecessary time throughout school days on sedentary behaviors. Brigden et al [115] designed interactive DBI for younger children based on the following characteristics: participation of parents, gaming functionality, additional therapist assistance, behavioral (rather than cognitive) approaches, and unique feedback and monitoring, shaping knowledge, repetition and substitution, and reward. Nicklas et al [108] conceptualized a multi-exposure theory-based motivational theater, which can be an efficient behavior technique to improve preschool children's intake of vegetable dishes that can be conveniently disseminated to a large sample. Lubans et al [36] used the Supportive, Active, Autonomous, Fair, and Enjoyable concepts to develop realistic strategies to engage young people with PA sessions to maximize involvement in PA and facilitate physical literacy by optimizing the results of affective, emotional, motivational, and movement skills. Burrows et al [79] supported the need for web-based delivery of a balanced lifestyle program that addresses higher nutritional parental issues rather than infant weight. Parents were interested in a web-based family healthy lifestyle program and shared a desire for the program's website to be easy to navigate and user-friendly, casual, but with personalized guidance and goal-setting opportunities. Carrà et al [41] investigated the Interactive Alcohol Risk Alertness Notifying Network for Adolescents and Young Adults (D-ARIANNA), a publicly accessible evidence-based eHealth app to estimate the current health risks by queries and fit-defined risk factors and include an overall risk score in percentage terms, accompanied by relevant images showing the main contributing factors in overview graphs and achievement. Helle et al [57] conducted a study and identified 6 main behavioral risk factors as strong determinants of chronic diseases in adolescents (risky alcohol consumption, smoking, low diet, physical inactivity, sedentary behavior, and unhealthy sleep patterns). The study revealed that web and mobile technology interventions benefit adolescent participation, scope, and scalability to prevent the identification of health risk behaviors. Stockwell et al [67] reported that PA and sedentary behavior are modifiable risk factors for lifestyle diseases and healthy aging; however, most of the older adults remain inadequately active. DBCIs can reach many older adults to promote PA and reduce sitting time. DBCIs may increase PA and physical function and reduce sedentary lifestyle and systolic blood pressure in older adults, but more high-quality testing is required. According to Stephenson et al [40], machines, smartphones, and wearable technology resources can reduce the average sedentary time (minutes/day). Weegen et al [62] showed that behavioral approaches were not successful without digital resources, and the integration of behavioral interventions with digital media proved to be an efficient way to stimulate PA. Geidl et al [98] performed a recommendation generation study in adults with lifestyle diseases for PA and PA promotion over a week with a guideline of performing at least 150 minutes of aerobic PA with moderate intensity, 75 minutes of aerobic PA with vigorous intensity, or a combination of both. The PA and PA promotion guidelines advise adults impacted by lifestyle diseases and health providers on how much PA for adults with lifestyle diseases would be ideal. The guidelines provided the best strategies and approaches for growing low PA levels in adults with lifestyle diseases to professionals entrusted with PA promotion. Gans et al [81] performed a study on 2525 worksite employees, and after 4 months, dietary fat intake decreased significantly with a multimedia-based (video) intervention strategy. Individually tailored videos helped office workers minimize dietary fat and increase fruit and vegetable consumption. Recently, to minimize sedentary behavior, technology-enhanced solutions such as mobile apps, activity monitors, prompting apps, SMS text messages, emails, and websites have been exploited. Step-count sensors can improve walking, helping to tackle physical inactivity (pedometers, body-worn trackers, and smartphone apps). Chaudhry et al [87] assessed the influence of step-count monitors on PA in community-dwelling adults in randomized controlled trials, including longer-term results and discrepancies between step-count monitors and components of the intervention. Muench et al [33] performed a multimedia-based (text) qualitative intervention to show the positive impact of digital triggers (such as SMS text messages, emails, and push alerts) in adults to change in curative conduct in health interventions. New technology apps for mobile health (mHealth) are emerging and provide the basis for fundamentally changing medical research, treatment practices, and scope. Lin et al [43] conducted a web-based study on 4144 adults, collaborating with Quit Genius, an mHealth app focused on cognitive behavioral therapy that helps users quit smoking, to explore the successful nature of an mHealth digital app, which provides its users with substantial benefits and helps them modify their habits for a healthy lifestyle. The app's ability to improve users' hedonic well-being and inspire them mentally in their everyday lives was described as essential to help users quit smoking. The findings found that users whose well-being was improved via the app were 1.72 times more likely to quit smoking successfully. Korinek et al [101] revealed that an adaptive phase target plus reward intervention using a mobile app appeared to be a feasible solution to increasing walking activity in overweight adults. Satisfaction with the app was strong, and the participants enjoyed having variable targets every day. Mummah et al [32] tested the effect of a mobile app to increase vegetable consumption among overweight adults seeking to sustain weight loss. The findings showed the effectiveness of a mobile app in increasing the consumption of vegetables among overweight adults. Hanze University [104] launched a health promotion initiative to enable workers to lead a less sedentary life. The use of an activity tracker for tracking the regular step count of participants was one of the program's measures. For a fortnightly coaching session, the regular move count acted as feedback. They argued that the use of machine learning in the process of automated personalized coaching might become an invaluable advantage. Individualized algorithms allow PA to be predicted during the day and provide the ability to intervene in time.

Machine learning techniques empower automatic coaching and personalization. Since attending a weight control program, many individuals who are overweight find it difficult to sustain weight loss. Self-weighing and telephone support are useful tools for weight loss monitoring. Partridge et al [82,84] and Sidhu et al [83] tested the efficacy of a weight maintenance program based on SMS text messaging to facilitate daily self-weighing in adults and found it to be effective for young men and women. Ball et al [69] organized an incentive-based, promising web-based intervention study to increase PA and reduce sitting among adults (ACHIEVE: Active Choices IncEntiVE). They explored the effectiveness, appeal, and impact of offering nonfinancial incentives for inactive middle-aged adults to encourage increased PA, decreased sedentary time, decreased BMI, and blood pressure. Franssen et al [90] performed a study on consumer wearable activity trackers to promote PA levels. Oosterveen et al [72] conducted a qualitative analysis of eHealth behavioral interventions aimed at analyzing smoking rates, nutritional habits, alcohol consumption, PA levels, and obesity in young adults and revealed that because of their high level of use of technology, eHealth interventions have potential among young adults.

Therefore, this RQ reveals that digital interventions have the potential to promote a healthy lifestyle (regular PA, healthy habits, and proper dietary intake) in all age groups, for personal weight management. In therapeutic approaches, self-monitoring is a crucial part of digital intervention [73]. According to a study [73], participants participating in behavioral interventions have lost 8%-10% of their initial body weight. These results are considered positive based on studies suggesting that losses of 5% can yield positive health improvements such as reductions in triglycerides, blood glucose, blood pressure, improved blood lipid levels, and a reduction in the risk of developing type 2 diabetes for a person. It is difficult to sustain long-term weight reductions achieved through behavioral therapy, and a different set of skills may be needed for success following interventions [1][32][42]. Many teenagers have low diet and PA patterns, which in later life can contribute to the development of lifestyle diseases. Web-based networks provide an affordable means of providing health interventions, but their efficacy is poorly understood. Investigation of the locations of PA and dietary patterns can promote setting-specific lifestyle interventions and increase knowledge of contextual vulnerabilities to poor health. As future directions for digital weight management, distribution, and policy implications should be emphasized [131]-[133].

Discussion

Research Questions

RQ1 helps us to identify that behavioral theory, design thinking, evaluation, and the identification of limitations in the existing digital intervention frameworks are essential for successful, healthy lifestyle management. In contrast, RQ2 reveals different approaches and methods associated with digital health interventions. Digital interventions for healthy lifestyle management have been categorized as discrete usefulness of advanced innovation applied to accomplish well-being goals and is executed inside digital well-being programs and information and communication technology frameworks, including communication channels, such as instant messages (SMS text message), alerts, and app-based notifications [116][117][118]. Digital intervention can motivate and stimulate individuals with self-tracking, goal setting, evaluation, and feedback or recommendation generation to promote a healthy lifestyle [118][119]. Different methods appear to impact health outcomes and usability. It would be interesting to test variants of component design and their impact on health outcomes and usability. Use of personalization to account for differences in preferences between groups of participants and even within groups of participants is essential in addition to cocreation between intervention developers and the target group [118][119][120][121]. Participants who attempted to self-manage their healthy lifestyle found that the most challenging part was to remain motivated [39]. They require apps that give them power and inspiration [39]. The study has confirmed that motivation is a multidimensional construct and people have different, sometimes competing, reasons for engaging in activities [39]. Moreover, human-centered analysis in digital intervention to study the intrinsic interactions of motivation and different regulations must be addressed. Despite the widespread use of mobile phones, digital literacy barriers are common among vulnerable people [39]. Participants have different participation levels in various activities, from higher to lower levels of participation. Researchers using traditional user-centered design methods should routinely measure these communication domains in their end-user samples. Future research should replicate these findings to a larger sample through direct observation, and persuasive prompts may be more effective in providing feedback to those with communication difficulties. RQ3 summarizes the evidence on the importance of digital intervention that were exclusively directed at promoting healthy lifestyles, especially in children, adolescents, adults, and older adults. In the next section, we discuss the importance of digital intervention on healthy lifestyle promotion elaborately.

Digital Intervention and Healthy Lifestyle

A healthy lifestyle is a lifestyle that reduces the risk of severe illness or early death. Not all diseases are preventable, but a large proportion of deaths can be avoided, especially lifestyle or noncommunicable diseases. According to the Harvard Medical School, the key lifestyle factors to be monitored are healthy diet, healthy PA level, healthy body weight, no tobacco consumption, and moderate alcohol intake [27]. According to RQ3, digital intervention can have a significant impact on healthy lifestyle management.

A study conducted by Steene et al [86] found significant country- and region-specific variations in PA and sedentary time in the European population, with lower PA levels. Boys in all age groups were more aggressive and less sedentary. At about 6 to 7 years of age, the initiation of age-related decline or leveling-off of PA and rise in sedentary time begins to become evident [86]. In children and adolescents, sedentary behavior strategies successfully decrease screen time; however, the scale of the effect tends to be limited [129]. The potential of digital intervention in older age groups outside of occupational settings and during sedentary leisure time must be examined in future studies. The sustainability of lifestyle changes in a positive direction remains a challenge [129]. Mobile apps to improve PA in young adults should include customized and personalized feedback and provide a coaching feature [58]-[60]. It is essential to create a well-oriented and easy-to-use interface with the ability to customize the app. The new area of mHealth is mHealth apps that target willing participants to enhance self-management of chronic conditions [58]-[60]. However, we found that only a small fraction of the mHealth apps available had been reviewed, and the amount of evidence was of inferior quality [58]-[60]. Improving the quality of evidence includes supporting prerelease app performance monitoring, designing few experiments, and performing better reviews with a rigorous risk of bias assessments [43][115]. Without enough evidence to back it up, for some time to come, digital intervention and app practicability will stall in their infancy [43][115][121]. Evidence suggests that an unhealthy lifestyle is associated with poor health outcomes [40][63]. It can have severe implications for health and well-being at any age [63][64][126]. Therefore, there is a need to review the effects of multicomponent, complex interventions that include effective unhealthy lifestyle reduction strategies. We must focus on optimizing the effects of an intervention. Future intervention studies should use more rigorous methods to improve the quality of studies, considering larger sample sizes, randomized controlled designs, and valid and reliable lifestyle measurements. An overview of intervention development methods can help researchers understand various existing methods and comprehend the range of actions taken in intervention development before evaluating feasibility or pilot interventions [32][126][135].

One way to encourage PA and enhance health is to change the physical environment, but research on intervention efficacy is mixed [92]-[94]. Theoretical perspectives and conceptual problems are used in evaluative studies, and related literature can contribute to these inconsistencies [92]-[94]. Environmental and policy initiatives are socially incorporated into the framework and function through it. Therefore, a philosophical viewpoint must be considered and should be understood by evaluators. Future research should aim to explain how interventions function across disciplinary fields by considering these structures, the context in which interventions occur, and the measurable and unmeasurable mechanisms that might work [92]-[94][98]. It can be beneficial to promote health-based actions, such as PA, by using innovative and interactive media-based health education [92]-[94][98][134]. Therefore, to successfully influence behavior, it is essential to establish user-based techniques and reinforce the theories and hypotheses of behavioral change based on digital media. Step-count tracking [87] leads to improvements in short- and long-term step counts. There is no proof that either wearable sensors or smartphone apps, or extra counseling or incentives have additional benefits over more straightforward approaches focused on the pedometer [63][64]. To overcome the public health issue associated with physical inactivity, basic step-count tracking strategies should be prioritized. In general, it is not clear how self-reported sedentary behavior (eg, questionnaires, logs, and momentary ecological evaluations) compares with system measurement measures (eg, accelerometers and inclinometers) [63][64]. Evidence from this study indicates that when compared with system tests, single-item self-report measures typically underestimate sedentary time [63][64]. Therefore, to evaluate the reliability and validity of different self-report measures for evaluating sedentary activity, studies should exercise caution when comparing associations between various self-report and system measures with health performance.

In addition, video and adapting technologies have been effective in diet change measures; however, these methods have never been combined with researching personalized video efficacy [81]. Theory-based mobile interventions could provide a low-cost, scalable, and efficient approach to improving dietary habits and preventing associated chronic diseases. To encourage a healthy dietary pattern, nutrition messages or nutrient labeling, offering healthier choices, and portion size management of unhealthy foods have been potentially effective strategies in tertiary education environments [75]. The reduction in rates and the increased availability of nutritious choices in conjunction with nutrition knowledge have contributed to changes in dietary habits [75]. Further studies comparing the long-term efficacy of the climate and the combination of environmental policies to improve health outcomes are warranted. Dietary consumption has increased by increasing the availability of nutritious foods and reducing the portion size of unhealthy foods. In terms of modifying overall dietary patterns, the existing evidence base is misleading, as rising intake of desirable food groups was more effective than reducing unfavorable food habits, and fruit or vegetable intake and sugar-sweetened beverage consumption are the most notable observed changes [75][79]. Social support, followed by a demonstration of conduct, self-monitoring, goal setting, and feedback, is the most popular digital health behavior intervention [55][67][85][96]. In addition, a customized Facebook-based obesity prevention program for teenagers in Korea (Healthy Teens) [76] revealed usability problems in terms of material, appearance, and navigation. Facebook [76][96] has tremendous potential in promoting communication and engagement with immigrant teens, considering its prominence among adolescents. Interventions focused on social media (eg, Facebook) [66][96] are productive in facilitating meaningful improvements in adolescent eating habits. However, more research is required to explore effectiveness variations based on component tailoring, best use stimuli to promote behavior change over time, and keep people involved in changing physical health behavior. The first step is to dismantle digital triggers into their parts and reassemble them according to their goals for improvement.

PA, sedentary time, and dietary habits vary across homes, schools, and other locations [95]. Health habits vary depending on the place or environment in which the participants are [95]. Although eating habits are typically more beneficial in home or school locations, PA is usually low and sedentary time in these locations is higher [95]. To optimize health habits in each area, digital interventions that address the various locations in which participants spend time and use location-specific behavior change techniques should be explored [95]. Among young people, binge drinking is prevalent [41]. eHealth technologies [41] are appealing to them and can be useful in raising awareness. However, to make eHealth apps suitable for longer-term effects, additional components, including daily feedback and repeated administration by different multimedia interventions, may be needed. Mass media campaigns [65] for smoking or tobacco programs are also effective over long periods. Digital interventions have been associated with decreased drinking and smoking frequency, with a slight yet persistent impact on teenagers and adults. Protective effects against alcohol and tobacco [65] use can be demonstrated through digital initiatives focused on a combination of social maturity and approaches to social influence. Evidence tends to be mixed with internet-based interventions, policy proposals, and incentives, and requires further study. Various distribution systems can enhance the effects of alcohol or tobacco misuse among teenagers and adults, including interactive platforms and policy initiatives. Adolescents are easily accessible by digital media and can represent a scalable and inexpensive opportunity to engage this audience in changing behavior [65]. Smartphone-based interventions [39]-[59] (such as apps, SMS text messages, sports, multicomponent interventions, emails, and social media) are readily available, inexpensive, and use tools already used by most teenagers. Therefore, it is essential to perform and publish high-quality academic literature studies and formally evaluate apps that have already been developed to inform the creation of potential interventions to change behavior. Essential improvements in behavior were also seen when interventions involved schooling, setting goals, self-monitoring, and parents' participation. Digital approaches [66] that include education, goal setting, self-monitoring, and parental participation can affect adolescents' meaningful health behavior changes. Most of the evidence relates to goal setting, further research into alternative media is needed, and it is essential to assess longer-term effects. There is a lack of evidence on the cost-effectiveness of digital health initiatives, and these data should be recorded in future trials. The young population has broadly embraced social media, so health researchers are searching for ways to exploit this social media involvement to deliver programs and health promotion campaigns [66][96]. In young adults, weight gain and suboptimal dietary choices are popular, and social media can be a possible instrument for encouraging and supporting healthy choices. The dissemination of information is now an appropriate use of social media by young adults. Careful evaluation is needed to use social media effectively for social support, either by private or by public sites, as its efficacy has yet to be demonstrated in experimental designs. In digital intervention studies aimed at manipulating weight, concerns about public social media use can lead to low engagement with social media [66][96][115]. Future research should explore how to use social media to better connect with young adults, how to use social media more efficiently to help young adults, and how to encourage social and peer-to-peer support to make healthy choices.

The systematic literature review has revealed that the identified digital intervention methods affect lifestyle behavior outcomes, focusing on PA, diet, habit, and associated primary and secondary health outcomes, such as fitness, motivation, reduced sedentary bouts, weight augmentation or weight status, blood pressure, glycemic responses, lipid profile, and quality of life in different study groups, as explained in the next section. Effectiveness (n=55), conceptualization (n=24), selection of appropriate methodology (n=25), effective and technological engagement (n=24), selection of strategies or techniques (n=20), motivation (n=15), feedback generation (n=15), environment (n=10), satisfaction (n=6), credibility (n=6), digital literacy (n=6), self-determination (n=5), and user-centric design (n=4) were responsible for the successful implementation of digital interventions for healthy lifestyle management. Here, n signifies the total number of overlapped studies in which the respective parameters are identified. Digital interventions [84][106][124] focused on mobile phone apps may be an acceptable and efficient way of encouraging weight loss in people who are overweight or obese. Digital health coaching can be a revolutionary approach to reduce barriers to access to much-needed weight loss therapies for obesity, given the ubiquity of mobile phones.

Strength and Limitation

A systematic literature review revealed that a healthy diet, healthy habits, and regular PA are powerful tools for reducing obesity and associated health risks. These findings bolster the use of digital interventions as a preventive option for obesity and overweight. Therefore, behavior change should be given the highest preference to avoid severe health damage. Planned digital interventions may potentially change growing negative behavior in humans with the adoption of persuasion, observation, goal evaluation, evidence-based personalized recommendation generation, health risk predictions (decision-making), automation, motivation, pragmatism, and trust. Developing and maintaining an empathetic relationship is perhaps the most critical determinant of successful digital intervention [106,124]. It is essential to know the participant first, and the interaction aspects are challenging owing to the delay in reaction time (both ways). Health care professionals need to ensure both relationship communication and goal-oriented coaching when using such digital intervention solutions. In the future, the quality of the interaction between the system and the participant will require attention if participants are to fully benefit from collaboration in digital intervention programs. Digital intervention for healthy lifestyle management has great potential as a scalable tool that can improve health and health care delivery by improving effectiveness, efficiency, accessibility, security, and personalization. Therefore, a knowledge base must be accumulated to provide information for developing and deploying digital health interventions [116,118]. However, the evaluation of digital health interventions poses unique challenges.

Methodological limitations, selection of appropriate intervention methods, evaluation of efficacy, limitations of research on different populations, loss to follow-up, attrition rate, lack of participation in tracking, financial incentives and intervention burdens (long term or short term), digital literacy, technical participation, personalization, useful evidence-based automatic tailored lifestyle recommendation generation (intervention design), research heterogeneity, meta-analysis, cost-effectiveness (technical and financial feasibility analysis), trial selection, trial recruitment, scalability, accessibility, ethics, policy development, cyberbullying, safety, trust, user-centeredness, adoption of health care and collaboration methods that promote cooperation, unsustainable growth in complexity, and efficacy evaluation are some of the existing limitations of digital health interventions that should be overcome in existing research [126,128]. Although new technologies and rapidly changing technologies pose many unsolved problems, the broad consensus is that successful intervention design requires user-centered iterative development methods, hybrid methods, and in-depth qualitative research to gradually improve interventions to satisfy users. Therefore, conceptual participation (effective engagement) is essential to understand the relationship between the involvement in digital interventions and required behavioral changes and to achieve population-level benefits. Interventions must be delivered effectively at scale. Small effect sizes and high dropout rates [78,126] often affect web-based computer-tailored interventions, particularly among people with a low education level. The results and attractiveness of these remedies can theoretically be enhanced by using videos as a delivery format. The most successful and most appreciated intervention was the web-based video version of the computer-tailored obesity prevention intervention.

Future research needs to analyze whether the results are sustained in the long run and how to maximize the intervention.

Conclusions

Digital intervention in health care is the intersection of health care, behavior science, computing, and engineering research and requires methods borrowed from all these disciplines. Digital interventions have effectively improved many health conditions and health behaviors; besides, they are increasingly being used in different health care fields, including self-management of long-term conditions, prevention of lifestyle diseases, and health promotion. In low-resource primary care environments, digital health strategies can be useful for preventing obesity. To minimize obesity and chronic disease risk among medically vulnerable adults in the primary care environment, digital health intervention uses an advanced digital health approach. The lack of user involvement hinders the full potential of digital interventions. There is an urgent need to develop effective strategies to promote user participation in digital interventions. One potential method is to use technology-based reminders or personalized recommendation generation. Compared with no strategy, technology-based strategies can promote participation. However, the findings of this systematic literature review should be understood with prudence, as only a few qualified studies have been identified for review, and the results are heterogeneous. The number and dates of studies indicate that a digital health intervention strategy is an emerging field. More research is needed to understand what strategic features are useful, their cost-effectiveness, and their applicability to different age groups. The results of this literature review will help to understand the concepts and parameters behind different DBI methods, thereby developing, testing, and evaluating the performance of a useful digital intervention in the future.

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Authors' Contributions

The authors (AC and AP) divided and distributed the articles to complete the screening using the Rayyan tool. After individual screening, the results were verified by other authors (MG and SM) to resolve discrepancies between the reviewers.

Conflicts of Interest

None declared.

Abbreviations

DBCI: digital behavior change intervention
DBI: digital behavior intervention
mHealth: mobile health
PA: physical activity
RQ: research question
SANRA: Scale for the Assessment of Narrative Review Articles
TUDER: Targeting, Understanding, Designing, Evaluating, and Refining

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Paper B

Human Coaching Methodologies for Electronic Coaching ..... Technology: Systematic Review

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Human Coaching Methodologies for Automatic Electronic Coaching (eCoaching) as Behavioral Interventions With Information and Communication Technology: Systematic Review

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Abstract – **Background**: We systematically reviewed the literature on human coaching to identify different coaching *processes* as behavioral interventions and *methods* within those processes. We then reviewed how those identified coaching processes and the used methods can be utilized to improve an electronic coaching (eCoaching) process for the promotion of a healthy lifestyle with the support of information and communication technology (ICT). **Objective**: This study aimed to identify coaching and eCoaching processes as behavioral interventions and the methods behind these processes. Here, we mainly looked at processes (and corresponding models that describe coaching as certain processes) and the methods that were used within the different processes. Several methods will be part of multiple processes. Certain processes (or the corresponding models) will be applicable for both human coaching and eCoaching. **Methods**: We performed a systematic literature review to search the scientific databases EBSCOhost, Scopus, ACM, Nature, SpringerLink, IEEE Xplore, MDPI, Google Scholar, and PubMed for publications that included personal coaching (from 2000 to 2019) and persuasive eCoaching as behavioral interventions for a healthy lifestyle (from 2014 to 2019). The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework was used for the evidence-based systematic review and meta-analysis. **Results**: The systematic search resulted in 79 publications, including 72 papers and seven books. Of these, 53 were related to behavioral interventions by eCoaching and the remaining 26 were related to human coaching. The most utilized persuasive eCoaching methods were personalization (n=19), interaction and cocreation (n=17), technology adoption for behavior change (n= 17), goal setting and evaluation (n=16), persuasion (n=15), automation (n=14), and lifestyle change (n=14). The most relevant methods for human coaching were behavior (n=23), methodology (n=10), psychology (n=9), and mentoring (n=6). Here, "n" signifies the total number of articles where the respective method was identified. In this study, we focused on different coaching methods to understand the psychology, behavioral science, coaching philosophy, and essential coaching processes for effective coaching. We have discussed how we can integrate the obtained knowledge into the eCoaching process for healthy lifestyle management using ICT. We identified that knowledge, coaching skills, observation, interaction, ethics, trust, efficacy study, coaching experience, pragmatism, intervention, goal setting, and evaluation of coaching processes are relevant for eCoaching. **Conclusions**: This systematic literature review selected processes, associated methods, strengths, and limitations for behavioral interventions from established coaching models. The identified methods of coaching point toward integrating human psychology in eCoaching to develop effective intervention plans for healthy lifestyle management and overcome the existing limitations of human coaching.

Introduction

Overview

A coach [1][2][3][4] is a trusted role model, adviser, wise person, friend, mensch (a person of integrity and honor), steward (supervisor), or guide. A coach facilitates experimental learning that results in future-oriented abilities. Coaches can shape new visions and plans to achieve desired results. Coaching has been implemented in management, leadership, entrepreneurship, health care, and performance management. It helps participants to cultivate themselves and become more successful in achieving their set goals. Successful coaching relies on a good relationship, mutual trust, and freedom of expression between coaches and participants [1][2][3][4][5][6]. Effective coaching leads to excellent performance, self-motivation, and self-correction. Coaching processes can be divided into the following two categories: (1) traditional offline human coaching (coaching by humans) and (2) electronic coaching (eCoaching).

Traditional offline human coaching processes involve the following methods [1][4][7][8][9] [10]: privacy, focus, goal orientation, performance improvement, and trust. The process associated with coaching by humans can be achieved either face-to-face or remotely (via telematic means). Furthermore, the coaching process can be categorized [5][6][7][8][9][10][11] [12][13][14][15][16] as health coaching to address negative behavioral change, cognitive-behavioral coaching, mental health coaching, in-house executive coaching in businesses, companies, or industries (corporate coaching), sports coaching, motivational coaching, educational coaching, and coaching to carry out activities of daily living. Traditional human coaching is a dialogic, goal-oriented, pragmatic learning practice. The human coaching process can be further enhanced through electronic modes, such as video, audio, email, chatbot, and text, with the support of information and communication technology (ICT), which is referred to as eCoaching. In the last decade, personal coaching for behavioral intervention has been increasingly used to promote a healthy lifestyle [17][18]. eHealth uses ICT for health [19][20]. eCoaching is a promising eHealth research direction for continuous customized ways of lifestyle support [21][22]. It is an evolution of offline human coaching with the flexibility of electronic services allowing ubiquitous access to the process. eCoaching technologies represent an evolving trend in the domain of human behavioral intervention. The coaching core behind an eCoaching system can be a human (eg, telemedicine), an artificial intelligence (AI) agent (eg, algorithm), or a combination of these. An eCoaching system consists of a set of programmed modules representing an artificial entity that may look at, query, examine from, and predict a consumer's behaviors in a specific context and in a specific period. Application domains of eCoaching include the following [18][23][24][25][26][27][28][29][30][31][32][33][34][35][36][37][38][39][40][41][42][43][44][45][46][47][48][49][50][51][52][53][54][55]: nutrition coaching, physical activity coaching, coaching for mental health, coaching for activities of daily living in the elderly, diabetic coaching, and cardiac rehabilitation. Studies in eCoaching can offer methods to help enhance individual health care with ICT. A virtual eCoaching recommendation system can guide people and convey the appropriate recommendations in real time to improve their lifestyle [21][22][56]. The leading methods of eCoaching processes are monitoring, decision-making, goal setting, persuasion, awareness provision (intervention), goal evaluation, and learning for future actions [24][27][32][33][34][57][58][59]. Digital techniques of lifestyle change with eCoaching have appeared as efficient and scalable options for intensive behavioral counseling when face-to-face or in-person programs are inaccessible or undesirable. eCoaching can make human behavioral interventions useful when combined with human coaching methods [57][60][61]. In the eCoaching processes, participants can remotely take part and avoid traveling, expenses, and transport risks. It is relevant to note that eCoaching will electronically handle data. Therefore, complying with general data protection regulations is critical for the safety and security of participants. eCoaching processes may ideally influence health outcomes, for which aspects, such as usability, efficacy, and adherence, may play important roles to influence health and/or health behavior. "Efficacy" means the effects of behavioral intervention following any coaching process (of any method, not only of eCoaching). "Usability" means the effectiveness, efficiency, and satisfaction when using a technology. "Adherence" means the degree to which the technology is used as intended [7][57][58]. Coaching as a human behavioral intervention is a personalized, planned process designed to reward and reinforce the positive behavior of human beings. Each behavioral intervention differs from others based on the participants who are the primary targets of the intervention, where psychology and context play crucial roles [21][56][60]. The methods of a successful behavioral intervention plan "focus" on the identification of problems, the analysis of identified problems, prevention strategies and modification techniques, encouragement or motivation, strategic planning to diminish negative behavior, and participant engagement [1][2][3][5][35][56][60][62]. The coaching process for behavioral intervention should include appropriate guidelines, mutual trust, a rewarding plan, participant feedback, goal setting, and goal evaluation methods to make it useful for coaching and eCoaching (coaching by an electronic coach [eCoach]) processes [1][23][63]. Time is a critical factor in determining the format of coaching. Integration of coaching methodologies into persuasive eCoaching for electronic personalized behavioral interventions creates new opportunities for a healthy lifestyle [1][2][3]. It is rewarding for participants to change negative behavior using evidence-based methods and to observe the increase in their health and strength [4][5][60].

Aim of the Study

The aim of this systematic literature review was to identify key processes from the coaching methodologies to tackle the existing challenges coupled with the human coaching and eCoaching processes as behavioral interventions. The focus on coaching is justified by the fact that health and wellness remote coaches are an asset to clinical practice, although they are underutilized in the health care system [6][21][56]. This systematic literature review addresses the following research questions (RQs):

RQ1: What are the existing human coaching processes?
RQ2: Which conceptual coaching models can be used to explain the coaching process?
RQ3: What are the basic coaching methods to make coaching processes successful for the promotion of a behavioral intervention?
RQ4: How can the methods of human coaching processes be incorporated into eCoaching for behavioral intervention to promote a healthy lifestyle?
RQ5: How can eCoaching promote a healthy lifestyle with proven coaching methods using ICT?

Methods

A systematic literature review was used to acquire a comprehensive overview of the current literature on the topic in a reproducible and transparent way. Systematic reviews represent a scientific synthesis [64][65] of evidence. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) evidence-based framework [64] was used for the systematic review and meta-analyses. Initially, we performed a random search in the "Google Scholar" database with the following four key terms: "coaching," "electronic coaching," "eCoaching," and "e-Coaching" (see Table B.1 for the results of the initial random search). It was observed that the keyword "electronic coaching" obtained the greatest number of results among the last three key terms.

Table B.1: Initial "Google Scholar" random literature search results according to publication year.

Key terms	1998-2019	2008-2019	2014-2019	2017-2019
Coaching, n	482,000	497,000	159,000	50,800
Electronic coaching, n	133,000	72,600	25,700	18,400
eCoaching, n	396	347	270	184
e-Coaching, n	5740	5100	3300	1710

Subsequently, literature searches were conducted with selected search string patterns (Table B.2) on the following electronic databases, as they compiled the greatest number of scientific sources related to coaching and eCoaching studies: Google Scholar, EBSCOhost, Scopus, ACM, Nature, SpringerLink, IEEE Xplore, MDPI, and PubMed. This study's search strategy was created in collaboration with the library of the University of Agder (UiA) in Norway, based on the following two main search topics: (1) coaching as a behavioral intervention and (2) eCoaching as a behavioral intervention. Related search keywords were identified using MeSH (Medical Subject Headings) terms, synonyms, keywords from relevant articles, and self-determined search terms. The means, such as EndNote (V.

X9), DOAJ, Sherpa/Romeo, and Microsoft Excel (MS Office 365 V. 16.x), were used to effectively search, collect, and select related articles. We aimed to include articles that described coaching methodologies and eCoaching related to behavioral interventions. Articles were categorized among the groups quantitative, qualitative, and editorial. The quantitative study deals with statistical analysis on systematically collected data to test a specific hypothesis, while the qualitative study focuses on words and meanings to explore ideas and experiences in depth. The search results are depicted in Multimedia Appendix 1. We included articles based on the following inclusion criteria: (1) peer-reviewed, full-length articles written in English, (2) eCoach articles published in the selected databases between 2014 and 2019, (3) coaching articles published in the selected databases between 2000 and 2019, (4) articles indexed in "Google Scholar," (5) journal papers, conference papers, or books, (6) qualitative (primary and secondary research) and quantitative studies, and (7) coaching articles related to human behavioral intervention. The traditional offline human coaching processes are older than eCoaching processes. Thus, the period for searching the selected electronic databases differs for "coaching" and "eCoaching".

Table B.2: Search strings used for article searching.

Category	Search Strings	Publication Year
eCoach	(mentoring OR "e-coach" OR "ecoach" OR "electronic coach*" OR counseling) n10 ((distance N1 (counseling OR educat* OR e-coach* OR ecoach* OR electro*coach*)) OR (telemedic* OR "mobile health" OR mhealth OR ehealth OR "e-therap*" OR "e-counseling")) AND (obesity OR overweight OR overnutrit* OR hypernutrit* OR lifestyle OR behavior) AND (persuasion OR recommendation OR intervention)	2014-2019
coach	(mentoring OR coaching OR counseling) n10 ((distance N1 (counseling OR educat* OR coach* OR executive* OR sport* OR activity* OR life*)) AND (health* OR "behavior" OR psychology OR lifestyle)	2000-2019

We excluded editorial articles, studies related to robotic coaching, philosophical papers, articles with a lot of similar content or articles that were exactly repeated, and articles that were neither "open access" nor accessible through the university library. The full process of selecting sources for this review is depicted in a flowchart (Figure B.1). The process includes the following four phases [66]: identification, screening, eligibility, and inclusion.

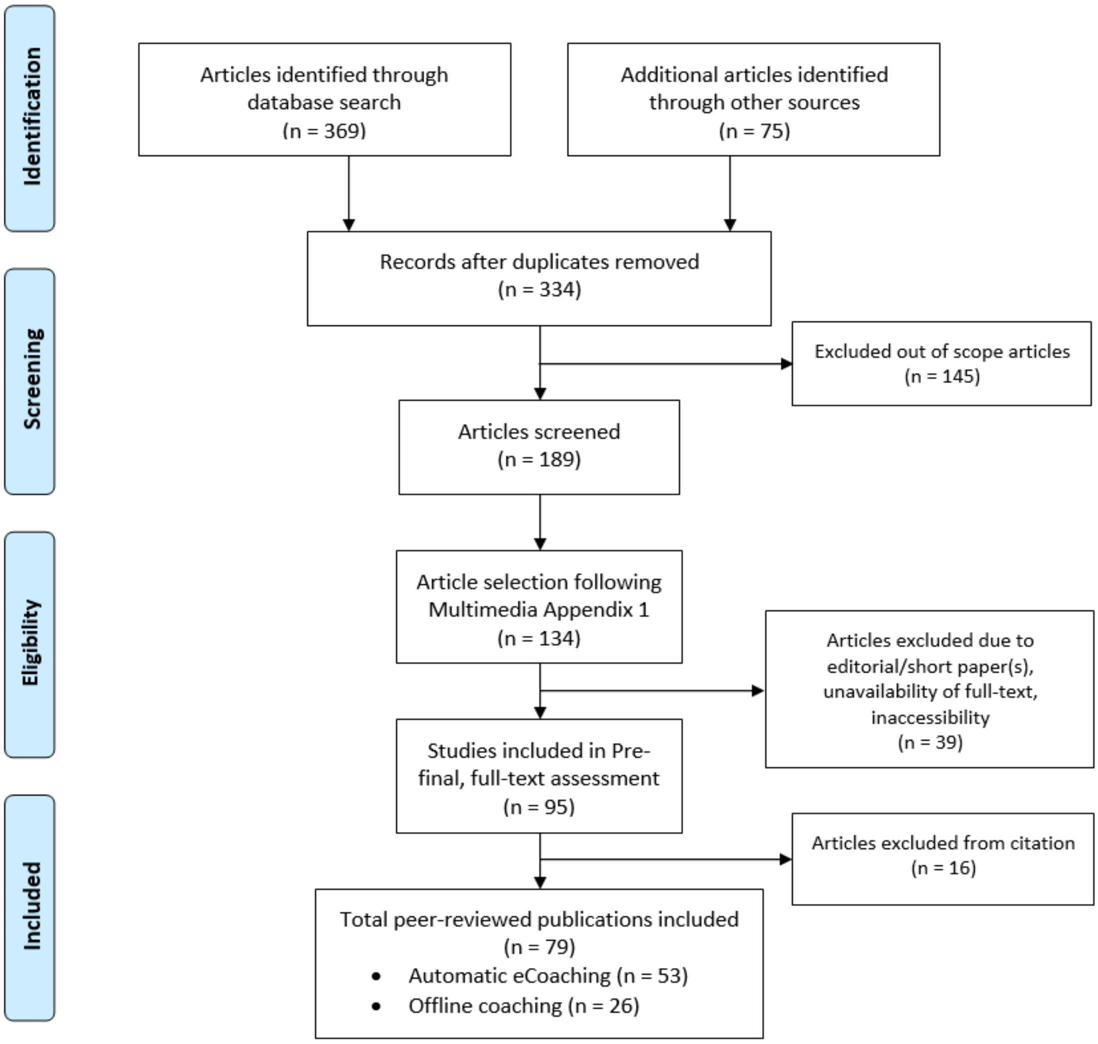

Figure B.1: PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart for the article selection process.

Results

Literature Search Results

The searches (electronic database and manual searches) resulted in 444 papers (369 in electronic databases and 75 identified manually), where 110 were duplicates. In the prefinal stage, we selected 95 articles for full-text review after checking the abstract, conclusion, length of the paper, and availability of full text. In the final search, we included peer-reviewed publications only, resulting in 79 core peer-reviewed articles related to "coaching" (53 papers) and "eCoaching" (26 papers). The categorical distribution (quantitative/qualitative) of the selected articles under "eCoaching" and "coaching" was as follows: coaching (23 quantitative, 30 qualitative) and eCoaching (7 quantitative, 19 qualitative).

This systematic literature review identified different coaching process descriptive models, as well as how they are carried out and in which context. We observed underlying theories to support traditional human coaching processes, such as hope theory [7] and amoeba theory [2], and different terms associated with both coaching and eCoaching processes, such as components, conceptual models, aspects, principles, concepts, activities, and methods. The usage of heterogeneous terms to describe similar or nearly similar coaching and eCoaching processes resulted in ambiguity, less contentedness, and reduced clarity. Therefore, throughout the study, we concentrated on *processes* and methods to answer and discuss our research questions. They can be explained as follows: processes describe different coaching and eCoaching models and their implementation style, and the success of a coaching and eCoaching process depends on the adopted *methods*. Their evaluation helps to determine the performance of the human coaching and eCoaching processes.

The identified methods help us to understand the principles, strategies, effectiveness, and constraints of coaching and eCoaching processes. An eCoach may create optimized, real-time, comprehensible, automated, contextual, evidence-based, and personalized intervention strategies for participants. Moreover, an eCoach may address the challenges associated with coaching, such as scope, the volume of the target audience, bias, cost, automation, accessibility, security, flexibility, credibility, conceptual clarity, location, and time independence, as revealed from the systematic literature review [2][4][6][21][35][56][62][66][67][68][69][70]. This systematic literature review identified 21 studies contributing to answering RQ1 regarding coaching methodologies; 17 studies contributing to answering RQ2 regarding a conceptual coaching model; 20 studies contributing to answering RQ3 regarding coaching methods for the promotion of "behavioral intervention;" 59 studies contributing to answering RQ4 regarding the integration of "coaching process" into "eCoaching for behavioral intervention;" and 35 studies contributing to answering RQ5 to advance "eCoaching for behavioral intervention" for a "healthy lifestyle" with proven "coaching methodologies" using ICT (several included overlapped studies contribute to multiple RQs).

RQ1: What Are the Existing Human Coaching Processes?

Bartlett [1] proposed a method where mutual trust, respect, and freedom of expression were considered as the elements of a successful coaching relationship. The model combines the establishment of a relationship between a coach and a trainee, recognizing an opening to assess obstacles related to coaching, observation, and assessment; enrollment of clients; and coaching conversations. Potrac et al. [66] proposed another model that combines systematic observation and interpretive interview techniques to gain a deeper and broader understanding of personal coaching's instructional process. The suggested multimethod framework concerns identification of the instructional behaviors within the practice environment, generation of the understanding of why coaches behave as they do within the practice environment, and examination of the impact on the instructional strategies and understanding by humans. Cunningham et al. [9] recommended a model based on hierarchical regression analysis with a stepwise process to show that an earlier success accuracy, collective coaching experience, collective professional coaching experience, and racial diversity are significantly associated with team performance. Côté [5] proposed that informal self-directed learning modes have relatively more significance than formal and nonformal learning. The proposed model combines the following three variables: (1) individuals with different backgrounds, experiences, and knowledge, (2) coaching work in various types of contexts with varying amounts of resources, equipment, and facilities, and (3) coaching work with participants varying in terms of age, developmental level, and goals. Their proposed coaching model divides variables into the two categories of ambient components (such as coach's and participant's characteristics, and contextual factors) and behavioral components (such as competition, organization, and training). The model proposed by Green et al. [7] included the concept of coaching psychology and hope theory, based on the belief that human actions are goal directed. They claimed that the cognitive-behavioral solution-focused coaching model provides preliminary evidence on life coaching that can enhance mental health, quality of life, and goal attainment. Goal setting and goal evaluation are central to lifestyle coaching and are the pillars of successful self-regulation. The coaching study focused on evaluating the effectiveness of a cognitive-behavioral, solution-focused, life coaching group program, and its impact on goal striving, well-being, and hope. The assessment included measures of the "Satisfaction with Life Scale (SWLS)" and the "Positive and Negative Affect Scale (PANAS)." Murphy et al. [6] proposed a model focused on executive coaching. With the support of conceptual clarity, executive coaching could unify efforts and resources and provide a common understanding to enhance human resource developmental programs. The human resource should play an active role in developing the organizational capacity for leadership. The proposed model of Richards [67] combines a recurrent process of suitable environment creation for coaching, learning for innovation and successful adaptation, and achievement (coaching performance) for sustained performance. Coaches need to rethink the discipline of coaching as if it is performed well, and coaching can increase motivation and contribute to sustaining high performance. Another model proposed by Richards [67] combines "tell" and "do" instructions. The model is based on the method of conventional thinking to improve a participant's performance by telling them or showing them what they are doing wrong in order to avoid any repetitive mistakes. This model is beneficial within a short-term context and frame of mind. However, overuse of the approach will undermine efforts to achieve long-term performance. The proposed model by Flaherty [2] was drawn from the concept of phenomenology and combines the following five methods in the coaching process: relationship building (based on mutual satisfaction, mutual respect, mutual trust, and freedom of expression), pragmatism (persistent correction following a feedback loop), two tracks (client and coach engagement), always/already (intervention planning), and identification of techniques that do not work (identification of challenges/ limitations). The proposed amoeba theory is discussed based on behaviorism and is used in management for changing behavior either by poking or giving rewards. Cox [3] proposed a model that is based on adult learning and human psychology. The study included the following eight learning theories relevant to coaching: andragogy, transformative learning, reflective practice, experimental learning, learning styles, life course development, values and motivation, and self-efficacy. The proposed model by Stober et al. [4] focusses on a humanistic approach to the process of coaching with four guiding principles, including the nature of the coaching relationship, the client as a source and director of change, the client as a whole and distinct person, and the coach as the facilitator of the client's growth. The model proposed by Knight [68] includes the method of instructional coaching. Visible learning (diagnosis, intervention, and evaluation) has been one of the research initiatives conducted in education in the past few decades. Simultaneously, instructional coaching (identify, learn, and improve) is becoming a popular form of professional development. Instructional coaching is used to support the realization of “visible learning” or other educational innovations. Standing [16] proposed a model to compare the use of “traditional” and “progressive” coaching styles to train a general male youth population to improve sprint and jump performances while assessing enjoyment to comment on the long-term application. The process includes the following steps: study design, participant selection, experimental procedure, data collection, statistical analysis, and performance measurement.

RQ2: Which Conceptual Coaching Models Can be Used to Explain the Coaching Process?

The actual definition of coaching concepts remains difficult to understand, and the working of the coaching interaction itself is still unknown [3]. The coaching approach may create a positive impact on the coaching environment and, subsequently, can improve the bottom-line performance of a target human group. An efficient coaching model is a tool to motivate personal learning, increase energy, improve ownership, and improve accountability. In contrast, no single coaching model can be labeled as the best, as coaching models change with the perspective and context of individual coaching. We found coaching model candidates for behavioral intervention that adequately explain the human coaching process. We divided our findings into the following two categories to have a better understanding of coaching process descriptive models: coaching process descriptive models and their application domain (Table B.3 [3][7][8][71]; Figure B.2 [8], Figure B.3 [71], and Figure B.4 [3]), and psychological approaches to describe coaching process models (Table B.4 [4][66][67][72]).

Table B.3: Coaching process descriptive models and their application domain.

Coaching process descriptive models	Application domain
Five level reviewing belief model [8]: The model explains the learned belief of a client who inherits or learns beliefs from his/her ancestors (parents) or teachers, or influential people to take any action from a decision. This model has the following five different levels from the bottom to the top: review (who am I), define (where do I want to go), plan (how am I going to get there), identify (how do I need to think, feel, behave), and continue (review and reward). When action is taken after a decision is made, the following five different levels are explored: beliefs and values, thoughts and expectations, emotions, behaviors, and actions. The model is shown in Figure B.2. ABCDE model [8]: It explains how to use the tools and techniques of cognitive behavioral coaching to challenge negative thinking, make positive changes, achieve goals, and improve (ABCDE model: A, activating event or situation; B, the belief; C, the consequential emotion; D, disputing the belief; E, exchanging the thought). Cognitive behavioral model [7]: It utilizes a cognitive behavioral solution-focused model of coaching. It provides preliminary evidence that evidence-based life coaching can enhance mental health, quality of life, and goal attainment.	Cognitive behavioral coaching
Dynamic coaching model [71]: A coaching system is made up primarily of three spaces that contain three conversations that interact together to create the coaching conversation. The first reflective space is the internal conversation within the client. The second space is the shared space created in between the coach and client. The third space is the space within the coach. The complete coaching model is depicted in Figure 3.	Dynamic coaching
Experiential coaching cycle [3]: It has the following three noticeable constituent areas: prereflective experience, reflection on experience, and postreflective thinking, as depicted in Figure B.4. The cycle additionally has the following three essential transition stages: touching experience, turning into critical, and integration. Transition phases regularly involve more emotional, cognitive, or physical effort than the constituent spaces and are particularly challenging for both coach and participant owing to the emotional struggle and inheritance of uncertainty.	Pragmatic coaching

Table B.4: Psychological approaches for coaching process models.

Coaching process descriptive models	Psychological approaches
Five elements model [68]: The model explains the practice of human resource development, focusing on improving performance/examining results with a way of equipping human beings with the methods, knowledge, and possibilities they want to broaden themselves and become more effective. The unidirectional sequence of five elements includes establishing relationships, recognizing opening, observation or assessment, enrollment of clients or participants, and coaching conversations. Goal focused executive coaching model [4]: It explains how to improve personal or professional performance, personal satisfaction, and effectiveness in the client's organization within a formally defined coaching agreement, and identify a set of goals using the following process: identification of an issue, setting of a goal, development of a cyclic action plan (act, monitor, evaluate, and change), and evaluation of the success score. Organization response cycle [69]: The model explains how to manage the pressure exerted on the department because of globalization, to produce faster, cheaper, and customized products and services. This model includes a cyclic loop of the following processes: learning (individual, team, organizational), innovation (products, and services), adaptation (responding to change and complexity), and results (enough or not).	Executive coaching
Humanistic coaching model [4]: The cyclic model of awareness-choice-execution (ACE) explains how to use the principles and tasks to teach participants how to harness their own growth process. In directing the process of coaching for change, the coach can ensure that the participant integrates "being (and awareness of that)" with "doing" such that the participant comes away with actual results.	Humanistic coaching
Effective coaching model [4]: It explains the core of the coaching process ("what is done!") and represents how the contextual themes are legislated with the following seven key principles that strengthen the human coaching process: collaboration, accountability, awareness, responsibility, commitment, action, and results.	Contextual coaching
Open innovation model [72]: It explains several key factors for organization development throughout the following life cycle stages: birth (innovation, awareness, intuition, vision, commitment, risk, and flexibility), growth (decision-making, delegation, team approach, state change, and ability to grow), maturity (feasibility, retain high performance, overcome obstacles, and responsiveness), revival (autonomy, integration, effective internal communication, and innovative high performance), and decline (renew strategy and structure, innovativeness, improve information processing, and increase tolerance level).	Organization development

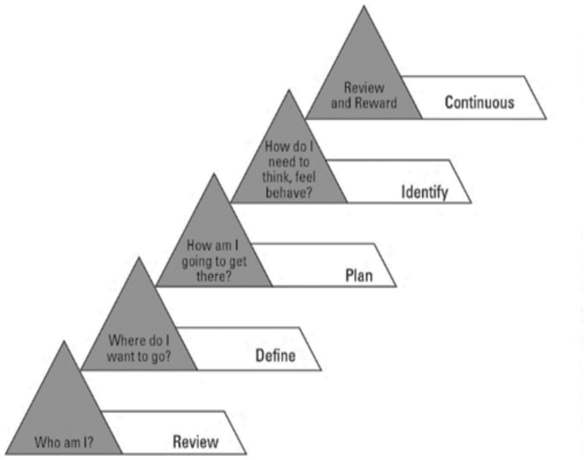

Figure B.2: The five-level reviewing belief model by Whitten.

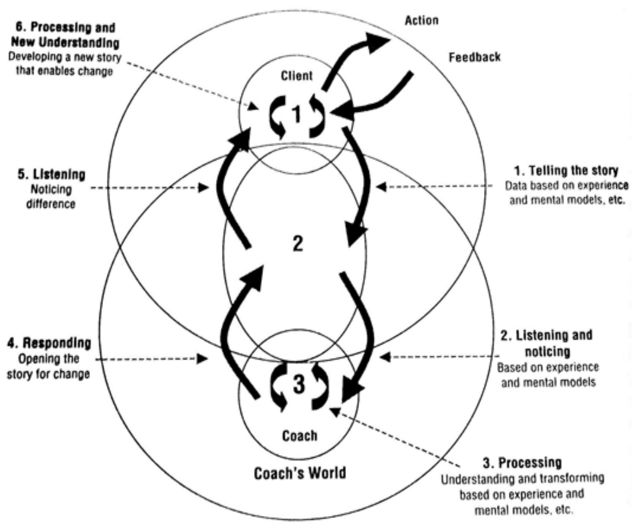

Figure B.3: The dynamic coaching model by Cavanagh et al.

Figure B.4: The experiential coaching cycle with six phases by Cox.

RQ3: What Are the Basic Coaching Methods to Make the Coaching Process Successful for the Promotion of a Behavioral Intervention?

A coach must sometimes strictly intervene with the client and insist on something or keep pressing on a point until a client is willing to look at it [2]. The process of human coaching includes an insight into how people learn and think, along with an understanding of what motivates them to achieve continuous high performance during behavioral intervention. Several coaching methods for the promotion of behavioral intervention are described in Table B.5 [1][2][3][4][5][7][9][21][22][23][57][59][67][69][70][73]. The answer to "RQ3" contributes to "RQ4" and "RQ5" to analyze what limitations to overcome and what methods of offline behavioral intervention to include in eCoaching for the promotion of a healthy lifestyle.

Table B.5: Coaching methods.

Method	Description
Systematic observation [7][23]	Systematic observation helps researchers to identify the instructional behaviors utilized by coaching practitioners within the practice environment. Observable and measurable data have the potential to solidify the scientific basis of the coaching process. Systematic observation must be capable of accurately and comprehensibly recording human behavior within a human coaching context.
Interpretive interview [2][3]	Achievement of the coaching process remains with observational data collection supplied with in-depth interviews that allow for the acquisition and interpretation of rich qualitative data based on the behavioral strategies of coaching.
Knowledge exchange [5]	In the search for an understanding of the coaching process, it is necessary to analyze and investigate the shared experience between the coach and participant.
Pragmatism [3]	Coaching is not a collection of techniques to apply or dogma to adhere to, rather it is a discipline that requires freshness, innovation, and relentless correction according to the outcomes being produced.
Understanding of human psychology [7][69][73]	Psychological principles on which coaching is based are essential. Without psychological understanding, coaches might go through the motions of coaching or use the behaviors associated with coaching, such as questioning, but fail to achieve the intended results.
Experience [5][7][67]	Experience is a skill that helps to improve competence and coaching outcomes, such as future advancement.

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Table B.5 – continued from previous page

Method	Description
Trust [1]	Trust is one of the complex issues for coaches, whether internal and external. It teaches how not to use personal information and not to disclose it to illegitimate people.
Relationship [1]	The relationship must be based on mutual respect, trust, and mutual freedom of speech.
Expression [1]	Language impacts the goals of coaching by providing a means to assist the participant in being self-correcting and self-generating. It is important to provide new language to the participant for better understanding and learning.
Mentoring [3][5]	Mentoring is a more formal process, based on a one-to-one relationship with someone in the organization. While a mentor can use all the coaching types, their purpose is broader in scope than that of a coach.
Values and motivation [1]	Values are ideas about what is good and bad, and how things should be. Motivation is the internally generated feeling that stimulates participants to act. Motivation is related to the needs and values that have a correlation with intrinsic motivation.
Feedback [1][4]	Feedback is important for coaches to improve their learning environment.
Evidence based [4][7]	Evidence-based life coaching can enhance health, quality of life, and goal achievement.
Contextual [4][7][69]	Understanding the context is essential in coaching perspective, as it gives insights into why many participants either fail to use or resist the coaching approach.
Decision-making [2][5][7]	Decision-making includes data collection related to coaching, the privacy of the collected data, data cleaning, statistical analysis of the collected data, and the development of a machine learning model for prediction or regression analysis.
Goal based (goal setting) and evaluation [3][5][23][59]	Goals must be stated and measurable. Goals include clearly stated pathways to the preferred alternative by identifying strategies. Goal setting and goal evaluation are two essential parts of a behavioral intervention to determine the effectiveness of coaching. Goals must be specific, measurable, actionable, relevant, and time related. Evaluation of goals is important to understand the strengths and limitations of participants to set further attainable goals when necessary and reach the objectives.

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Table B.5 – continued from previous page

Method	Description
Self-efficacy [9]	Self-efficacy has its core in social learning theory. It can be explained as the general or definite belief that people have concerning their capability to accomplish assigned tasks.
Personalization [21]	The concept of personalization or user tailoring is used in coaching to explain the variation in preferences between groups of participants and within the groups of participants to make recommendations more effective.
Persuasion [58]	Persuasion is a process that has been designed to change negative attitudes or behaviors of participants through advice, faith, and social influence. It is regularly used in the domain of public health where human-human or human-computer interaction is applied. It can be categorized as instruction style (authoritative and nonauthoritative), social feedback (cooperative and competitive), motivation type (extrinsic and intrinsic), and reinforcement type (negative and positive) [22].
Interaction and co-creation [70]	People are subject to self-regulation failures as follows: cravings, distractions, and deferring the right things. Therefore, people may need guidance through an eCoaching process to achieve the intended goal. Interaction is an integral part of pervasive computing that guides people to "do the right thing." It requires improving automated logging of health (behavior) data and integrating this into coaching processes, as well as designing more intelligent and interactive coaching processes that incorporate user preferences and plans, contextual/situational priorities, and health data consequences. For successful design, the concept of co-creation or co-design is essential, where the system is designed together with its users.

RQ4: How Can the Methods of Human Coaching Processes be Incorporated Into eCoaching for Behavioral Intervention to Promote a Healthy Lifestyle?

The concept of eCoaching is constructed on the foundation of traditional coaching, and the technological revolution has boosted its performance and real-time acceptance. The World Health Organization (WHO) [49] claimed that chronic illnesses associated with modifiable lifestyle factors would be responsible for premature death worldwide. Therefore, change in negative health behavior should be given priority to avoid considerable losses caused by lifestyle diseases. An eCoach system can empower human beings to manipulate a healthy lifestyle with early health risk prediction and beneficial customized recommendations [22][61]. The pillars of eCoaching for behavioral intervention [56] are mostly inspired by the coaching methods as described in Table B.5. They consist of data collection, data storage, analysis of data, goal setting, recommendation generation (intervention), monitoring, data privacy and ethics, goal evaluation, credibility, co-creation, feedback generation, and model evaluation [24][27][32][34][35][74]. Behavioral intervention is the process of intervening. As defined by WHO [49], a health intervention is an act performed for, with, or on behalf of a person or population, whose purpose is to assess, improve, maintain, promote, or modify health, functioning, or health conditions. Health interventions are used to promote a healthy lifestyle. Lifestyle or behavioral interventions include exercise, diet, and at least one other method (counseling, stress management, or healthy habits). Effective intervention planning is essential for an eCoach system for behavioral intervention to promote a healthy lifestyle change.

From the included "eCoach" articles, we found that the following methods are most appropriate for eCoaching processes: "personalization" (n=19) [21] "interaction and co-creation" (n=17) [70], "behavior change with technology" (n=17) [58], "goal setting" [59] and "evaluation" (n=16) [23][59], "persuasion" (n=15) [57], "automation" (n=14) [1], and "promotion of a healthy lifestyle" (n=14) [21]. These are relevant methods for eCoaching following a top-down ranking. "Personalized" recommendations are required to make intervention plans effective, and for that, personal "interaction" is necessary. For efficacy evaluation of eCoaching, personalized goal setting and goal evaluations are important. "Automation" is relevant to deliver automatic behavioral recommendations ("persuasion") to participants for the promotion of a "healthy lifestyle."

Methods in eCoaching, such as personalization, persuasion, goal setting and evaluation, interaction, and co-creation, are borrowed from traditional offline human coaching (Table B.5). In eCoaching, persuasion is developed by trusting self-report or automation that observes human behavior using sensors, which is followed by health risk prediction with pattern recognition algorithms. The remaining four are core eCoaching methods. The first aspect is *automation* [1]. It helps to deliver automatic behavioral recommendations to users to maintain a healthy lifestyle. The decision support system (DSS) [22][61] within an eCoach system periodically monitors health and wellness parameters collected over time through sensors, questionnaires, and feedback forms, and predicts health risks. Once risk prediction is made, the DSS sends an automatic alert or recommendation to users. The second aspect is *behavior change with technology* [58]. Recent advancements in ICT have improved personal health care. The health care segment is still looking for an interactive, easy-to-use, optimized, cost-effective, and secure eCoach system for behavioral intervention for the promotion of a healthy lifestyle. The system should have the capability to normalize different formats of personalized data with appropriate ontological studies, ensuring the privacy of data. It should use AI algorithms based on ethical principles to analyze human psychology, monitor human behavior, and guide participants accordingly. Technology can support an eCoach by supporting coaching types, process management, human-computer interaction, remote collaborative work and communication, data collection and storage, data security and privacy, data analysis, recommendation generation, evaluation, and self-tracking. The third aspect is *promotion of a healthy lifestyle* [21]. Good health is the result of a healthy lifestyle, where caring about physical activities and nutrition are vital concerns. However, today, nutritional disorders are increasing rapidly. It is affecting children, adults, and older people, mainly due to limited nutrition knowledge and the lack of a healthy lifestyle. A commonly adopted approach for these imbalances is monitoring physical activity and daily habits, such as recording exercise and creating custom meal plans to count the number of macronutrients and micronutrients acquired in each meal. Behavioral interventions (nutritional and physical exercise coaching) through eCoaching have become popular (eg, Food4Living [17], TrainME [17], and RunningCoach [21]) for the promotion of a healthy lifestyle.

RQ5: How Can eCoaching Promote a Healthy Lifestyle With Proven Coaching Methods Using ICT?

The point of interest of eCoach initiatives is to deliver high-quality, evidence-based, comfortable, cost-effective, and timely care to assist human beings in retaining a healthy way of life [1][23][57]. eCoaching methods represent an evolving trend as they diverge from the conventional methods that tend to devalue user behavior. Health eCoaching is a complex process that demands careful planning and cooperation of several scientific domains, such as psychology, computer science, ethics, and medical science [23]. An effective eCoach design focuses on co-creation, co-design, and personalization of the intervention by the user and the system [23][30][32][35][59]. There are six primary attributes when modeling an eCoach system as follows [24][27][32][34][35][58][59][74]: (1) identification of the target group of participants, (2) selection of the study case, (3) type of data to be collected and data collection method, (4) target of coaching, (5) approach of coaching, and (6) evaluation of the intervention plan.

According to the findings in studies on coaching regarding the importance of the personal relationship between a coach and trainee, personalization of coaching strategies, motivation, goal setting, and engagement of the eCoach with the trainee/coached citizen/patient has to be customizable and easily available. Therefore, the user interface design of an eCoach system must be unambiguous and easily understandable [23][24], and it must not include unwanted artifacts. It must be designed following a standard co-creation process. eCoaching systems are an emerging trend with a design criterion to reduce the involvement of human specialists with AI-inspired algorithms and robots for decision-making based on supervised, unsupervised, and reinforced learning. In contrast, in several eCoach designs for behavioral intervention, human therapists or doctors, or other coaching experts are included [23][27][34][62]. The experts have access to the observation data, and they get involved or contribute to the coaching process.

eCoaching has other possibilities when compared to traditional coaching in terms of value addition, performance, and competence. Efficacy [52] study is a problem in both kinds of coaching to date, as revealed in the systematic literature review, for the following reasons: insufficient planning in study selection and study design [1][23], lack of conceptual/contextual clarity [24][25], inappropriate selection of sample size for statistical analysis [61], dearth of proper background education [74], lack of reliance and self-disclosure [1][22], absence of variation in a selected population [22][61], and lack of competence and experience with technology (digital illiteracy) [22][75].

Discussion

Overview

From the systematic literature review, we analyzed existing well-established traditional human coaching processes, descriptive models and the application domain, psychological approaches to describe coaching process models, methods in the coaching processes, and their applicability in eCoaching with the advancement of ICT to promote a healthy lifestyle. In this section, we discuss the findings associated with each individual research question.

Discussion on RQ1
The answer to "RQ1" helped us to identify key methods in the coaching process, as defined in Table B.6 [1]-[7][9][16][66][67][68]. We studied their significance in eCoaching. The identified key methods in the coaching process are based on a review of established coaching process description models relevant for this RQ. Identified coaching methods are used to answer "RQ4." Appropriate coaching skills, knowledge to coach, method selection, proper implementation, personal interaction, and idea exchange are part of an effective coaching practice.

Discussion on RQ2
We depicted the top three coaching descriptive models from Table B.3, such as the models of Cavanagh et al. [71], Whitten [8], and Cox [3] on "dynamic coaching," "cognitive-behavioral coaching," and "pragmatic inquiry into the coaching process," respectively. These models seemed to be suitable candidates to construct a personalized eCoaching process model for behavioral intervention for the promotion of a healthy lifestyle, contributing to the answer of "RQ4."

Discussion on RQ3
Systematic observation methods are recognized as useful research tools for providing quantitative descriptions of coaching behavior. Furthermore, coaching psychology mechanisms are also relevant for enhancing well-being, work performance, and personal life [7]. Therefore, researchers need to use systematic observation [64] and psychological coaching [7] to study coaching behavior in order to establish a database of meaningful coaching behaviors in different contexts. Besides the discussed strengths and potentials, constraints related to coaching as behavioral interventions are reviewed in the following text. Language is a medium of communication between people. Coaching may lead to language interpretability issues when selecting inappropriate language. Without proper communication, participants will be unable to perform the needed or desired tasks [2][66]. Regarding understanding, the humanistic nature of the coaching process remains little understood and an underresearched area [66]. Regarding ethical dilemma, researchers need to develop an ethical standard, adequate training, and presential coaching within a specific context. In many cases, coaches have not fully understood the performance-related psychological principles on which coaching is based [69]. Regarding diversity, the coaching study should

consider diversity in all its forms, such as organizational and occupational tenure, age, race, educational background, attitude, and personality [9]. Regrading human behavior, many coaches do not ground their practice in behavioral science. Participants should be selected from a diverse community, as members of a single community cannot represent the general population [7]. Regarding conceptual clarity, besides the popularity, the human coaching process reveals lack of conceptual clarity, imprecise description, and paucity of efficacy studies [6]. There persists a wide gap between what practitioners believe coaching is and what many executives think about coaching [67]. Regarding implementation challenge, the most formidable challenge in the field of coaching is the challenge of translating research into practice. Thought needs to be given to the sharing of all visible learning aspects in a way that is manageable and a part of goal-directed learning [68]. Regarding bias, due to background and bias, experts do ignore psychological problems they do not understand and may worsen the intervention. Thus, psychotherapeutic intervention is essential [4]. Regarding human psychology and pressure, most coaching-related studies are inclined to psychology rather than the way to do coaching. Pressure-based coaching hampers team functioning by negatively influencing team loyalty through increased levels of tension within the group [48].

Table B.6: Search strings used for article searching.

Research group	Key methods associated with coaching
Potrac et al [68]	Behaviors, actions, and motivations
Cunningham et al [9]	Experience and racial diversity
Bartlett [1]	Trust, language, practice, and behavior
Côté [5]	Coach education and learning
Green et al [7]	Goal, psychology, evidence based, and cognition
Murphy [6]	Mentoring, evaluation, and leadership
Richards [69]	Intelligent coaching, learning, innovation, adaptation, Sustainability, and model performance
Flaherty [2]	Constraints of learning
Cox [3]	Pragmatism, experiencing, listening, clarifying, reflecting, and questioning
Stober et al [4]	Psychology, contextual, goal focus, cognition, and humanistic perspective
Knight [70]	Instructional coaching and visible learning
Standing et al [16]	Coaching, data collection, statistical analysis, and performance evaluation

Discussion on RQ4

The answer to "RQ2" revealed that the coaching model could be implemented in the following two ways: (1) the coach at the center and participants ("citizens") around, and (2) participants at the center and the coach around. Gerdes et al [61] proposed an eCoach concept based on monitoring, quantification of data, and AI, emphasizing human-centered design, with participants placed at the center, as depicted in Figure B.5 [61]. The loop of the pictured eCoach model can be closed with an effective behavioral intervention plan, based on the selection of study cases, to guide people and deliver contextual and personalized recommendations to maintain a healthy lifestyle. This systematic literature review can help us understand how to solve the "What" (to coach) and "How" (to coach) questions related to eCoaching. In the eCoach model, as illustrated in Figure B.5, the critical methods of coaching, as depicted in Figures B.2-B.4, fit together for behavioral intervention.

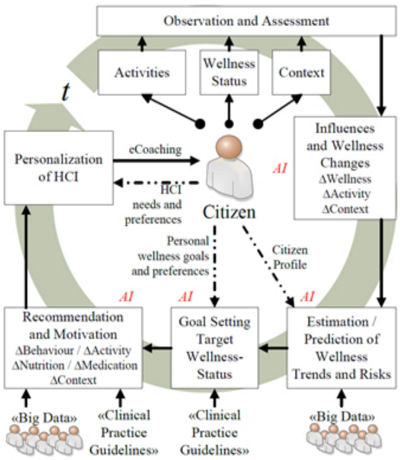

Figure B.5: A holistic electronic coach (eCoach) model proposed by Gerdes et al. AI: artificial intelligence; HCI: human-computer interaction.

Discussion on RQ5

Digital methods [17] for behavioral intervention with personal coaching have emerged as effective and scalable options. They include methods for intensive behavioral counseling, supporting face-to-face consultations with accessibility, attractive and personalized interaction, efficient use of time, and managing costs. eCoaching has the potential to overcome problems, such as language, bias, conceptual clarity, ill-defined matters, freedom of expression, pressure, and tension, which are expected in traditional coaching, as discussed in the answer to "RQ3." A smart eCoach may ideally deliver solutions asynchronously and on-demand with better flexibility and increased accessibility for personalized context-based coaching services. In this review, we have identified the following critical elements for effective eCoaching with AI [22][57][61][75][76][77]: real-time feedback, suggestion, and alert generation; preference sharing; comprehensible user experience (UX) design; interactive interaction (eg, intelligent chatbot); DSS; wellness vision (physical/social/emotional/spiritual); encouragement based on positive human psychology; assessment of human behavior based on physiological and contextual data; credibility; ethics; digital literacy to make the human-eCoach interaction effective; and generation of automatic, personalized, and context-specific recommendations to achieve health and wellness goals.

Strength and Limitation

This systematic literature review helps to identify key processes from coaching methods to solve existing challenges and use human coaching and eCoaching processes as behavioral interventions. Coaching consists of observation, offering hints, feedback, reminders, and new tasks and redirecting participant attention to a salient goal to enhance participant performance. Coaching is applied to unveil the potential of participants to maximize their performance. A coach facilitates experimental learning that results in future-oriented abilities. A coach can shape new visions and plans to generate desired results. Despite the underutilization of remote coaching of health and wellness in the health care system as an asset of clinical practice, the focus on coaching is justified. The integration of offline human coaching methods into the eCoaching process faces challenges related to privacy, ethics, coaching environment, skills, trust, motivation, intervention plans to change negative behaviors, human centeredness, and evaluation of preset goals. Despite the challenges, it is very promising to integrate human coaching methods into the eCoaching process [4][5][61]. An important limitation of this study is that we did not search the JMIR database, which has e-collections on the present topic. Future studies on this topic should search the JMIR database. This study serves as a basis for further research with a focus on designing an eCoach system based on the identified key coaching methods for the generation of personalized recommendations to achieve personal wellness goals.

Conclusions

An ideal coach should have the potential to conceptualize and navigate through changing complex environments. The coaching process is adopted to bridge inadequacies in areas where human resource structures and practices should play a more active mediating role. The success of the coaching process is an art, and impact analysis is important to evaluate its accomplishment. An evaluation of the human coaching process is also necessary. Therefore, the learning environment of active coaches needs to be continuously revisited and adapted. Health monitoring and fitness coaching with AI has the potential to contribute to research in eHealth. An optimized system for health eCoaching and management of personal health data that ensures data protection and privacy are significant challenges associated with eCoach-related research. The prediction of human behavior by analyzing human psychology for the generation of useful lifestyle recommendations is another challenging task to overcome, as human behavior is continuously changing. This review will provide eHealth researchers with an overview of different coaching and eCoaching processes, with the aim to promote a healthy lifestyle. In addition, this review can be used as a basis for further research focusing on the design, development, testing, and evaluation of the performance of an eCoach in order to generate automatic, meaningful, evidence-based, contextual, and personalized recommendations to achieve personal health goals.

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Conflicts of Interest

None declared.

Abbreviations

AI: artificial intelligence
DSS: decision support system
eCoach: electronic coach
eCoaching: electronic coaching
ICT: information and communication technology
RQ: research question
WHO: World Health Organization

Multimedia Appendix 1

Search results from electronic databases[1].

[1] https://www.jmir.org/2021/3/e23533/

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Paper C

An Automatic Ontology-Based Approach ... for Healthy Lifestyle Management: Proof-of-Concept Study

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An Automatic Ontology-Based Approach to Support Logical Representation of Observable and Measurable Data for Healthy Lifestyle Management: Proof-of-Concept Study

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Abstract – **Background**: Lifestyle diseases, because of adverse health behavior, are the foremost cause of death worldwide. An eCoach system may encourage individuals to lead a healthy lifestyle with early health risk prediction, personalized recommendation generation, and goal evaluation. Such an eCoach system needs to collect and transform distributed, heterogeneous health and wellness data into meaningful information to train an artificially intelligent health risk prediction model. However, it may produce a data compatibility dilemma. Our proposed eHealth ontology can increase interoperability between different heterogeneous networks, provide situation awareness, help in data integration, and discover inferred knowledge. This "proof-of-concept" study will help sensor, questionnaire, and interview data to be more organized for health risk prediction and personalized recommendation generation targeting obesity as a study case. **Objective**: The aim of this study is to develop an OWL-based ontology (UiA eHealth Ontology/UiAeHo) model to annotate personal, physiological, behavioral, and contextual data from heterogeneous sources (sensor, questionnaire, and interview), followed by structuring and standardizing of diverse descriptions to generate meaningful, practical, personalized, and contextual lifestyle recommendations based on the defined rules. **Methods**: We have developed a simulator to collect dummy personal, physiological, behavioral, and contextual data related to artificial participants involved in health monitoring. We have integrated the concepts of "Semantic Sensor Network Ontology" and "Systematized Nomenclature of Medicine—Clinical Terms" to develop our proposed eHealth ontology. The ontology has been created using Protégé (version 5.x). We have used the Java-based "Jena Framework" (version 3.16) for building a semantic web application that includes resource description framework (RDF) application programming interface (API), OWL API, native tuple store (tuple database), and the SPARQL (Simple Protocol and RDF Query Language) query engine. The logical and structural consistency of the proposed ontology has been evaluated with the "HermiT 1.4.3.x" ontology reasoner available in Protégé 5.x. **Results**: The proposed ontology has been implemented for the study case "obesity." However, it can be extended further to other lifestyle diseases. "UiA eHealth

Ontology" has been constructed using logical axioms, declaration axioms, classes, object properties, and data properties. The ontology can be visualized with "Owl Viz," and the formal representation has been used to infer a participant's health status using the "HermiT" reasoner. We have also developed a module for ontology verification that behaves like a rule-based decision support system to predict the probability for health risk, based on the evaluation of the results obtained from SPARQL queries. Furthermore, we discussed the potential lifestyle recommendation generation plan against adverse behavioral risks. **Conclusions**: This study has led to the creation of a meaningful, context-specific ontology to model massive, unintuitive, raw, unstructured observations of health and wellness data (eg, sensors, interviews, questionnaires) and to annotate them with semantic metadata to create a compact, intelligible abstraction for health risk predictions for individualized recommendation generation.

Introduction

Overview

Lifestyle diseases are an economic burden to an individual, household, employer, and government, and lead to financial and productivity risks for poor and rich countries alike [1][2][3]. The key risk factors behind lifestyle diseases are the excessive use of alcohol, inappropriate food plan, physical inactivity, excessive salt intake, saturated fat consumption, and tobacco use [1][2][3]. These result in excess weight gain, elevated blood glucose, high blood pressure (BP), elevated total cholesterol in the blood, and social isolation. Obesity is one of the foremost lifestyle diseases that lead to other noncommunicable diseases such as cardiovascular diseases, chronic obstructive pulmonary disease, cancer, diabetes type II, hypertension, and depression [1][2][3]. eHealth monitoring has become increasingly popular, providing information and communications technology (ICT)–based remote, timely care support to patients and health care providers [1-3]. An eHealth virtual coaching recommendation system can guide people and convey the appropriate recommendations in context with enough time to prevent and improve living with lifestyle diseases. It requires capturing physiological (vital signs such as BP, pulse, lipid profile, glycemic response, BMI), behavioral (sleep, diet, exercise), and contextual data (position, and weather) from secure wearable sensors, manual interactions, feedback, and customized questionnaires over time, to train an artificial intelligence (AI) model for behavior analysis and early prediction of wellness trends and risks [4][5][6]. However, data collection from heterogeneous sources may lead to data interoperability, annotation, and semantization problem.

Background and Problem Description

Health and wellness data collected from heterogeneous sources (eg, multimodal sensors, interviews, questionnaires) are of different format and lead to well-known problems in health informatics, which are related to logical data representation, aggregation, data analysis, data standardization, and data interoperability [7][8]. Targeted personal, habitual, physiological, activity, and nutrition data are generally collected via secure wearable sensors, manual interactions, interviews, web-based interactions, smartphone apps, customized questionnaires, and feedback forms over time. Weather application programming interfaces (APIs) and external weather sensors are useful for the collection of contextual weather data over time. The wearable activity monitors need to connect to a personal smartphone via Bluetooth nearfield communication technology (Bluetooth low energy [BLE]) [9][10]. The device can seamlessly measure and transfer high-resolution raw acceleration data and multiple activity parameters to a secure storage to process the data further with a machine intelligence module [11]. High-end, time-dependent activity data collection with wearable BLE devices has become accessible and feasible for ubiquitous monitoring. Some of the activity data, such as nonwear time or intensive activity details, are questionnaire-dependent.

Physiological data are collected either invasively (eg, glycemic response, cholesterol level) or noninvasively (eg, weight, BP, heart rate, body assessment data). The questionnaire-dependent nutrition data are collected either daily or on an alternate day or on a weekly basis. The assessment of nutrition data helps to determine the type of food, amount of food, conceptual information (temporal/spatial), dietary pattern, and intake of alcohol or energy drinks. Some baseline data (medical history, habit, preference, personal details, initial weight and height, initial BP, and initial body assessment data) are collected during the initial recruitment of the participant or every month for either demographic statistics or population clustering or individual goal assessment. Each data have their unit and range following a standard guideline based on the context and domain (eg, data on temperature are applicable for both health and environment domain with a different range, meaning, and context). Therefore, each measurement process owns separate challenges related to logical or semantic data representation, proper usage of data, and improving data reusability. The data usability involves the transformation of data into an understandable computer format. It creates a challenge to systematically and syntactically analyze health and wellness data in aggregation with other clinical data. Incorporation of physical activity, diet as a care procedure, or investigating how it afflicts healthy outcomes involves a more detailed and diverse representation of participant's behavioral level and physiological condition [7][8][12][13].

Furthermore, the challenges of reusing the existing physiological and behavioral data of a participant within the electronic health record remain and include concerns related to opacity and semantic inconsistency [7][8]. Besides, these health and wellness data are still mostly hidden in clinical narratives with highly variable forms of expression. In this regard, ontology can provide a framework to allow the mentioned heterogeneous health and wellness data to be organized, compact, structured, consistent, machine understandable, and queried through high-level specifications. Ontology helps to annotate diverse health and wellness data with semantic metadata to increase interoperability among heterogeneous networks, data integration, discovery, and situation awareness. An eHealth ontology can reuse the concept of existing, proven, well-accepted ontologies (eg, semantic sensor network [SSN] ontology [14], Systematized Nomenclature of Medicine—Clinical Terms [SNOMED CT] ontology [15]) to enhance its vocabularies and better semantic representation.

A rule-based decision support system (DSS) can use such an eHealth ontology model to measure and predict health risks, and to generate useful personalized recommendations following proven clinical rules. If the collected health and wellness data are not annotated accurately with semantic metadata in the medical domain, then the DSS may fail to deliver accurate decisions to both physicians and patients or participants in the form of incorrect recommendation plan, goal setting, and goal evaluation. DSS decision inaccuracy may appear primarily due to the following effects—improper design of knowledge base (KB), the inadequacy of tools or technologies applied in the execution of DSS, problems related to the ontology reasoning engine, and issues associated with inferring new knowledge.

Aim of the Study

After studying existing ontology models, we found that many ontologies and regulated terminologies cover aspects of obesity and related chronic illness domains, but concept analysis remains incomplete. After reviewing relevant ontologies, we proposed a freshly created OWL-based ontology to deal with different data inputs (internet of things [IoT] sensors, interviews, and questionnaires) and annotate them with semantic data. The proposed ontology will support data interoperability, logical representation of collected health and wellness data in context, and to build a rule-based DSS for health risk prediction related to obesity and afterward generation of lifestyle recommendations for a healthy lifestyle.

We have not evaluated the impact of the suggested recommendations on participants as we executed the complete scenario under a simulated environment. Still, we evaluated the performance of the proposed ontology model. In the proposed ontology, we annotated every participant's data with semantic web language rules and stored the generated OWL file in a triple-store format for better readability (Multimedia Appendix 1). The proposed ontology model allows automatic inferencing, efficient knowledge representation, balancing a trade-off between complexity and eloquence, and reasoning about formal knowledge. The entire study is divided into the following 2 segments: (1) ontology design and development and (2) its verification. This study addresses the following identified research questions:

RQ1: How to annotate distributed, heterogeneous health and wellness data received from sensors, questionnaires, and interviews into meaningful information to build a future machine learning model for health risk prediction for obesity?
RQ2: How to integrate existing IoT and medical ontologies to design and develop proposed eHealth ontology for obesity study case?
RQ3: How to verify the proposed ontology with rule-based behavioral recommendation generation?

For this set of semantic data, which will be considered as asserted True facts, the primary goal of the paper is to trigger logical rules of the shape (A IMPLIES B) or trigger rules in a logically equivalent way, that is, (NOT(A) OR B). If some specific variables are inferred to be true, then some recommendations shall be provided to the user from whom the semantic data are originating.

Related Work

This section offers existing background knowledge applicable for this research. It includes (1) a discussion of existing, relevant eHealth ontology models for chronic illness, health monitoring, and ontology-based DSS, (2) ontologies in the IoT domain for modeling sensor data, and (3) ontologies in the medical domain.

Existing eHealth Ontology Models

Different research groups have conducted different studies on eHealth ontology modeling for chronic illness, health monitoring, and ontology-based clinical decision support system (CDSS). For example, Kim et al. [16] developed an ontology model for obesity management with the nursing process in the mobile device domain for spontaneous participant engagement and continuous weight monitoring. The scope of the obesity management included behavioral interventions, dietary recommendations, and physical activity, and for this purpose, the study included assessment data (BMI, sex, and hip-to-waist circumference), inferred data for representing diagnosis results, evaluations (cause of obesity, success, or failure of behavioral modifications), and implementation (education, suggestion, intervention). Sojic et al. [17] modeled an obesity domain–specific ontology with OWL to design inference patterns to individualize health condition assessment as age and gender-specific. The ontology helped classify personal profiles based on the changes of personal behavior or feature over time and infer personal health status automatically, which are important for obesity evaluation and prevention. The ontology rules were written in semantic web rule language (SWRL). Kim et al. [18] proposed an ontology model for physical activity (PACO) to support physical activity data interoperability. The ontology was developed in Protégé (version 4.x), and the FaCT++ reasoner verified its structural consistency. Lasierra et al [19] developed an automatic ontology–based approach to manage information in home-based scenarios for telemonitoring services based on the automatic computing paradigm, namely, MAPE (monitor, analyze, plan, and execute). They proposed another 3-stage ontology-driven solution [20] (stage 1: ontology design and implementation; stage 2: ontology application to study personalization issues; and stage 3: software prototype implementation) for giving personalized care to chronic patients at home. The proposed ontology was designed in OWL DL language in Protégé-OWL version 4.0.2 ontology editor and was verified using FACT++ reasoner. The ontology development involved data from heterogeneous sources, such as clinical knowledge, data from medical devices, and patient's contextual data. Yao and Kumar [21] proposed a novel CONFlexFlow (Clinical cONText based Flexible workFlow) approach using ontology modeling for incorporating flexible and adaptive clinical pathways into CDSS. They developed 18 SWRL rules for practical explanation of heart failure. The model was verified with the Pellet Reasoner Plug-in for Protégé version 3.4. Additionally, they developed a "proof-of-concept" prototype of the proposed approach using the Drools framework. Chi et al. [22] constructed a chronic disease dietary consultation system using web ontology language (OWL) and SWRL. The KB involved heterogeneous sources of data and interaction of factors, such as the illness stage, the physical condition of the patient, the activity level, the quantity of food intake, and the critical nutrient constraints. Rhayem et al. [23] proposed an ontology-based system (HealthIoT) for patient monitoring with sensors, radiofrequency identification devices, and actuators. They claimed that data obtained from medically connected devices are enormous, and thereby lack repressibility and understandability, and are manipulated by other systems and devices. Therefore, they proposed an ontology model to represent both the connected medical devices and their data based on a semantic rule, followed by model evaluation with the proposed IoT Medicare system that supports decision-making after analyzing the vital signs of the patients. Galopin et al. [24] proposed an ontology-based prototype CDSS to manage patients with multiple chronic disorders following clinical practice guidelines. The KB decision rules were based on the "if–then" rules, following clinical practice guidelines and patient observation data. Sherimon et al. [25] proposed an ontology system (OntoDiabetic) using OWL2 language to support a CDSS for patients with cardiovascular disease, diabetic nephropathy, and hypertension following clinical guidelines and "if–then" decision rules. Hristoskova et al. [26] proposed another ontology-driven ambient intelligence framework to support personalized medical detection and alert generation based on the analysis of vital signs collected from the patients diagnosed with congestive heart failure. The DSS system can classify personalized congestive heart failure risk stages, and thereby, notify patients through ambient intelligence's inference engine. Riaño et al. [27] proposed an ontology-based CDSS for monitoring and intervening chronically ill patients to prevent critical conditions, such as incorrect diagnoses, undetected comorbidities, missing information, and unobserved related diseases. Jin and Kim [7] designed and implemented an eHealth system using the IETF YANG ontology based on the SSN concept. The approach assisted in the autoconfiguration of eHealth sensors (responsible for collecting body temperature, BP, electromyography, and galvanic skin response) with the help of internet and communication technologies and querying the sensor network with semantic interoperability support for the proposed eHealth system. The proposed eHealth system consisted of 3 main components: SSN (eHealth sensors, patient, unified resource identifier [URI]), internet (eHealth server, KB), and eHealth clients (patient, and professionals). The proposed semantic model used a "YANG to JSON translator" to convert YANG semantic model data to JSON semantic model data for semantic interoperability before storing them in the database (KB). Ganguly et al. [28] proposed an ontology-based model to manage semantic interoperability problems in eHealth in the context of diet management for diabetes. The development of the framework included rules of dialogue games, DSS with KB (rule base and database), a dialogue model based on decision mechanism, the syntax of dialogue game, decision mechanism, and translational rules.

Ontologies on the Internet of Things Domain

Ontology [29] provides a framework for describing sensors. SSN-XG (W3C Semantic Sensor Network Incubator Group) developed the SSN ontology to model sensor devices, systems, processes, and observations. SSN annotates sensor data with semantic metadata (semantic sensor web) to increase interoperability among diverse networks, data integration, discovery, and situation awareness. The Sensor Model Language (SensorML) was developed by the Open Geospatial Consortium (OGC), which provides syntactic descriptions using XML to describe sensors, observations, and measurements. While SensorML provides an XML schema for defining sensors, it lacks the repressibility provided by ontology languages such as OWL [30][31][32]. Semantic sensor web, a combination of sensor and semantic web technologies, helps to annotate spatial, temporal, and thematic semantic metadata for the more artistic representation of sensor data, advanced access, formal analysis of sensor resources, and data standardization. SSN ontology is used to describe sensor devices; sensing; sensor measurement capabilities; and sensor observations, process, and systems [30][31][32]. SSN allows its network, sensor devices, and data to be installed, structured, managed, queried, and controlled through high-level specifications. Sensors Annotation and Semantic Mapping Language offers XML schema to transfer sensor data and sources into the instances of SSN ontology based on a predefined XML-based document (resource description framework [RDF]), which is achieved automatically with sensor data to RDF mapping algorithm [33]. “M3 Ontology” (machine-to-machine) was developed based on the “SenML” protocol (designed for simple sensor measurement), which is an extension of SSN, to enable the interoperable design of domain-specific or cross-domain-specific applications which are termed as Semantic Web of Things [13]. AeroDAML, KIM, M3 Semantic Annotator, MnM, and SemTag are different available semantic annotators for sensor observations for their corresponding semantic models (DAML, KIMO, M3, Kmi, and TAP) [34]. Like SSN, there are other IoT-based contextual ontologies, such as IoT-Ontology, IoT-Lite, and IoT-O [35]. SCUPA, CoBrA-Ont, CoDAMoS, PalSPOT, the delivery context ontology, and Fuzzy-Onto are different IoT-based ontologies for activity recognition [34]. URI, HTTP, HTML5, REST, SOAP, Web Socket, Web feed, MQTT, CoAP, and AMQP are some standard IoT protocols applicable to Web of Things [14][34][36][37]. In this study, we integrated the concept of SSN ontology to model sensor observations.

Ontologies in Medical Domain

SNOMED CT, 11th edition of the International Classification of Diseases (ICD-11), Unified Medical Lexicon System (UMLS semantic network), Foundational Model of Anatomy, OpenEHR, Gene Ontology, DOLCE, Basic Formal Ontology, Cyc’s upper ontology, Sowa’s top-level ontology, the top level of GALEN, and Logical Observation Identifiers Names and Codes (LOINC) are biomedical ontologies introduced to deliver semantic interoperability and complete knowledge related to the specific biological and medical domains [38]. Most laboratory and clinical systems send out data using the HL7 (version 2) protocol and in an HL7 message, the LOINC codes represent the “question” for a laboratory test or experiment and the SNOMED CT code represents the “answer.” In this study, we have reused the SNOMED CT ontology for modeling the health condition based on health and wellness data, and recommendation generation [8]. SNOMED CT was designed in 1965 as a controlled medical vocabulary licensed and supported by the International Health Terminology SDO. It is an organized list of a wide variety of clinical terminology defined with unique codes (ICD). It covers a wide range of medical terminologies for disorders and findings (what were observed!), procedures (what was done!), events (what happened!), substance/medication (what was consumed or administered!), and anything related to medical data. It offers a shared language that enables a reliable way of indexing, storing, reclaiming, and accumulating clinical data across fields and care sites. It is a complete, multilingual clinical terminology that gives clinical content and clarity for clinical documentation and reporting [8][38][39].

As described above, most studies have developed ontologies using OWL to solve the data interoperability problem. Still, integration among the electronic health data, semantic rules, semantic annotation, clinical guidelines, health risk prediction, and personalized recommendation generation remains an issue in eHealth. This study addresses it and proposes a prototype ontology model for obesity as a case study, to integrate data from heterogeneous sources (eg, sensor, questionnaire, and interview) in order to enable data interoperability, information search and recovery, and automatic interference. We integrated SSN and SNOMED CT ontologies into our proposed eHealth ontology because of their vast vocabularies, appropriateness, and semantic capabilities as discussed above [40][41][42][43].

Methods

Basics of Ontology

Ontology commenced as a philosophical discipline studying the existence and being and expanded into information technologies. Ontology is a formalized model for specific domains with the following essential elements: individuals/objects, classes, attributes, relations, and axioms. A class diagram of a program written in object-oriented programming [44] is a visual representation of an ontology. Ontology is a philosophy that has been around for thousands of years, and it allows for design flexibility by reusing existing ontologies [45]. It follows the open world assumption knowledge representation style using OWL, RDF, and RDF schema (RDFS) syntaxes. It can be optimized with ontology patterns, and its logical and structural consistency is verified with ontology reasoners.

Overview

The proposed eHealth ontology encompasses the following steps: (1) ontology design approaches and used vocabularies; (2) ontology modeling in Protégé; (3) defining the scope; (4) integrating existing IoT and medical ontologies in the proposed ontology to annotate sensor and clinical observations; (5) ontology implementation (mapping the concepts to the proposed ontology classes and their properties in Protégé); and (6) rule expression (rule base) and basic SPARQL queries as a part of ontology verification. We further discuss how rule-based lifestyle recommendation messages (regarding activity and nutrition) could be delivered to the participants following an asserted hierarchy in the proposed eHealth ontology model, as depicted in Figure C.1.

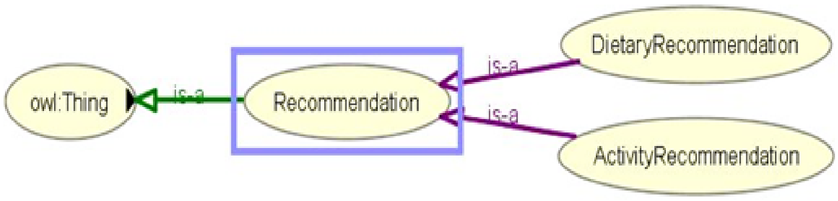


Figure C.1: Asserted hierarchy for lifestyle recommendation for obesity management.

Ontology Design Approaches and Used Terminologies

Ontology design approaches can be classified into the following 5 categories: inspirational, inductive, deductive, synthetic, and collaborative [46]. We adopted a combination of inspirational and deductive approaches in our ontology design and development. The inspirational approach helped us identify the need for the ontology (what to design?) and obtain expert views to create the ontology (how to design?). The deductive approach helped us to adopt and adapt general principles to create the intended ontology tailored toward obesity as a study case. It includes the general notions being filtered and refined to be personalized to a specific domain subset (obesity). The overall approaches are divided into 5 phases as follows: in phase 1, we performed a systematic literature review to understand the need for an ontology to support the logical representation of observable and measurable data for healthy lifestyle management targeting obesity as a case study. In phase 2, we consulted experts with a research background in ICT, eHealth, nursing, and nutrition for designing the ontology. In phase 3, we developed the ontology to model and annotate health and wellness data observations with semantic metadata to create a lightweight, intelligible abstraction for health risk predictions for the personalized generation of recommendations based on rule-based decision-making. In phase 4, we created rules for SPARQL queries and personalized recommendation generation (rule-based deduction). In phase 5, we verified the ontology with simulated data based on rule-based decision support.

The semantic web is W3C recommended, and it allows the specification of metadata that permit automatic reasoning [47][48]. The W3C-maintained specifications related to this study are XML, URI, RDF, turtle, RDFS, ontology web language (OWL), SPARQL Protocol and RDF Query Language (SPARQL), and SWRL. The following terminologies are relevant for our eHealth ontology representation and processing: propositional variable (an atomic name of a truth value that may change from one model to another), constant (the unique propositional variables TRUE and FALSE such that their truth value cannot be changed), and operators (the set of logical connectors in each logic). Besides, in this case, we use the operators (NOT, AND, OR, IMPLIES, and EQUIV); quantifiers (the set of logical quantifiers in a given logic; FORALL for the universal quantifier and EXISTS for the existential quantifier); quantified clause (a set of propositional variables linked together by operators and quantifiers); clause (a quantified clause without any quantifiers); formula (a collection of clauses and quantified clauses related together by logical operators); and model of the procedure (a group of assignments for each propositional variable, such that when simplified, it leads the procedure to the constant TRUE).

Protégé, TopBraid Composer ($), NeOn Toolkit, FOAF editor, WebOnto, OntoEdit, Ontolingua Server, Ontosaurus, and WebODE are some popular ontology editors [49]. These ontology editors are open-source ontology development tools with OWL support. A reasoner is a crucial component for working with OWL ontologies. It derives new truths about the concepts that are being modeled with OWL ontology. Practically, all querying of an OWL ontology (and its import closure) can be done using a reasoner [50][51]. That is why knowledge in an ontology might not be explicit, and a reasoner is required to deduce implicit knowledge so that the correct query results are obtained. The OWL API includes various interfaces for accessing OWL reasoners. For accessing reasoner via the API, a reasoner implementation is necessary. Reasoners can be classified into the following groups: OWL DL (Pellet 2.0*, HermiT, FaCT++, RacerPro), OWL EL [CEL, SHER, snorocket ($), ELLY], OWL RL [OWLIM, Jena, Oracle OWL Reasoner ($)], and OWL QL (Owlgres, QuOnto, Quill) [50][51][52][53][54][55][56][57]. In this study, we utilized Protégé ontology editor and HermiT reasoner to create and validate the structure of the ontology.

Apache Jena is a Java-based framework used for building semantic web applications. It provides an API to extract data from and write to RDF graphs. A Jena framework includes the following: (1) RDF API to parse, create, and search RDF models in XML, N-triple, N3, and Turtle formats. Triples can be stored in memory or database; (2) ARQ Engine/SPARQL API, which is a query engine for querying and updating RDF models using the SPARQL standards; (3) tuple database engine as a high-performance RDF store on a single machine; (4) ontology API for handling OWL and RDFS ontologies; and (5) Apache Jena Fuseki, which is the SPARQL server for supporting query and update. It is tightly integrated with tuple database to deliver a robust, transactional persistent storage layer. The framework has internal reasoners and an OWL API [58][59]. In this study, we used Apache Jena Fuseki for SPARQL processing with triple database.

Knowledge representation in computer-understandable form is well accepted among AI communities. Knowledge representation with symbols facilitates inferencing and the creation of new elements of knowledge. By contrast, the KB is a database for knowledge management. It provides a means for information to be collected, organized, shared, queried, and utilized for inferring new information. Knowledge engineering helps to obtain specific knowledge about some subject and represents it in a quantifiable form. KB consists of terminology models or TBox (atomic and complex) and assertions model instance or ABox (asserted and inferred). Inferred statements come as a logical outcome of the asserted statements and logical rules [35][60][61] A KB is a pair (T, A) where T is a TBox and A is an ABox. The idea behind this paper is that the TBox concepts and relations are coming from the freshly created ontology, and the ABox is a list of clauses assigning truth values to some variables. The TBox is coming from integration with the SSN Ontology and the SNOMED CT ontology, plus additional concepts specific to the recommendation test case considered. The ABox is the semantic data, coming from the different data inputs (IoT sensors, interviews, and questionnaires). The satisfiability of the KB, and thus the model output, is obtained by using the hyper-tableau-based [62] reasoning solver HermiT [55]. The whole approach has been tested with 4 generated test cases to ensure that the whole mechanism can indeed set the propositional variables to true and thus send the corresponding recommendation message when needed.

Ontology Modeling

An ontology can be modeled with the following 2 ways in Protégé: frame based and OWL based. The Protégé frame editor ensures ontology development following the Open Knowledge Base Connectivity Protocol with the help of classes, properties, relationships, and instances of classes (objects). By contrast, the Protégé OWL editor (applied in this study) enables ontology development for the Semantic Web with the help of classes, properties, instances, and reasoning. We have used the following steps to model our proposed OWL-based eHealth ontology using the Protégé OWL editor.

Step 1
Create a new empty OWL project in Protégé and save it as a local file with "owl" or "ttl" extension ("ttl" signifies the turtle resource description framework [RDF] format).
Step 2
Create named classes under the "owl:Thing" super class following consistency

- Create a group of meaningful and required classes
- Define disjoint classes
- Define subclasses and disjoint subclasses

Step 3
Create OWL properties

- Object properties (associates object to object)
- Data properties (relates object to XML schema datatype or rdf:literal)
- Annotation properties (to add annotation information to classes, individuals, and properties)

Step 4
Define object properties if they are subproperties, inverse properties, functional properties, inverse functional properties, transitive properties, symmetric properties, and reflexive properties.
Step 5
Define property domain and ranges for both object and data properties (it is used as axioms in reasoning).
Step 6
Define property restrictions as follows:

- Quantifier restrictions (existential and universal)
- Cardinality restrictions (one or many)
- hasValue restrictions (eg, string/integer/double)

Step 7
Ontology processing with a reasoner to check consistency in OWL DL, and to compute the inferred ontology class hierarchy.

- Blue color class in the inferred hierarchy signifies that the class has been reclassified.
- Red color class in the inferred hierarchy signifies an inconsistent class.

Step 8
Remove inconsistencies before importing the ontology file in Apache Jena for further processing, querying (Simple Protocol and RDF Query Language [SPARQL]), and storing it into tuple database for persistence. Tuple database supports the full range of Jena application programming interfaces. It can be used as a high-performance RDF store on a single machine.

Scope of the Proposed Ontology

We have planned to integrate the proposed eHealth ontology into a simulated eCoach system used for automatic rule-based recommendation generation to inspire individuals to manage healthy lifestyles with early health risk predictions. The planned system will have 2 main modules, as depicted in Figure C.2: a data collection module and a data annotation module. The data collection module will collect an identified fabricated set of habit, baseline, nutrition, personal, contextual, activity, and physiological data over time via a simulator, as depicted in Figure C.3.

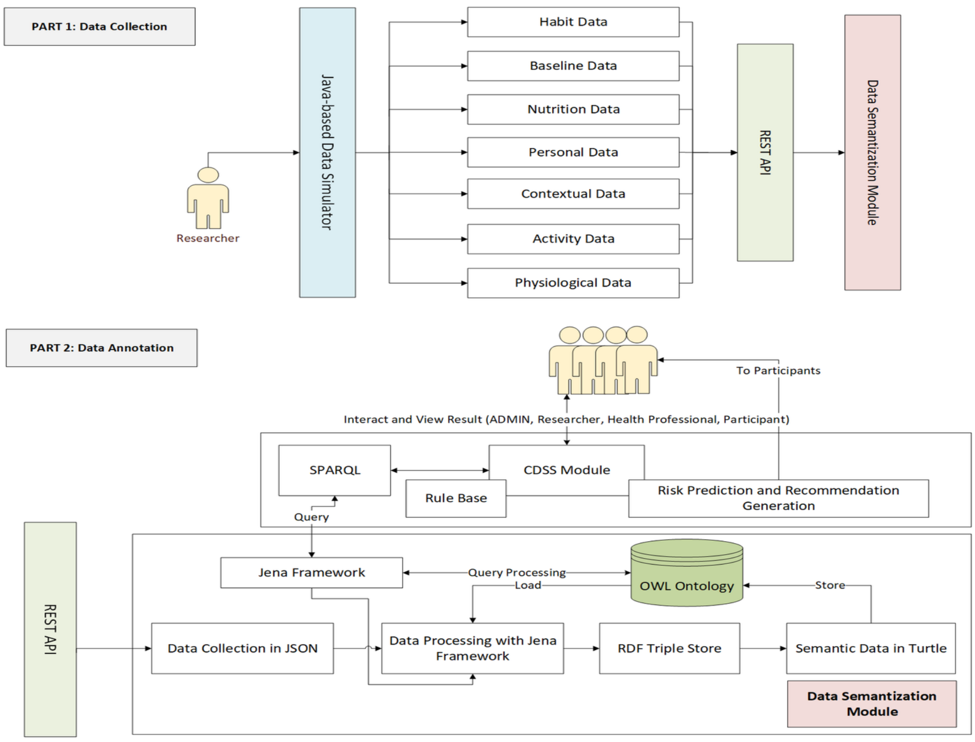


Figure C.2: Proposed eCoach system architecture for data semantization.

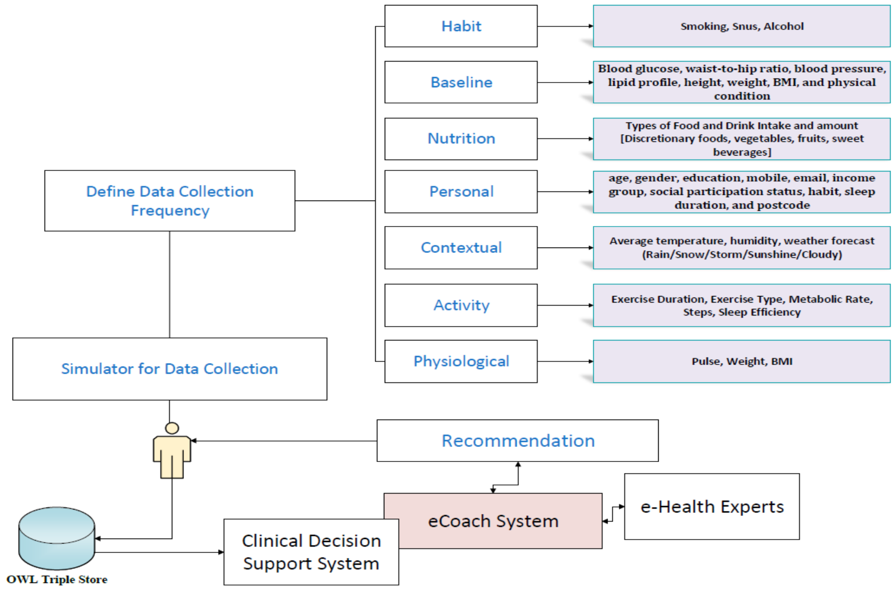


Figure C.3: Types of data to be collected from participants.

The accumulated data were annotated with semantic metadata (RDF triple store graph) and stored in tuple database in turtle format. The DSS, rule base, SPARQL, risk prediction, and recommendation generation modules are not the core, and they are used for ontology verification as a test engine. The scopes of DSS are as follows: (1) periodic querying of the ontology with Jena framework using preset SPARQL queries [63][64][65] to assess the health condition; and (2) mapping the query result to preset clinical rules in "rule base" to generate lifestyle recommendations. This study involves 4 different user types: administrator, researcher, participants, and health professionals (eg, nurses; Figure C.4). The ontology is protected from personal identity disclosure, as no unique identifiers (eg, national identifiers) of participants were collected and stored in the simulated environment in accordance with the Norwegian Centre for Research Data guidelines [66]. Core eCoach and DSS concepts, AI integration for health and wellness data (activity and nutrition) analysis, real-world data collection from actual participants through web applications/mobile apps, real-life personalized recommendation generation, goal evaluation, pregnancy, genetics, child obesity, and obesity in older adults are beyond the scope of this study. This study's primary focus is to design and develop an eHealth ontology for the obesity case and to verify it with artificial data and behavioral recommendation generation with a rule-based DSS. Defined rules for test setup may vary with change in the context and is not the key focus of this paper.

We simulated habit, nutrition, contextual, activity, and physiological data for 4 dummy participants (2 healthy weight [N] and 2 overweight [O] participants aged between 18 and 40) for the very first day (day-n; n>0); see Multimedia Appendix 2. We assumed all the dummy participants are from the same region, so the contextual information is the same. Rule-based recommendations based on data analysis on "day-n" will be carried out by targeted participants on "day-(n+1)." Recommendations inform individual participants about their daily activity (sedentary or not), dietary intake, and activity/dietary plans. For dietary assessment, we have relied on the daily self-reported questionnaire, rather than

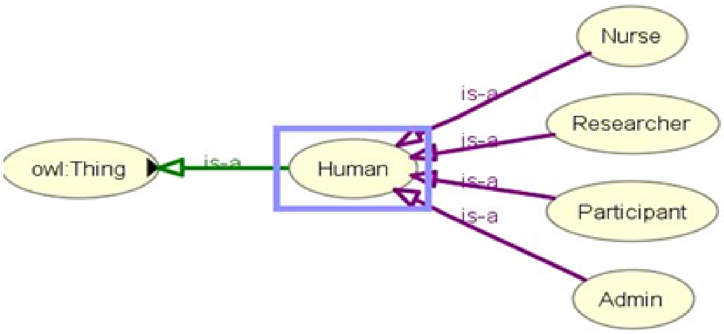


Figure C.4: Different types of users involved in the eCoach System.

on direct calorie calculation for basal metabolic rate. Baseline data help to compare (at the end of each month until the process ends) whether any improvement or deterioration occurred as a result of behavior change based on lifestyle recommendations. For example, reduction in BMI and BP for an obese person/overweight, and maintaining safe BMI and BP for a person with healthy weight upon following the behavioral recommendations is a good indication of maintaining a healthy lifestyle. We consulted 5 experts with a research background in ICT, eHealth, nursing, and nutrition for simulating activity and nutrition data. Obesity-related information and guidelines were obtained from the World Health Organization (WHO) [67], the National Institute for Health and Care Excellence (NICE) [68], and the Norwegian Dietary Guidelines [69].

Integration With SSN Ontology and SNOMED CT

We integrated the SSN ontology [30][36][70][71][72] into our proposed eHealth ontology to describe sensors (activity sensors and external weather sensors), their observations, and methods adopted for sensing individual activities and context (Figure C.5). Observation data related to activity and external weather are annotated with SSN ontology concepts and object properties.

Concepts and object properties in the ontology are commented and connected with "rdfs:label," "rdfs:isDefinedBy," "rdfs:seeAlso," "rdfs:comment," "dc:source," "isProxyFor," "has value," "is produced by," "has property," "hasTimeStamp," "isRegionFor," "attached system," "in deployment," "has measurement capability," "detects," "hasOutput," "observes," "implements," "has deployment," "has operating range," "has subsytem," "has survival range," "on platform," "deployment process part," "deployed on platform," "deployed system," "is property of," "feature of interest," "observation result time," "observation sampling time," "observed property," "quality of observation," "sensing method used," "includesEvent," and "observedBy." The SSN ontology is constructed on the foundation of a central ontology design pattern, so-called the stimulus–sensor–observation pattern to describe relationships between sensors, stimulus, and observations [30], and the same concept is reused in our proposed eHealth ontology model. The perspectives of SSN ontology can be classified as follows [30]: a sensor perspective, an observation perspective, a system perspective, and a feature and property perspective. Namespaces for the SSN and DUL ontologies are reused in our ontology, prefixing

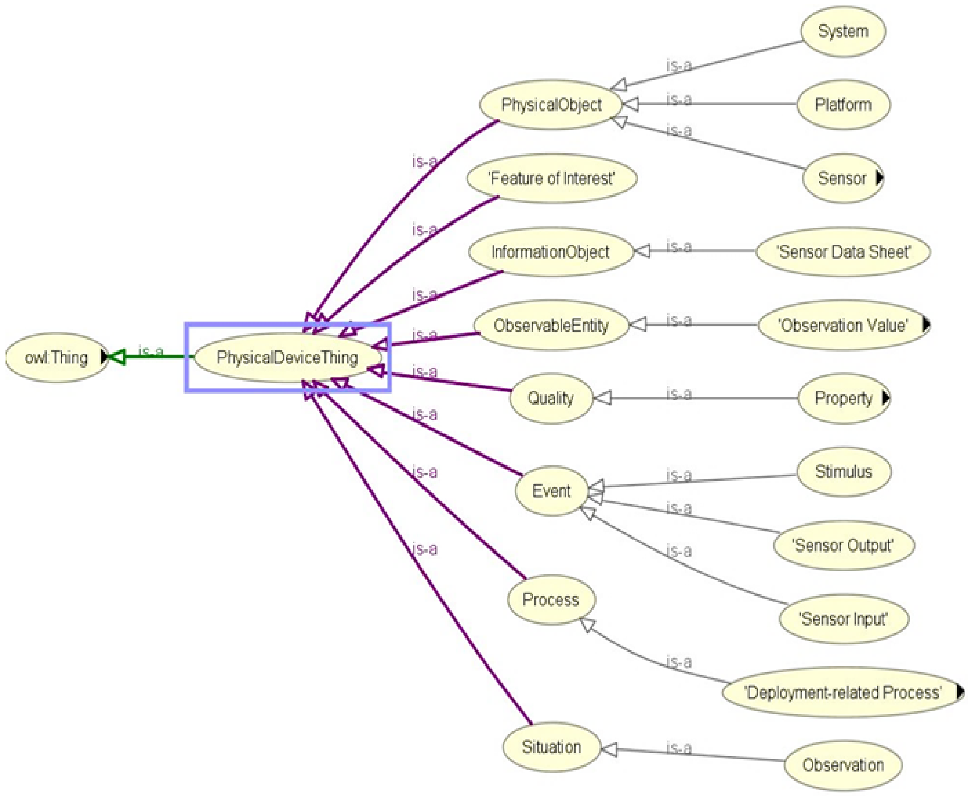


Figure C.5: Asserted hierarchy for sensor-based data collection with OWLViz.

concepts and properties as ssn: and dul:, respectively. “PhysicalDeviceThing” (a class), which behaves as a superclass of classes related to sensor-based observations, is a subclass of “owl:Thing,” the universal ontology superclass.

We incorporated selected concepts from SNOMED CT [73] into our proposed ontology model to define how information about the participant’s state is to be structured and processed. The SNOMED CT ontology combines hierarchical “is-a” relationships and other related relationships for vital signs, process, body measurements, and observations to describe clinical attributes as depicted in Figure C.6. SNOMED CT simplifies the search for respective diseases, process, function, clinical state, measurements, and vital signs, and every concept is identified with an SCTID or SNOMED CT identifier with an object property “hasSCTID” (eg, Obese_finding hasSCTID value “414915002”^^xsd:long) [74].

Figures C.7-C.9 describe the class hierarchy to process participant’s clinical information using the SNOMED CT hierarchy for the vital signs (eg, BP, pulse) and body measurement (eg, obese or overweight) based on the observable entities [75][76][77][78][79]. Observable entities and clinical findings are linked with the objectProperty: isFoundBy. The proposed ontology model can be extended for additional clinical findings [73][74].

Ontology Implementation

In Figure C.10 we describe how we implemented the proposed eHealth ontology for our future eCoach system with required classes, object properties, and data properties to

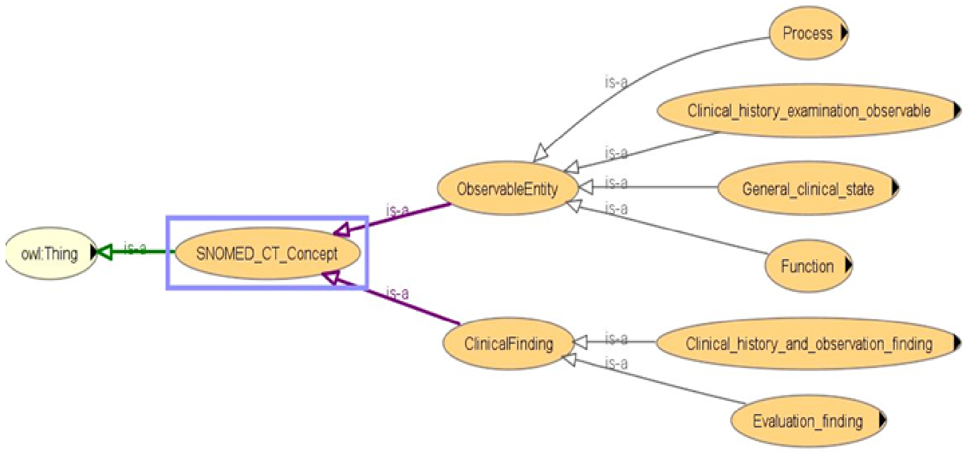


Figure C.6: Asserted hierarchy of SNOMED_CT concept with OWLViz.

annotate collected data. The administrator, health professionals, researchers, and participants are subclasses of the "Human" class. They have their designated role, password, and userId to authorize themselves in the system with the following associated objectProperties: hasRole, hasPassword, and hasUserId, respectively. Administrator, health professionals, and researchers have their office address (hasOfficeAddress), and personal data (hasPersonalData) to describe themselves. Their office address consists of a phone number, a postcode, and a room number with the following associated dataProperties: hasOfficePhone, hasOfficePostCode, and hasRoomNo, respectively. Their personal data include age, designation, email, first name, last name, gender, and mobile number with the corresponding dataProperties hasAge, hasDesignation, hasEmail, hasFirstName, hasLastName, hasGender, and hasMobile. The "Participant" is an important class, and participants are at the core of the system. Participants have their health record, personal data obtained through interview process by trained health professionals, status (active/inactive), and recommendation with the associated objectProperties hasHealthRecord, hasInterviewPersonalData, hasStatus, and hasReceivedRecommendation as depicted in Figure C.11. "ActivityData," "BaselineData," "HabitData," "NutritionData," "PhysiologicalData" are subclasses of the "ParticipantHealthRecord" class as depicted in Figure C.11. Activity data are an observable entity and are planned to be collected via activity sensors (activity bouts, steps, sleep time, activity duration, sedentary bouts, metabolic rate, nonwear time) and questionnaire (duration of intensive activity and nonwear sensor time) daily. Intensive activities are running, weightlifting, cycling, swimming, and skiing. Based on the activity type, participants can be classified into the following 4 groups: sedentary, light active, moderate active, and active. Baseline data (blood glucose, waist-to-hip ratio, BP, lipid profile, height, weight, BMI, and physical condition) are planned to be collected by trained health professionals at the time of recruitment of participants and on a monthly basis following an interview process. Habit data (smoking, snus, and alcohol consumption) and nutrition data (types of foods and drinks with amount) are planned to be collected daily with a pre-set questionnaire. Physiological data (pulse, weight, and BMI) are planned to be collected daily via activity sensors and pre-set questionnaire, as depicted in Figure C.12. Personal data (age, gender, education, mobile, email, income

Figure C.7: SNOMED CT class hierarchy based on selected concepts.

group, social participation status, habit, sleep duration, and postcode) of healthy participants are planned to be collected following an interview process by trained health professionals during recruitment. Gender, education, income range, and social participation are essential for demographic classifications. The data properties related to data collection are depicted in Figure C.13.

The asserted class hierarchy of the methods used for participant's data collection is depicted in Figure C.14. Each method ensures a collection of simulated data sequences, maintaining a timestamp, as depicted in Figure C.15. Contextual data are observable weather-related data (weather status, current temperature, rain forecast, snow forecast, storm forecast, sunny forecast, high and low-temperature forecast, fog forecast), which are planned to be collected daily via sensing devices. The relationship between data and data collection methods are linked with the objectProperty: hasBeenCollectedBy and hasConductedBy (for interview).

Behavioral recommendations for a healthy lifestyle can be classified in the following 2 categories: activity (A) and dietary (D). Each recommendation is personalized and contextual. Therefore, the recommendation generation depends on evaluating participants' health status (health risk, vital signs, body measurement data) and contextual information. Each generated recommendation consists of a message and the corresponding timestamp (Figure C.16). A bad habit (H) has a significant impact on healthy dietary practice. Activities are related to the context (C). Contextual data help recommend

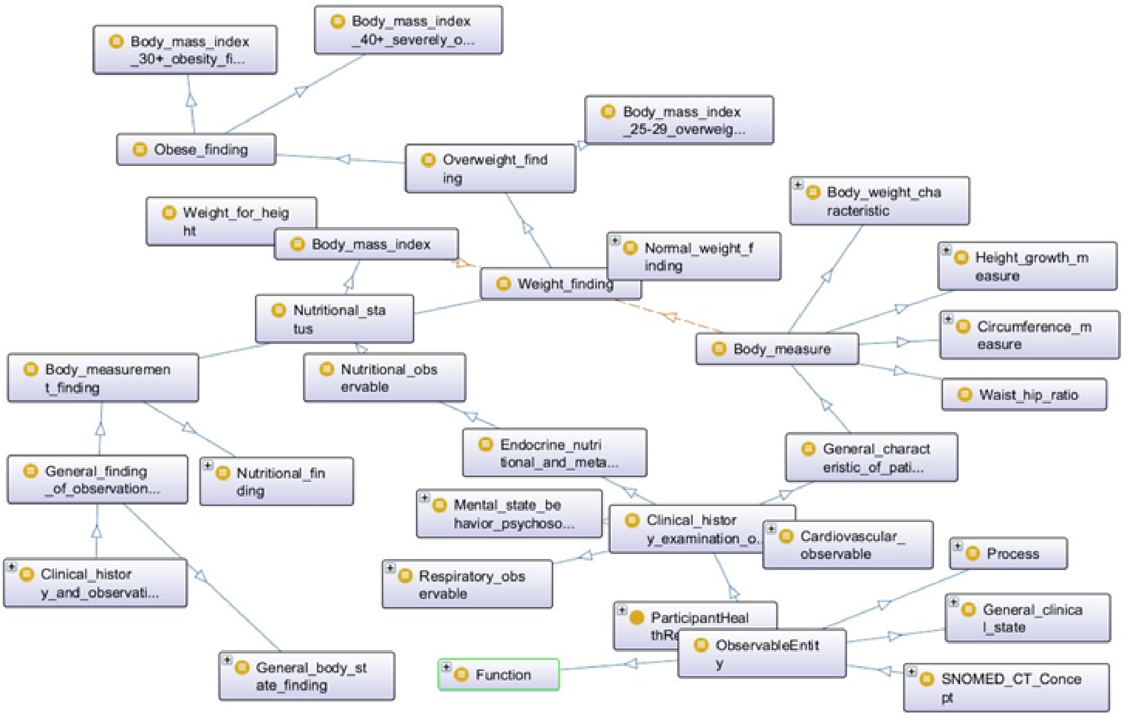


Figure C.8: SNOMED CT ontology visualization with OntoGraf based on selected concepts.

participants to plan for indoor/outdoor activities based on the following day's external weather conditions. The data properties of "RecommendationMessages" for activities are "hasActivityMessages" and "hasContextualMessages," whereas those for the diet are "hasDietaryMessages" and "hasHabitRelatedMessages." The identified set of recommendation messages for test setup (ontology verification) is presented in Multimedia Appendix 3, and is prepared based on the positive psychology [79] and the persuasion [80] concept.

Description logic [35][81] is a formal knowledge representation of the ontology language that offers a good trade-off between expressivity, complexity, and efficiency in knowledge representation and reasoning about structured knowledge. To ensure that the paper is perfectly understood, we have the propositional variables with their linked recommendation messages. Now, we need a set of clauses such that some models will assign these variables to true and thus trigger the sending of a recommendation. The description logic SROIQ [82][83], which is logic providing a formal underpinning of OWL2, has been used as the formal logic to reason in this paper (Multimedia Appendix 4).

Rule Creation for Querying, Recommendation Generation, and Ensuring Satisfiability

A rule consists of a premise (antecedent) and a conclusion (premise). For every condition mentioned in Multimedia Appendix 3, DSS executes SPARQL queries daily to determine what type of recommendation message is to be delivered to each participant as depicted in the unified modeling language sequence diagram (Figure C.17). The execution of every predefined semantic rule as specified in Multimedia Appendix 4 relies on the

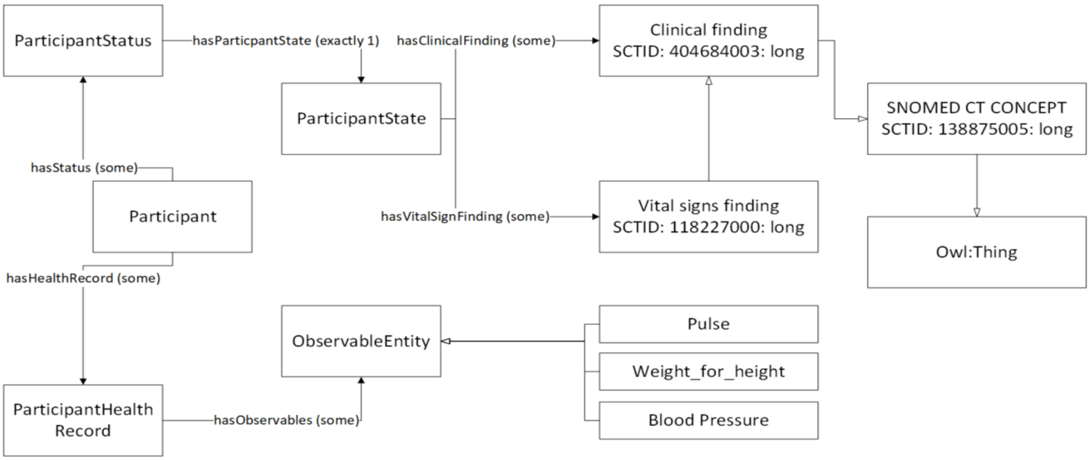


Figure C.9: Selected concepts from SNOMED CT Ontology for vital signs, body measurement, and observations.

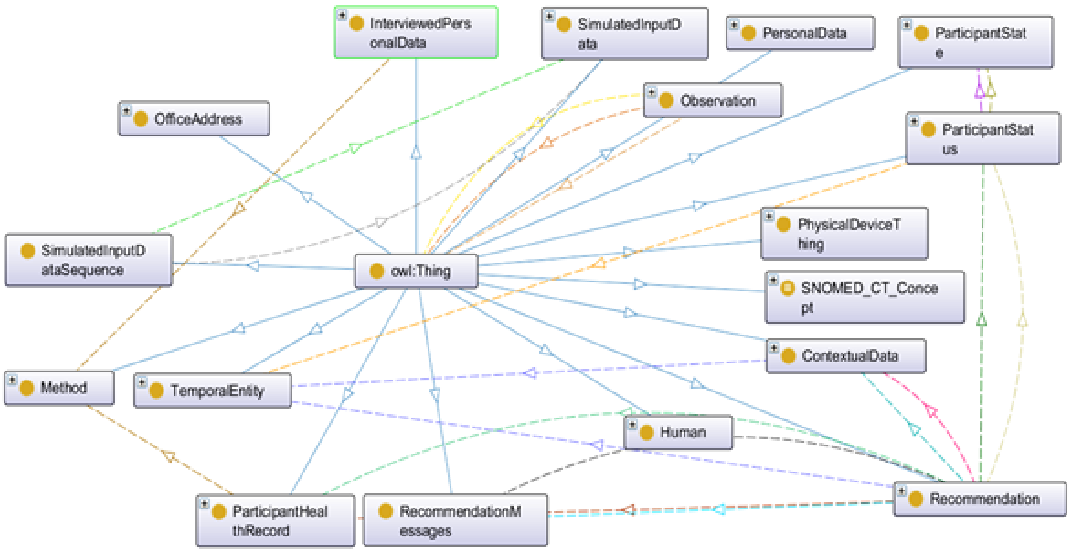


Figure C.10: Proposed eHealth Ontology implementation in Protégé 5.x.

SPARQL query execution, and the rules are created following clinical guidelines, as stated in Multimedia Appendix 5 [62][84][85][86][87][88][89][90][91][92]. In this study, 20 semantic rules are subdivided into activity-level classification (8), habit-related classification (3), dietary classification (4), weather-level classification (1), obesity-level classification (3), and satisfiability (1) (please also see Multimedia Appendix 4). Moreover, except for the already-existing ontologies used, to ensure some consistency regarding what a participant is, what are the participant health records, etc., the concepts and the rules added are relatively easy to follow, and therefore they will be relatively easy to use.

The observable and measurable parameters associated with activities, habit, nutrition, and context (as described in Multimedia Appendix 4) for individual participants on a timestamp are obtained based on the execution of SPARQL queries by DSS on a daily scheduled interval as specified in Multimedia Appendix 6. The rules 17-19 in Multimedia Appendix 4 assign truth values to variables that ensure consistency with concepts already existing in the SNOMED CT ontology, where the body measurement is defined. We have

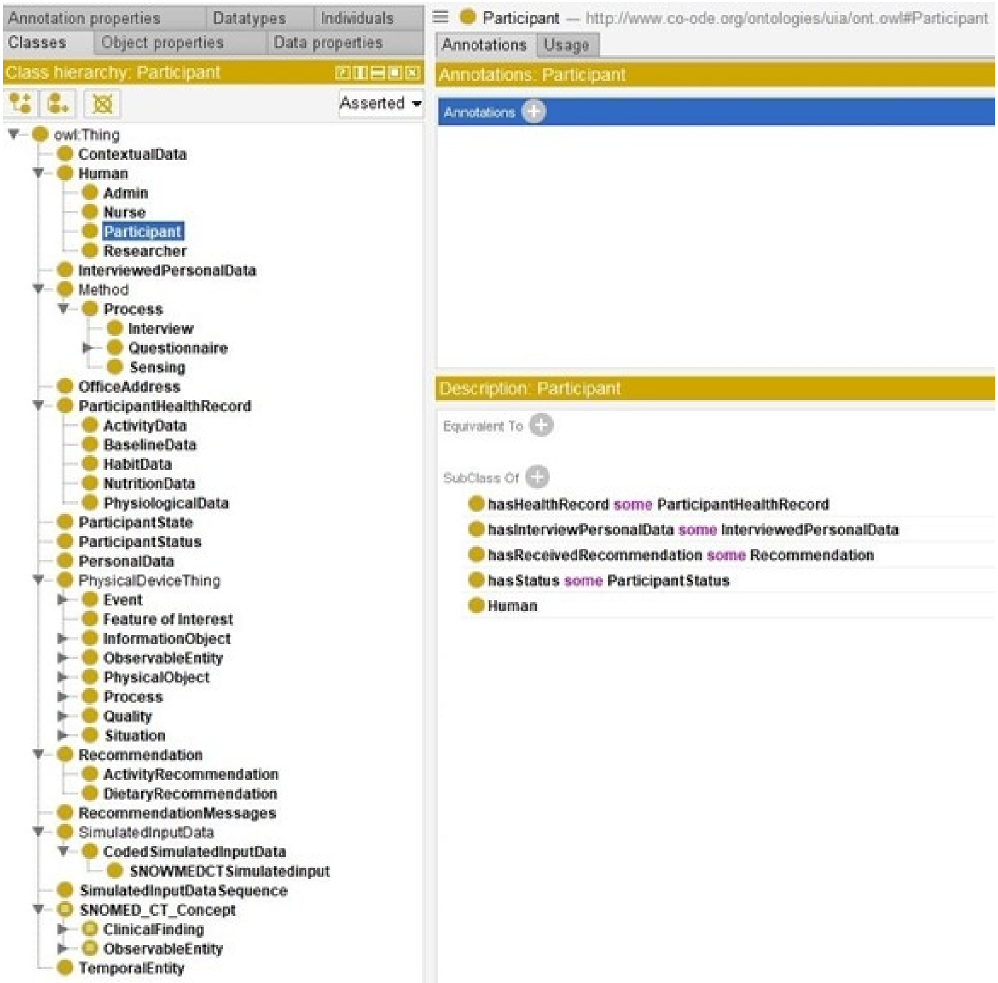


Figure C.11: The class hierarchy of the proposed eHealth ontology and the description of participant class.

confirmed with HermiT that for 4 specific cases the correct recommendation messages are triggered. However, one would need to ensure that there is not a combination of variables such that the whole formula is unsatisfiable (ie, no model can satisfy the procedure). One would also need to ensure that only 1 message can be triggered at a time. In this study, we have a formal guarantee that 2 “once-a-day” messages can neither be triggered simultaneously nor for every possible combination of variables, there is, every time, a model output by HermiT. If we put the different variables used in the first 19 rules (Multimedia Appendix 4) into propositional variables, we would have an exponential number of “possible participants.” One formal way to ensure a model’s existence is to negate all our rules and ensure the same. Then, the formula is indeed unsatisfiable. As 2 messages cannot be triggered at the same time, and to satisfy the same, we added a rule (rule 20) on the variables used in the recommendations started “once-a-day.” If rule 20 is false, then the whole set of rules (considered as a large conjunction) will be set to false. It will result in “no execution” of the proposition (see Multimedia Appendix 3) and will help us to debug our defined semantic rules (rules 1-19) as defined in Multimedia Appendix 4. If it is set to true, we have a formal guarantee that no 2 “once-a-day” messages can be triggered at the same time, no matter the truth values we put into our ABox.

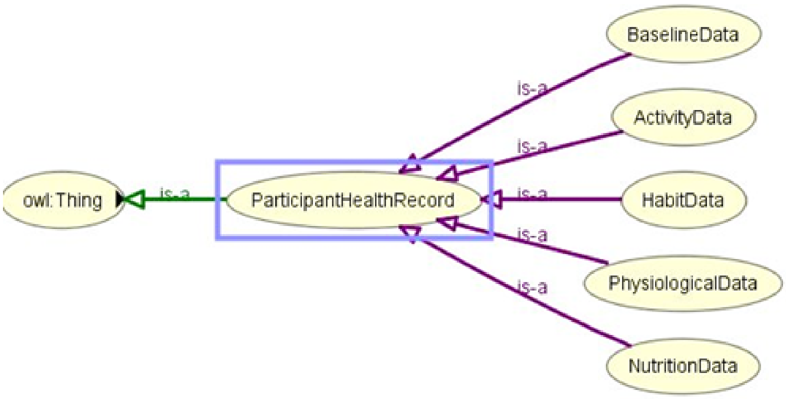


Figure C.12: The asserted class hierarchy of participant's health record with OWLViz.

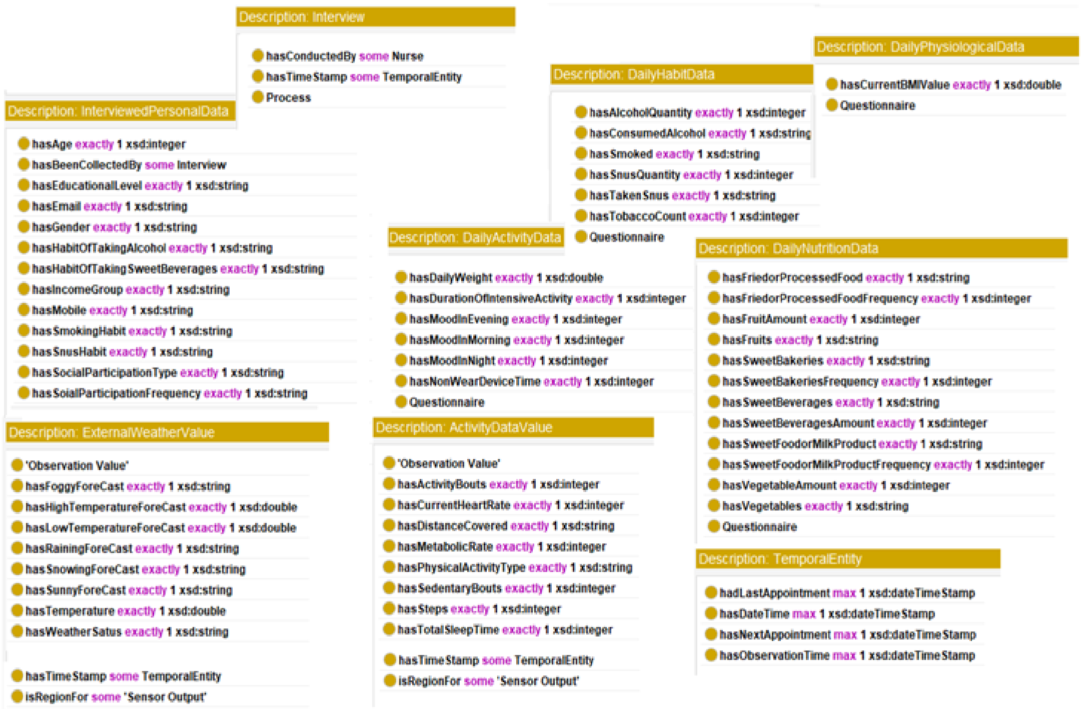


Figure C.13: Data properties related to data collection.

Results

The test setup to verify the proposed eHealth ontology's performance and reliability consisted of a DSS module (health risk prediction and recommendation generation for a healthy lifestyle), SPARQL, and rule base. As an outcome of ontology verification, we generated personalized and contextual recommendations (behavioral) following semantic rules to balance individual weight change with adopting healthy behavior to balance a trade-off between physical activity, healthy habit, and a healthy diet as depicted in Figure C.18. We executed all the semantic rules as stated in Multimedia Appendix 4 in the form of SPARQL queries using the Jena ARQ engine on each participant's simulated data as mentioned in Multimedia Appendix 2. We then determined what type of recommendation messages would be required to be delivered for each participant to manage his/her healthy

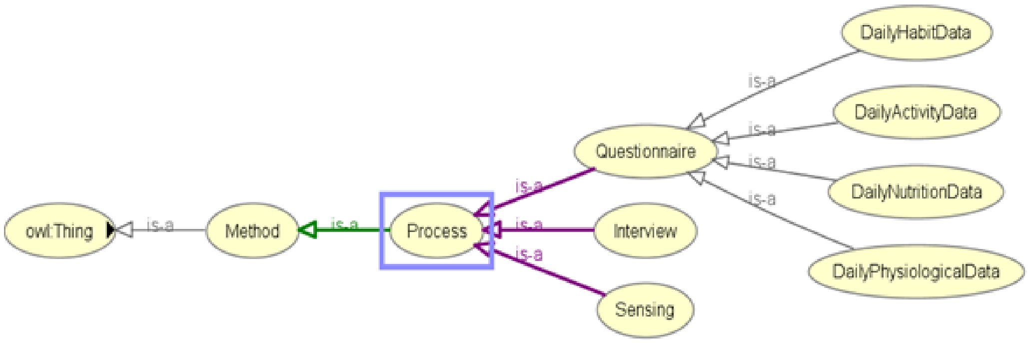


Figure C.14: The asserted class hierarchy of participant's data collection methods with OWLViz.

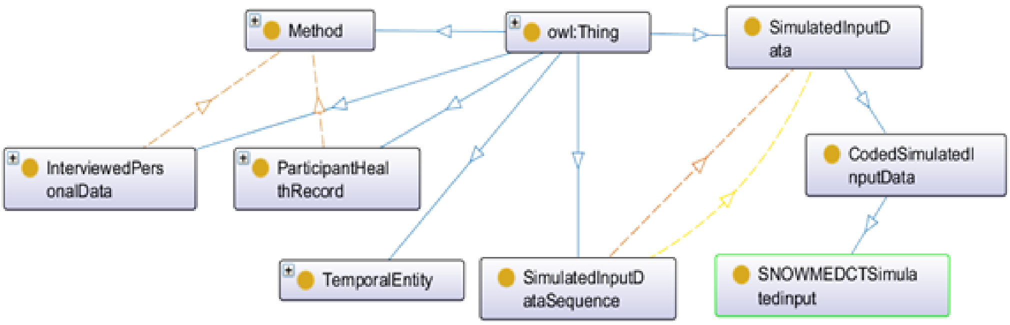


Figure C.15: Ontology for data collection from simulated input.

lifestyle. These findings are detailed in Table C.1.

Table C.1: Recommendation generation for participants for Day-(n+1) [n>0].

Participant	Profile	SCTID	Healthy habit on Day-n	Healthy diet on Day-n	Physically active on Day-n
Individual_1	Normal weight	43664005	No	No	Yes
Individual_2	Normal weight	43664005	No	Yes	No
Individual_3	Overweight	162863004	No	No	No
Individual_4	Overweight	162863004	Yes	No	No

Discussion

Principal Findings

According to Table C.1, "Individual_1" and" Individual_2" are healthy weight participants, and "Individual_3" and "Individual_4" are overweight participants as assessed based on their daily ("Day-n") BMI (weight/height2) value. According to Figure C.1, a healthy weight is a trade-off between healthy habits, healthy diet, and physical activity. On "Day-n" (n¿0), "Individual_1" has been physically active, and this is the reason he

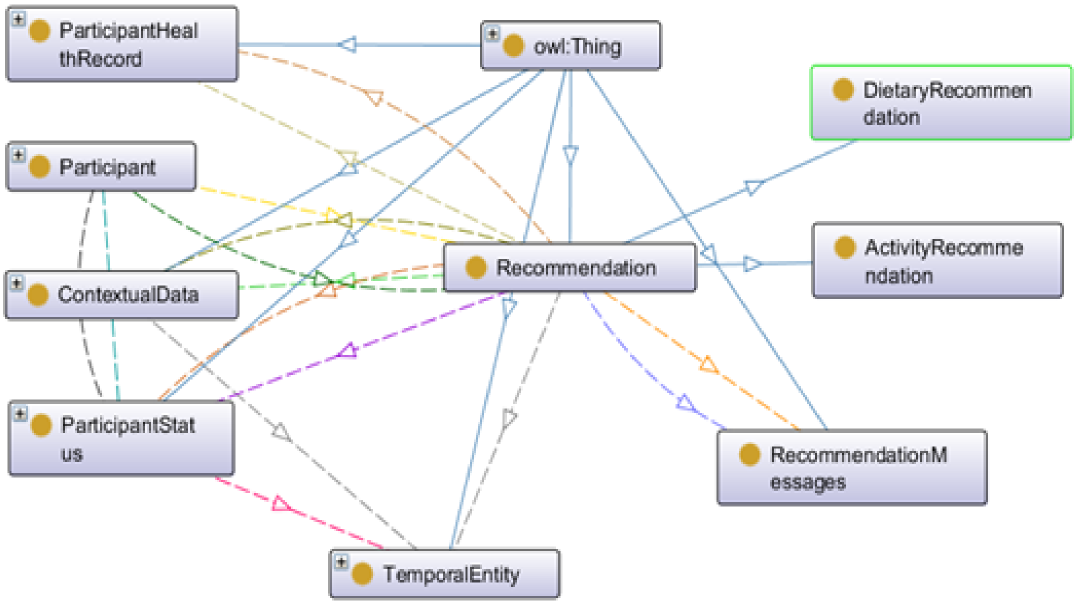


Figure C.16: Ontology for recommendation generation.

has been encouraged to keep up the same activity level (A-4). By contrast, he has shown some addiction toward "snus," sweet beverages, and fried/processed foods, which might grow negative behavior in the participant and increase his weight. Therefore, he has been recommended to reduce tobacco consumptions (H-1) and to refrain from discretionary food items (D-2 and D-3). The simulated data for "Individual_2" has demonstrated that she is inclined to a healthy diet (D-4), but growing some negative behavior with consumption of alcohol and tobacco (H-1, H-2). She is just one step behind to become physically active (A-3). Hence, she has been recommended to take a healthy dietary plan, refrain from tobacco and alcohol, and increase activity level to become active. "Individual_3" is neither physically active nor adhered to healthy habits or healthy dietary plans. He is addicted to alcohol, fried/processed foods, sweet beverages, sweet food/milk products. His consumed number of vegetables and fruits is not adequate for a healthy diet (¡400 g). Therefore, he has been recommended to reduce alcohol consumption (H-1), to follow a healthy dietary habit (D-1, D-2, D-3), and to become more physically active (A-2) with adequate sleeping (A-5). The fabricated data for "Individual_4" has shown that she has an unhealthy diet plan, and she is mostly leading a sedentary lifestyle. Therefore, she has been recommended to stay away from discretionary food items (D-2), to incline on "core-foods" (D-1), and to increase activity level by one step (A-1). The analysis of contextual data reveals that the weather on "Day-(n+1)" is suitable for outdoor activities. The purpose of the individualized recommendation generation is to guide and encourage individual participants to keep up a healthy lifestyle by maintaining a balance between healthy habit, healthy diet, and physical activity. It encourages people with a normal weight to maintain their healthy weight, and those with obesity/overweight to reduce their weight.

The rule-based decision support has generated personalized and contextual recommendations (Table C.1) using SPARQL queries, as depicted in Figure C.19, based on the proposed ontology without any "false-positive" case. The proposed ontology's reason-

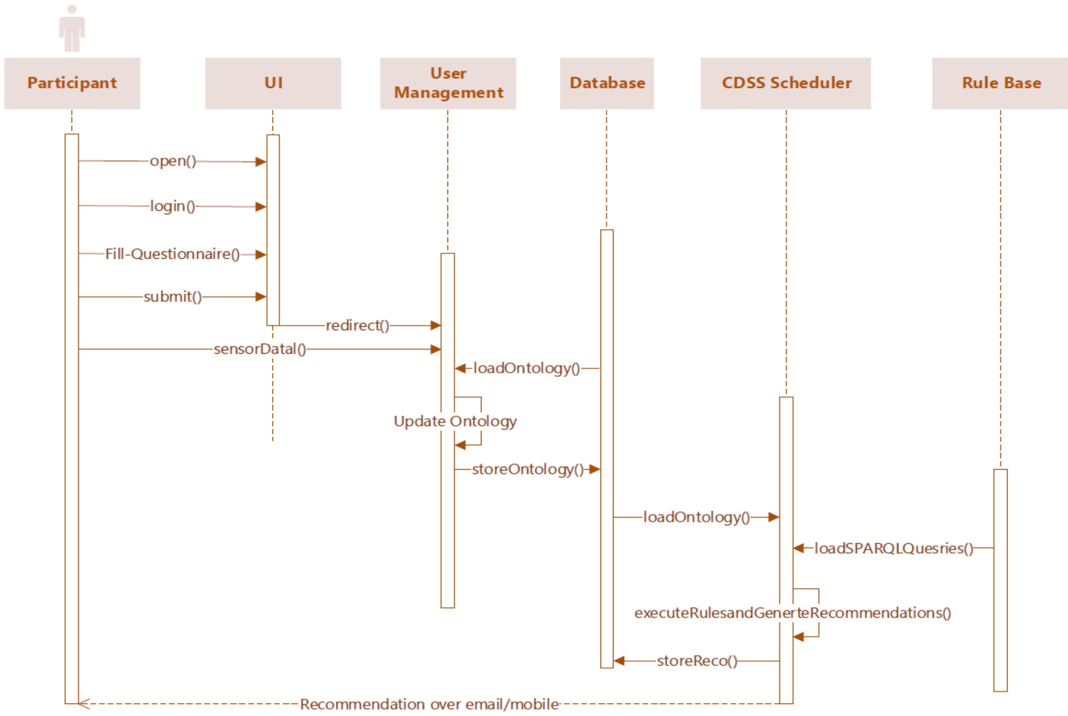


Figure C.17: UML sequence diagram for recommendation generation and delivery.

ing time has been measured as ¡30.0 seconds in Protégé with HermiT reasoner without reporting any inconsistencies. The reading time of the ontology after loading it in the Jena workspace was about 2.0-3.5 seconds with the "OWL_MEM_MICRO_RULE_INF" ontology specification in the "TTL" format (OWL full), "in-memory" storage, and "optimized rule-based reasoner with OWL rules." Then, we queried ontology classes, ontologies, "predicate, subject, and object" of every statement using Jena in ¡1.5 seconds, ¡0.5 seconds, and ¡3.5 seconds, respectively. Each ontology model (complete RDF graph) is related to a document manager (default global document manager: "OntDocumentManager") to assist with the processing and handling of ontology documents. All the classes in the ontology API that represent ontology values have "OntResource" as a common super-class with attributes (versionInfo, comment, label, seeAlso, isDefinedBy, sameAs,

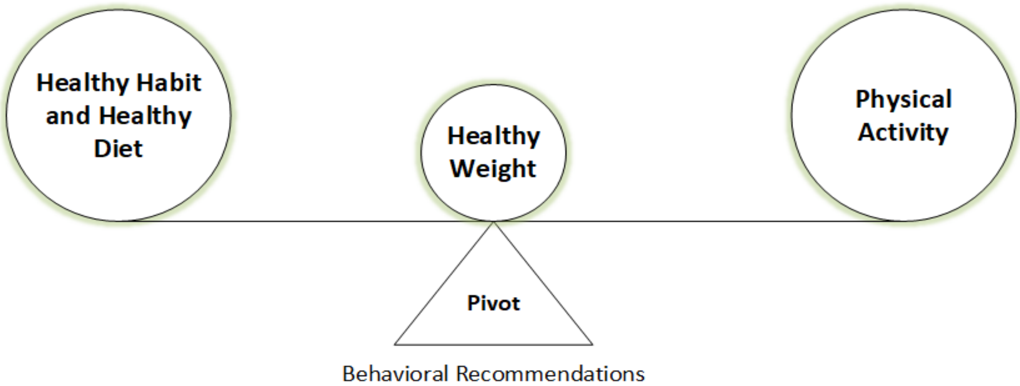
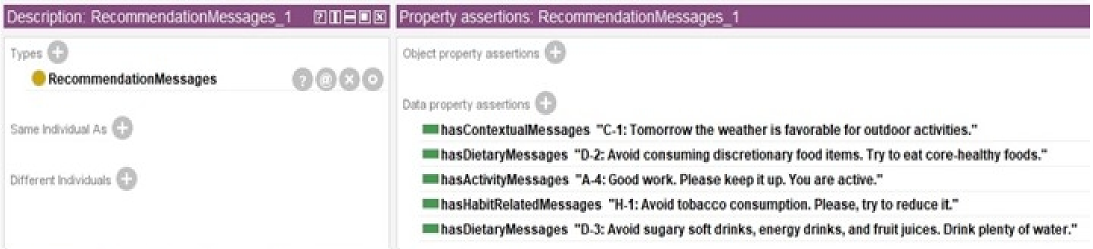


Figure C.18: Behavioral recommendation generation (pivot) for the management of healthy lifestyle (a trade-off between physical activity, healthy habit, and healthy diet).

and differentFrom) and methods (add, set, list, get, has, and remove). We used the implementation of the RDF interface, provided by Jena, to store the modeled ontology and its instances persistently in the tuple database and load it back to process further. Jena Fuseki is tightly integrated with tuple database to provide a robust, transactional persistent storage layer (Figure C.20).

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PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX ssn: <http://purl.oclc.org/NET/ssnx/ssn#>
PREFIX : <http://www.co-ode.org/ontologies/uia/ont.owl#>

SELECT  ?participant ?activitymessages ?habitmessages ?dietarymessages ?contextualmessages ?timedateinfo
WHERE {
  ?participant :hasReceivedRecommendation ?recommendation .
  ?recommendation :hasMessages ?recommendationmessages .
  ?timestamp :hasDateTime ?timedateinfo .
  ?recommendationmessages ssn:hasActivityMessages ?activitymessages .
  ?recommendationmessages ssn:hasHabitRelatedMessages ?habitmessages .
  ?recommendationmessages ssn:hasDietaryMessages ?dietarymessages .
  ?recommendationmessages ssn:hasContextualMessages ?contextualmessages .
}
LIMIT 25
```

Figure C.19: Sample SPARQL query for recommendation finding (e.g., "Individual_1").

In the future study, the recommendation process can be automated with the amalgamation of a hybrid DSS system (rule based and data driven) and AI algorithms. The scope of the proposed ontology can be enhanced with the integration of (1) real sensor activity devices; (2) mood assessment of participants; (3) collection of nutrition data on a detailed level through multiple questionnaires (daily, on every alternative day, and weekly); (4) semantic annotation of the recommended messages; (5) weekly suggestion generation after evaluating daily generated recommendations, and followed by a ranking of participants based on their weekly performances; (6) help-desk management for technical support; (7) assessment of baseline data; (8) trend analysis of health risks as a function of habit, diet, and activity with machine intelligence; and (9) automated interview management by trained health professionals (nurses).

Conclusions

In health care, with the research advancement on the IoT domain, an increasing number of sensors, actuators, mobile, and web-based health monitoring devices are deployed into

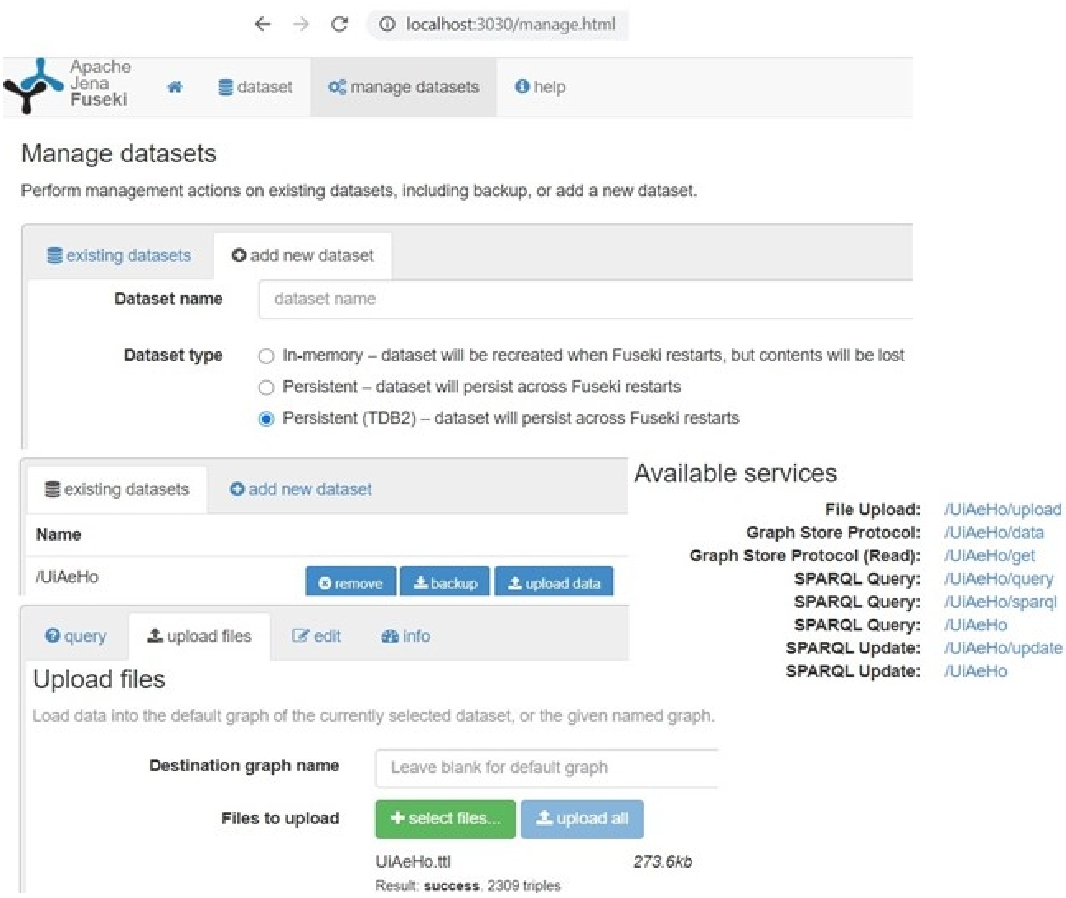

Figure C.20: Integration of TDB with Jena Fuseki for ontology store in the “ttl” format and querying.

our daily life for remote health monitoring. It produces enormous personalized health and wellness observable and measurable data with hidden patterns. Data collected by multichannel sensors or devices demonstrate significant differences in data formats, types, and domains, which might lead to a problem in machine understandability. Therefore, a semantic representation of collected health and wellness data from heterogeneous sources is necessary, and the ontology serves the purpose. In this pilot study, we have proposed an eHealth ontology model in association with SSN and SNOMED CT, to support a semantic representation of collected observable and measurable data to manage a healthy lifestyle focusing on obesity as a case study. The ontology represents collected data with OWL-based web language in RDF triple-store format. The performance of the proposed ontology has been evaluated with the simulated data (eg, sensor, interview, and questionnaire) of 4 dummy participants. The proposed ontology’s structural and logical consistency has been evaluated with a Protégé reasoner (HermiT 1.4.3.x). The proposed ontology model has been used by a rule-based DSS to generate personalized and contextual recommendations with the execution of SPARQL queries against a preset rule base (with the help of Apache Jena library) to promote a healthy lifestyle for obesity management. In the future study, we will recruit real participants following inclusion and exclusion criteria and provide them real activity devices to replicate the whole scenario and evaluate the efficacy of the recommendation generation plan. The proposed ontology can be extended to annotate observable and measurable data for other related lifestyle diseases, such as diabetes type II, chronic obstructive pulmonary diseases, cardiovascular diseases, and mental health.

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Conflicts of Interest

None declared.

Abbreviations

AI: artificial intelligence
API: application programming interface
BLE: Bluetooth low energy
BP: blood pressure
CDSS: clinical decision support system
DSS: decision support system
ICD-11: International Classification of Diseases (11th edition)
ICT: information and communications technology
KB: knowledge base
LOINC: Logical Observation Identifiers Names and Codes
NICE: National Institute for Health and Care Excellence
RDF: resource description framework
RDF: resource description framework
RDFS: RDF schema
SNOMED CT: Systematized Nomenclature of Medicine—Clinical Terms
SPARQL: Simple Protocol and RDF Query Language
SSN: semantic sensor network
SWRL: semantic web rule language
UMLS: Unified Medical Lexicon System
URI: unified resource identifier
WHO: World Health Organization

Multimedia Appendix

Appendices 1–6[1]:

1. Proposed ontology model's OWL file with annotated participant data.

[1]https://www.jmir.org/2021/4/e24656/

2. Simulated data for 4 participants.
3. Propositional variables with their linked recommendation messages.
4. Scoped recommendation conditions, and corresponding rules (rule-base) for test set-up.
5. Health parameters and corresponding clinical rules [70-78].
6. Prefixes and queries.

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Paper D

Personalized Recommendations for Physical Activity e-Coaching (OntoRecoModel): Ontological Modeling

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Personalized Recommendations for Physical Activity e-Coaching (OntoRecoModel): Ontological Modeling

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Abstract – **Background**: Automatic e-coaching may motivate individuals to lead a healthy lifestyle with early health risk prediction, personalized recommendation generation, and goal evaluation. Multiple studies have reported on uninterrupted and automatic monitoring of behavioral aspects (such as sedentary time, amount, and type of physical activity); however, e-coaching and personalized feedback techniques are still in a nascent stage. Current intelligent coaching strategies are mostly based on handcrafted string messages that rarely individualize to each user's needs, context, and preferences. Therefore, more realistic, flexible, practical, sophisticated, and engaging strategies are needed to model personalized recommendations. **Objective**: This study aims to design and develop an ontology to model personalized recommendation message intent, components (such as suggestion, feedback, argument, and follow-ups), and contents (such as spatial and temporal context and objects relevant to perform the recommended activities). A reasoning technique will help to discover implied knowledge from the proposed ontology. Furthermore, recommendation messages can be classified into different categories in the proposed ontology. **Methods**: The ontology was created using Protégé (version 5.5.0) open-source software. We used the Java-based Jena Framework (version 3.16) to build a semantic web application as a proof of concept, which included the Resource Description Framework application programming interface, World Wide Web Consortium Web Ontology Language application programming interface, native tuple database, and SPARQL Protocol and Resource Description Framework Query Language query engine. The HermiT (version 1.4.3.x) ontology reasoner available in Protégé 5.x implemented the logical and structural consistency of the proposed ontology. To verify the proposed ontology model, we simulated data for 8 test cases. The personalized recommendation messages were generated based on the processing of personal activity data with contextual weather data and personal preference data. The developed ontology was processed using a query engine against a rule base to generate personalized recommendations. **Results**: The proposed ontology was implemented in automatic activity coaching to generate and deliver meaningful, personalized lifestyle recommendations. The ontology can be visualized using OWLViz and OntoGraf. In addition, we developed an ontology verification module that behaves similarly to a rule-based decision support system to analyze the generation and delivery of personalized recommendation messages following a logical structure. **Conclusions**: This study led to the creation of a meaningful ontology to generate and model personalized recommendation messages for physical activity coaching.

Introduction

Overview

Currently, risk factors associated with unhealthy lifestyles have been recognized as the foremost contributors to chronic illness and mortality in developed countries [1][2][3][4][5][6]. An e-coach system can guide people and convey the appropriate recommendations in context with sufficient time to prevent and improve living with chronic conditions. It is a set of computerized components that constitute an artificial entity that can observe, reason about, learn from, and predict a user's behaviors, in context and over time, and engages proactively in an ongoing collaborative conversation with the user to aid planning and promote effective goal striving using persuasive techniques [7][8][9][10]. Motivating people toward a healthy lifestyle has been challenging without the appropriate and continuous support and correct intervention planning [7][8][9][10]. Personalized recommendation technology in health care may be helpful to address such challenges. It requires the proper collection of personal health and wellness data and the right recommendation generation and delivery in a meaningful way. Our previous study [11] focused on creating a meaningful, context-specific holistic ontology to model raw and unstructured observations of personal health and wellness data collected from heterogeneous sources (eg, sensors, interviews, and questionnaires) with semantic metadata and create a compact and logical abstraction for health risk prediction. However, this comprehensive study concentrated on rule-based recommendation generation and semantic modeling of recommendation messages for physical activity coaching.

Motivation

The generation of motivational messages is essential in e-coaching. Motivational messages provide quick information on time in a more natural and meaningful manner to translate behavioral observations into inspiring, easy-to-follow, and achievable actions. Moreover, these messages must be diverse to make the e-coach system more reasonable and reliable. In activity coaching, personalized motivational messages can offer inspiration for a day, week, or month based on the activity goals. It helps to regain motivation when the individual has lost motivation to attain activity goals. The medium of recommendation delivery can be diverse and depends on personal interaction choices (eg, graphical visualization, pop-up textual notification, and audiovisual material). In existing studies, motivational messages have textual forms that follow a static predefined format; therefore, they are difficult to individualize. Existing ontologies do not include model recommendation message intent, components, and contents important to automatically select accurate messages in e-coaching. Personalized recommendation generation for a healthy lifestyle is closely related to personal preferences. Thus, personal preferences can be of 3 types: activity goal setting (eg, nature of goals—direct vs motivational goals and generic vs personalized goals), response type (eg, mode to communicate extended health state, health state prediction, and customized recommendations for activity coaching), and nature of interaction with the e-coach system (eg, mode, frequency, and medium). In this study, we have gone one step ahead to perform semantic (ontological) modeling of preference data and recommendation messages beyond static textual form to describe its characteristics, metadata, and content information.

The use of ontologies has certain benefits while modeling recommendation messages. It helps to interpret which recommendation message is to be generated using a binary tree-like structure (if-then or if-then-else conditional statement). Interpretability makes identifying the cause-and-effect relationships between data input and data output easy. In ontology, the logical and structural representation of knowledge, hierarchical model structuring (eg, class and subclass model), and inferred knowledge generation with reasoners can solve interpretability problems in decision-making. Furthermore, benefits such as extensibility, flexibility, generality, and decoupling of knowledge help ontology develop an appropriate solution to model recommendation messages in automatic coaching.

Aim of the Study

This study proposes a Web Ontology Language (OWL)-based ontology (OntoRecoModel) to deal with personal preferences and recommendation messages and annotate them with semantic metadata information. The OntoRecoModel will not only support a logical representation of data and messages but also encourage rule-based decision-making to generate personalized recommendation messages using SPARQL Protocol and Resource Description Framework (RDF) Query Language (SPARQL) as a verification study against different test cases with simulated data. Moreover, we assessed the performance of the ontology against mean reasoning time and query execution time. In OntoRecoModel, we annotated the participant's data with Semantic Web Rule Language (SWRL) and stored the resultant OWL file in a triple-store format for better readability. The OntoRecoModel allows automatic knowledge inferencing and efficient knowledge representation to balance a trade-off between complexity, persuasiveness, and reasoning about formal knowledge. The entire study was divided into the following two sections: (1) OntoRecoModel design and implementation for semantic annotation and (2) its verification with simulated data. The main contributions of this study were the following:

1. Annotation of personal preferences data (activity goal setting, response type, and interaction type) and recommendation messages in the OntoRecoModel.

2. Preparation of semantic rules to execute SPARQL queries for different test cases.

3. Use of the prepared rules to generate personalized activity recommendations.

For this set of semantic data, it will be regarded as an assertion of True facts. The main goal of this paper was to trigger a logical rule of shape (A IMPLIES B) in a logically equivalent manner (NOT [A] or B). If some specific variables are inferred to be true, some suggestions should be provided to the participants of the semantic data source.

Related Work

This section offers existing knowledge relevant to current research and a qualitative comparison between our proposed ontology and the existing ontologies based on selected categories in Table D.1. An ontology is a formal description of knowledge as concepts within a domain and their relationships. It uses existing technologies to develop new ideas through conceptual modeling or proof-of-concept studies to solve general real-world or project-specific semantic modeling problems. There are other approaches to knowledge representation that use formal specifications, such as vocabularies, taxonomies, thesaurus, topic maps, and logical models. However, unlike taxonomy or relational database schemas, ontologies express relationships and allow users to bring together or link multiple concepts in novel ways. Furthermore, all the related ontologies are not available in open source. Therefore, it is not straightforward to make quantitative comparisons between different related studies.

Kim et al. [12] developed an ontology model for obesity management, which realizes the spontaneous participation of participants and continuous weight monitoring through the nursing process in the field of mobile devices. The scope of obesity management includes behavioral intervention, dietary advice, and physical activity. Similarly, the study includes evaluation data (BMI, gender, and hip circumference), inferred data to express diagnostic results, evaluation (causes of obesity), success or failure in behavior change, and implementation (education, advice, and intervention). Sojic et al. [13] used OWL to model a specific ontology in the obesity field to design reasoning models to personalize health status assessments to be age-specific and gender-specific. The ontology helps to classify personnel files according to changes in personal behavior or characteristics over time and automatically infer personal health status, which is of great significance for obesity assessment and prevention. They used SWRL to write the ontology rules. Kim et al. [14] proposed a physical activity ontology model to support the interoperability of physical activity data. The ontology was developed in Protégé (version 4.x), and the FaCT++ reasoner verified its structural consistency. On the basis of the automatic calculation paradigm, Monitoring, Analysis, Planning, and Execution, an automatic ontology-based method was developed by Lasierra et al. [15] to manage information in the home-based remote monitoring service scenario. Furthermore, they proposed the following three stages [16] for ontology-driven home-based personalized care for patients with chronic illnesses: stage 1—ontology design and implementation, stage 2—the application of ontology to study the personalization problem, and stage 3—software prototype implementation. The proposed ontology was designed in the Protégé-OWL (version 4.0.2) ontology editor using OWL–Description Logic (OWL-DL) language and verified using the FaCT++ reasoner. Ontology development involves data from heterogeneous sources, such as clinical knowledge, data from medical devices, and patient contextual data. Yao and Kumar [17] proposed a new flexible workflow based on the clinical context method, which used ontology modeling to incorporate flexible and adaptive clinical pathways into a clinical decision support system (CDSS). They developed 18 SWRL rules to explain practical knowledge of heart failure. The model was verified using the Pellet Reasoner plug-in for Protégé 3.4. In addition, they developed a proof-of-concept prototype of the proposed method using the Drools framework. Chi et al. [18] used OWL and SWRL to construct a dietary consultation system. The knowledge base (KB) involves the interaction of heterogeneous data sources and factors such as the patient's disease stage, physical condition, activity level, food intake, and key nutritional restrictions. Rhayem et al. [19] proposed an ontology (HealthIoT)–based system for patient monitoring using sensors, radio frequency identification, and actuators. They claim that the data obtained from medically connected devices are huge, and therefore, lack restraint and comprehensibility and are manipulated by other systems and devices. Therefore, they proposed an ontology model that represents connected medical devices and their data according to semantic rules and, then, used the proposed Internet of Things medical insurance system for model evaluation, which supports decision-making after analyzing the patient's vital signs. Galopin et al. [20] proposed an ontology-based prototype CDSS to manage patients with multiple chronic diseases in accordance with clinical practice guidelines. They prepared a KB based on the clinical practice guidelines and patient observation data. The KB decision rule is based on the if-then rule. Sherimon and Krishnan [21] proposed an ontology system (OntoDiabetic) using OWL2 language to support CDSS for patients with cardiovascular disease, diabetic nephropathy, and hypertension to follow clinical guidelines and if-then decision rules. Hristoskova et al. [22] proposed another ontology-driven environmental intelligence (AmI) framework to support personalized medical detection and alert generation based on the analysis of vital signs collected from patients diagnosed with congestive heart failure. The CDSS system can classify individual congestive heart failure risk stages and notify patients through AmI's reasoning engine. Riano et al. [23] proposed an ontology-based CDSS to monitor and intervene in patients with chronic diseases to prevent critical situations, such as misdiagnosis, undetected comorbidities, lack of information, unobserved related diseases, or prevention. An eHealth system was designed and implemented by Jin and Kim [24] using the IETF YANG ontology based on the semantic sensor network (SSN). This method helped to automatically configure eHealth sensors (responsible for collecting body temperature, blood pressure, electromyography, and galvanic skin response) with the help of information and communication technology and supported querying the sensor network through semantic interoperability for the planned eHealth system. The proposed eHealth system consisted of 3 main components—SSN (eHealth sensor, patient, and URI), internet (eHealth server and KB), and eHealth client (patients and professionals). The proposed semantic model used YANG to JavaScript Object Notation converter to convert YANG semantic model data into JavaScript Object Notation semantic model data to achieve semantic interoperability, and then, stored it in a database or KB. Ganguly et al. [25] proposed an ontology-based model for managing semantic interoperability issues in diabetic diet management. The development of the framework includes dialogue game rules, DSS with KB (rule library and database), dialogue model based on decision-making mechanism, dialogue game grammar, decision-making mechanism, and translation rules. Bouza et al. [26] proposed a domain ontology-based decision tree algorithm and a reasoner to separate instances with more general features for recommender system (SemTree) that outperformed comparable approaches in recommendation generation. Chatterjee et al. [11] focused on the creation of a meaningful, context-specific ontology (University of Agder eHealth Ontology [UiAeHo]) to model unintuitive, raw, and unstructured observations of health and wellness data (eg, sensors, interviews, and questionnaires) with semantic metadata and create a compact and logical abstraction for health risk prediction. Villalonga et al. [27] proposed a holistic ontology model to annotate and classify motivational messages for physical activity coaching.

Table D.1: A qualitative comparison between our proposed study and the existing studies.

Study	Used technologies	Annotation of sensor data	Annotation of PGHD	Rule-based reco	Annotation of pref data	Annotation of reco msg
Our study	OWL, HermiT, RDFb, SPARQLc, TDBd, OWLViz, OntoGraf, and Java	Yes	No	Yes	Yes	Yes
Chatterjee et al [11]	OWL, HermiT, RDF, SPARQL, TDB, OWLViz, SSNe, SNOMED-CTf, OntoGraf, and Java	Yes	Yes	Yes	No	No
Kim et al [12]	OWL	No	Yes	No	No	No
Sojic et al [13]	OWL and SWRLg	No	Yes	No	No	No
Kim et al [14]	OWL and FaCT++	No	Yes	No	No	No
Lasierra et al [15]	OWL, RDF, and SPARQL	No	Yes	Yes	No	No
Yao and Kumar [17]	OWL and SWRL	No	Yes	Yes	No	No
Chi et al [18]	OWL and SWRL	No	Yes	Yes	No	No
Rhayem et al [19]	OWL and SWRL	Yes	No	Yes	No	No
Galopin et al [20]	OWL and SWRL	No	Yes	Yes	No	No
Sherimon and Krishnan [21]	OWL and SWRL	No	Yes	Yes	No	No
Hristoskova et al [22]	SOA, Amigo, OWL, and SWRL	No	Yes	Yes	No	No
Riano et al [23]	OWL	No	No	Yes	No	No
Jin and Kim [24]	SSN and IETF YANG	Yes	No	No	No	No
Ganguly et al [25]	OWL	No	No	Yes	No	No
Bouza et al [26]	OWL, Decision Tree, and Java	No	No	Yes	No	No
Villalonga et al [27]	OWL and SPARQL	No	No	Yes	No	Yes

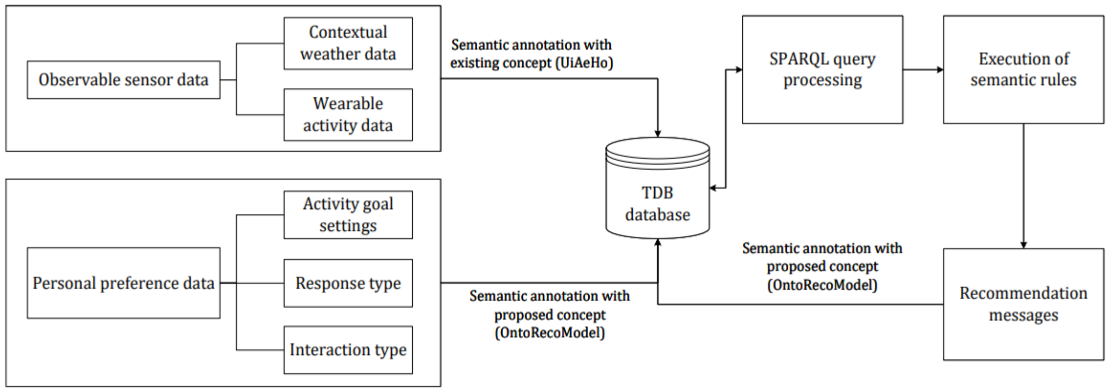

Figure D.1: High-level representation of the proposed approach. SPARQL: SPARQL Protocol and Resource Description Framework Query Language; TDB: tuple database; UiAeHo: University of Agder eHealth Ontology.

Most studies have developed ontologies that use OWL to solve data interoperability and knowledge representation problems. However, integrating personal health and wellness data, sensor observations, preference settings, semantic rules, semantic annotations, clinical guidelines, health risk prediction, and personalized recommendation generation remains as a problem in eHealth. We gathered ideas from existing studies to conceptualize our ontology design and implementation. In our previous study [11], we developed UiAeHo ontology to annotate personal and person-generated health and wellness data, sensor observations, health status in OWL format, combining SSN and Systematized Nomenclature of Medicine–Clinical Terms. Here, we extended the study to annotate preference settings and activity status and tailored recommendation messages for activity e-coaching. The design and development of UiAeHo were focused more on obesity and overweight case studies However, this study focuses strictly on activity coaching and recommendation modeling. In addition, our proposed ontology was verified with semantic rules to generate different categories of recommendation messages for different cases. The high-level graphical representation of the proposed approach has been depicted in Figure D.1 to show a distinction between OntoRecoModel and UiAeHo ontologies. OntoRecoModel annotates the following 3 types of data: sensor data (activity and weather), personal preference data, and personalized recommendations. Annotation of the sensor data in OntoRecoModel was based on the existing UiAeHo ontology following a semantic structure. Sensor data (activity data and contextual weather data) were included in this ontology design to exhibit that our OntoRecoModel can generate contextual and personalized recommendations in combination with personal preference data and semantic rules.

Methods

Domain Ontology

Ontology supports flexibility in its design to solve real-world modeling and knowledge representation problems. It is a formal model of a specific domain, with the following essential elements: individuals or objects, classes, attributes, relationships, and axioms. The class diagram of a program written using object-oriented programming [28][29] visually depicts an ontology. The concept of ontology was created thousands of years ago in the philosophical domain, and it has the design flexibility of using existing ontology [29][30].

The open-world assumption knowledge representation style uses OWL, RDF, and RDF schema syntax. It can be optimized using the ontology model, and the consistency of its logic and structure can be verified using the ontology reasoning machine. An ontology "O" is defined as a tuple Ω=(Ć, R), where Ć is the set of concepts and R is a set of relations. An ontology has a tree-like hierarchical structure (O_h) with the following properties [31][32]:

1. L=levels ((O_h)) = total number of levels in the ontology hierarchy, 0≤n≤L, where n $\in$ Z^+ and n=0 represent the root node

2. $C_{n,j}$= a model classifying "O" at a level n; where, j $\in \{0, 1, ...|C_n|\}$

3. $|C|$= number of instances classified as class C

4. E= edge ($C_{n,j}$, C_{n-1}, k)= edge between node $C_{n,j}$ and its parent node $C_{n-1,k}$.

Ontology Design Approach

An ontology can be designed in 5 ways: inspirational, inductive, synthetic, deductive, and collaborative [33]. We used a mixed method in our ontology design after combining the inspirational and deductive approaches. The inspirational approach helped us to identify the need for the ontology design, and the deductive approach focused more on the development of the OntoRecoModel model in Protégé. Moreover, the deductive approach helped us to adapt and adjust general principles to develop an anticipatory ontology of personalized activity recommendations as a study case. It includes general concepts that are filtered and refined to personalize specific domain subsets. The overall approaches were distributed in the following phases:

1. Literature search: We identified the necessary ontology components in healthy lifestyle management through a literature review, as described in the Related Work section. This study aimed to integrate ideas from the related ontology development in our proposed work.

2. Ideation: We discussed with 12 experts in the domain of information and communication technologies with research backgrounds in health care to design the concept of the ontology to fit in an activity e-coaching.

3. Annotation: We designed and developed the OntoRecoModel ontology to annotate personal preference data and motivational recommendation messages.

4. Rule base: We created a rule base for the SPARQL query engine for query execution and personalized recommendation message generation (rule-based inference).

5. Verification: We verified our proposed OntoRecoModel ontology using simulated data against different test cases.

The feasibility study of the proposed OntoRecoModel consists of the following steps—(1) designing the ontology to fit in the activity e-coaching concept; (2) modeling the ontology in the Protégé open-source platform and reasoning with HermiT reasoner; (3) integrating the concepts, such as annotation of personal preference data and motivational recommendation messages in OntoRecoModel; (4) implementing OntoRecoModel with logical axioms, declaration axioms, classes, instances, object properties, data properties; and (5) setting up the rule base for ontology verification with SPARQL queries. We further discussed how interpretation can be associated with rule-based activity recommendation generation.

The specifications related to this study, as maintained by World Wide Web Consortium, are XML, URI, RDF, Turtle, RDF schema, OWL, SPARQL, and SWRL. The following terms are related to OntoRecoModel representation and processing:

1. Propositional variables (the atomic name of the truth value can be changed from one model to another)

2. Constant (the only propositional variables are TRUE and FALSE; thus, their truth values cannot be changed)

3. Operators (a set of logical connectors in each logic)

Here, we used operators, such as NOT, AND, OR, IMPLIES, EQUIV, and quantifiers (a set of logical quantifiers in a given logic). In this study, we used FORALL as the universal quantifier, EXISTS as the existential quantifier, quantification clause (a set of propositional variables connected by operators and quantifiers), clause (a quantification clause without any quantifier), formulas (a collection of clauses and quantified clauses linked together by logical operators), and process models (a collection of assignments for each propositional variable, so that when simplified, the process will lead to the constant TRUE).

Different open-access ontology editors are available in the market, such as NeOn Toolkit, Protégé, FOAF editor, TopBraid Composer, WebOnto Ontolingua Server, OntoEdit, WebODE, and Ontosaurus. The editors support the development of OWL-based ontologies. In addition, these editors support reasoning. The reasoner is a crucial component for using OWL ontology [11]. It derives new truths about the concepts that are modeled using OWL ontology. All queries on OWL ontology (and its imported closures) can be performed using reasoners [11][34][35]. Therefore, the knowledge in the ontology may not be explicit, and a reasoner is needed to infer the implicit knowledge to obtain the correct query results. If reasoner implementation is needed, the reasoner must be accessed through the application programming interface (API). The OWL API includes various interfaces for accessing OWL reasoners. Reasoners can be categorized into 3 groups—OWL-DL, OWL–expression language, and OWL–query language [11][34][35][36][37][38][39][40][41][42]. This study considered Protégé (version 5.x) as an ontology editor for ontology design and development, OWLViz for ontology visualization, and HermiT (version 1.4.x; ∈ OWL-DL) reasoner for validating the ontology structure. In addition, we used an open-source Apache Jena Fuseki server [39] for SPARQL processing [43][44] with a tuple database (TDB). TDB supports Jena APIs [45][46] and can be used as a stand-alone high-performance RDF storage.

Ontology Modeling

Ontology modeling in Protégé can be classified into the following 2 categories: OWL-based and frame-based categories. We have used the Protégé-OWL editor to model OntoRecoModel following the open KB connectivity protocol using classes, instances (objects), properties (object properties and data properties), and relationships. The steps of OntoRecoModel modeling in Protégé are described as follows –

Step 1
Creation of a new Web Ontology Language project in Protégé and save it as a Turtle Resource Description Framework (RDF) format (OntoRecoModel.ttl)
Step 2
Create named classes under the superclass owl:Thing, maintaining consistency

- Create a group of classes (G=[C1, C2,......, Cn])
- Define disjoint classes (Cx ∩ Cy=[ø], where Cx and C_y ∈ G)
- Define subclasses
- Define disjoint subclasses

Step 3
Creation of Web Ontology Language properties after identifying classes and their properties

- Object properties (association between objects)
- Data properties (relates objects to XML schema datatype or rdf:literal)
- Annotation properties to annotate classes, objects, and properties

Step 4
Define the nature of the properties

- subproperties (A ⊆ B, where A and B are two non-empty sets)
- Inverse properties (x×y=I, where x, y ∈ A; I=identity element)
- Functional properties (X=A×X, where X is the set of all sequences ¡a1, a2,..., an¿ for a1, a2,.., an ∈ A)
- Inverse functional properties (for a function f: X → Y, its inverse f-1: Y → X, where X, Y ∈ R)

- Transitive properties ($\cup S \subseteq S$ or if x=y and y=z, then x=z, where x, y, z $\subseteq$ S set)
- Symmetric properties (if x=y, then y=x, where x, y $\subseteq$ S set)
- Reflexive properties (x=x, where x $\in$ R)

Step 5
Addition of existing ontology classes (eg, semantic sensor network ontology classes to annotate sensor observations)
Step 6
Define property domain (D) and range (R) for both object properties and data properties as axioms in reasoning
Step 7
Define property restrictions

- Qualifier restrictions (existential and universal)
- Cardinality restrictions ($\geq$1)
- hasValue restrictions (datatype)

Step 8
Ontology processing with reasoner to check structural and logical consistency and compute the inferred ontology class hierarchy

- Blue color class in the inferred hierarchy for reclassification
- Red color class in the inferred hierarchy for inconsistent class

Step 9
Remove inconsistencies from the ontology tree using the pruning method
Step 10
Query processing with SPARQL Protocol and RDF Query Language and storing the Terse RDF Triple Language file into a tuple database for persistence

Ontology Implementation

Scope

We have planned to integrate the proposed OntoRecoModel model into an automatic activity coaching system for the semantic representation of activity sensor data, weather sensor data, personal preference data, and recommendation messages. The annotation of sensor data was pre-existing, and we used the concept from our previous study [11]. Furthermore, we showed a direction to use the proposed ontology model for automatic rule-based tailored activity recommendation generation with SPARQL queries to motivate individuals to maintain a healthy lifestyle. OntoRecoModel has gone one step forward to represent motivational recommendation messages beyond the string representation. Furthermore, the rule base helped to interpret the logic behind recommendation generation with logical (AND) and (OR) operations. We verified the ontology against a few test cases, which consisted of simulated data.

The targeted activity e-coach system has three modules, as depicted in Figure D.2 | (1) data collection and annotation module, (2) health state monitor and prediction module, and (3) recommendation generation module. In the data collection and annotation module, we showed a direction to annotate personal preference data essential for personalized recommendation generation. Health state monitor and prediction models periodically load individual activity data and analyze them using a data-driven machine learning (ML) approach or a rule-driven binary conditional approach. We considered a rule-driven approach for monitoring individual activity data using SPARQL queries. It determines whether a participant is sedentary or active over a day based on the recorded activity data. The annotated query processing results are stored in the database. Then, the personalized recommendation generation module combines the annotated SPARQL query results with the annotated preference data to generate tailored recommendation messages for motivation, which may help individuals to achieve their activity goals.

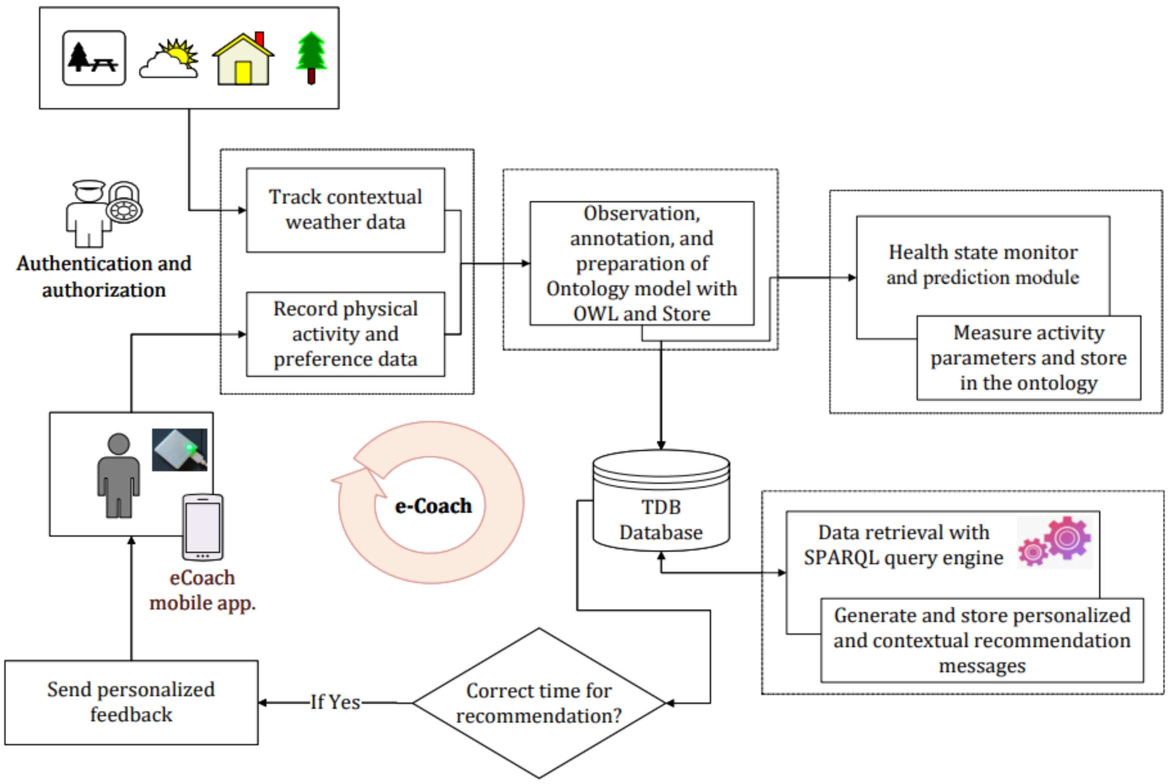

Figure D.2: The modules of the e-coach prototype system. OWL: Web Ontology Language; SPARQL: SPARQL Protocol and Resource Description Framework Query Language; TDB: tuple database.

Annotation of Sensor Data

As shown in our previous study, this study achieved annotation of activity sensor data and contextual weather sensor data using pre-existing SSN ontology [11]. We used a similar logic; however, we annotated them more realistically. We examined the recorded activity parameters of different wearable activity sensors, such as Fitbit Versa, MOX2-5, and Garmin, and discovered that the following parameters are essential and common across these activity sensors: sedentary time, low physical activity (LPA) time, medium physical activity (MPA) time, vigorous physical activity (VPA) time, and total number of steps. Therefore, in this ontology, we annotated these activity parameters. Similarly, we analyzed data from different weather APIs, such as AccuWeather, Yr.no, and OpenWeather API. We found that the following observable weather parameters are common across these APIs: city, country, weather code, status, description, temperature, real feel, air pressure, humidity, visibility, and wind speed. Thus, it may help OntoRecoModel to be functional, irrespective of the choice of standard activity sensor and weather APIs.

Annotation of Personal Preference Data

Personal preferences reflect individual expectations from an e-coach system. We planned to collect personal preference data at the beginning of the individual e-coaching session. We classified preference data into three categories: (1) activity goal settings, (2) response type for coaching, and (3) interaction type. Activity goals were categorized into 2 groups: personalized versus generic and direct versus motivational. The generic goals in activity coaching are the general activity guidelines set by the World Health Organization [47]. Personalized activity goals can be of multiple types (eg, weight reduction, staying active, body fat level, and proper sleeping). Direct goals tell the participant to perform direct activities (such as walking 2 km tomorrow).

In contrast, motivational goals inspire the participants to perform some tasks through persuasion (eg, If you walk 1 km further, you can watch an excellent soccer game). Response type for e-coaching can be either direct (eg, a pop-up message or notification to receive activity progression alert) or indirect (eg, graphical representation of activity progression). Individuals can be encouraged with personalized, evidence-based, and contextual response generation and its purposeful presentation (eg, graphic illustration, selection of colors, contrasts, visual aspects of movements, and menus, which are adjustable with device type). Interaction is an action that occurs owing to the mutual effect of $\geq$2 objects. The concept of 2-way effects is essential in interaction, not 1-way causal effects. The interaction types can be the mode (eg, style and graph), medium (eg, audio, voice, and text), and frequency (eg, hourly, daily, weekly, and monthly). Notification generation is a subcategory of interaction and may be persistent or nonpersistent.

Annotation of Recommendation Messages

The recommender module generates personalized, and contextual recommendations based on the prediction status. The recommendations can be direct (eg, pop-up notifications as alerts) or indirect (eg, visual representation). Direct or immediate notifications can contain 2 types of messages: to-do or formal (eg, You need to complete 1500 more steps in the next 2 hours to reach your daily goal) and informal (eg, Good work, keep it up! You have achieved the targeted steps). Therefore, we broke down the recommendation message concepts into intents and components. Intent defines the message's intention (eg, formal or informal). Message components define time, element (eg, data types in XML schema definition language), action (eg, pop-up and graphical visualization), and subject. An individual can receive ¿1 meaningful recommendation message based on the one-to-many relationship.

Ontology Classes and Properties

Figure D.3 to D.6 describe OntoRecoModel with mandatory classes to annotate the sensor, preference, and recommendation data.

Participant is the subclass of the human class (Figure D.3). They have dedicated role and credentials (objectProperties: hasRole, hasPassword, and hasUniqueUserId) to authorize and authenticate themselves in the system. Participants are adults (both men and women), digitally literate, and clinically fit individuals. They are associated with the data properties such as hasAge, hasDesignation, hasEmail, hasFirstName, hasLastName, hasGender, and hasMobile. Each participant has their health record (hasHealthRecord), such as activity data; status (hasStatus), such as active or inactive; context information, such as weather status; preferences (hasPreferences); and recommendations (hasReceivedRecommendation).

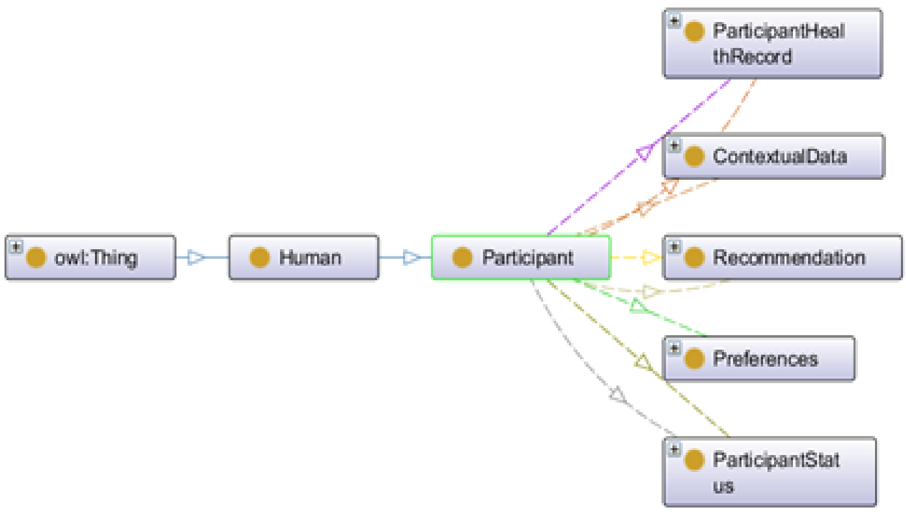

Figure D.3: High-level graphical representation of participant using OntoGraf in Protégé. OWL: Web Ontology Language.

Sensor data are ObservableEntity (Figure D.4). Observation value is the subclass of ObservableEntity. ActivityDataValue and ExternalWeatherValue are the subclass of Observation value class. ActivityData and ActivityDataValue are linked to represent individual activity data. ActivityData class is a subclass of ParticipantHealthRecord and has objectProperty—hasBeenCollectedBy to represent associated activity data values (class: ActivityDataValue) as an observable entity. We have planned to collect activity data (such as steps, LPA, MPA, VPA, sleep time, and sedentary bouts) with a wearable MOX2-5 activity sensor. In contrast, contextual data are observable weather-related data (city, country, weather code, status, description, temperature, real feel, air pressure, humidity, visibility, and wind speed), which are planned to be collected through the OpenWeather web interfaces. ContextData class is the subclass of ContextualData class and linked with ExternalWeatherValue to represent contextual weather data. TemporalEntity class represents the time stamp when the observational data have been captured and personalized recommendations have been generated (data property: hasDateTime).

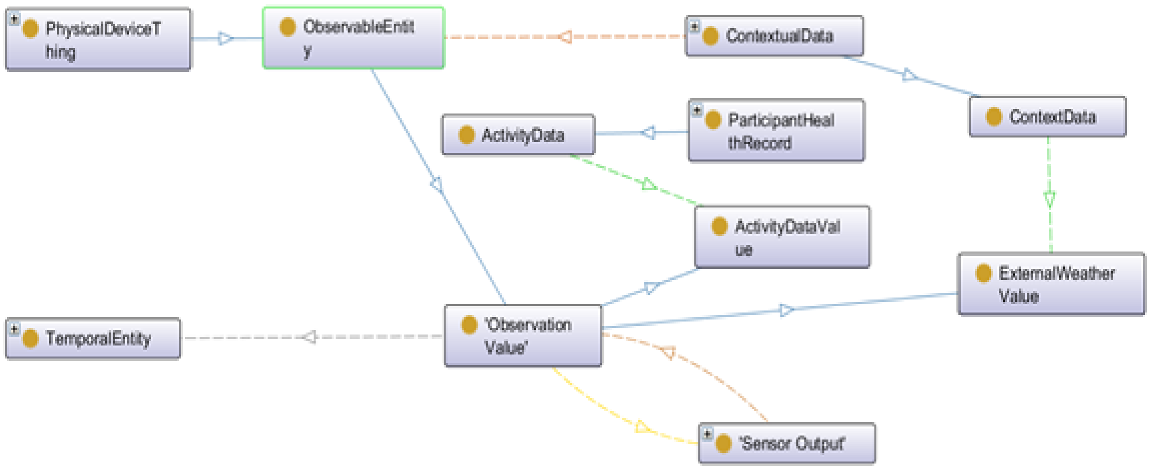

Figure D.4: High-level graphical representation of observable data using OntoGraf in Protégé.

Recommendation is a broad area, and we considered only activity recommendations in this study. ActivityRecommendation is a subclass of Recommendation class and parent to the MessageIntent and MessageComponent with the following objectProperties: hasMessageIntent and hasMessageComponent. MessageIntent class is the parent to To-Do and Informal classes with the following objectProperties: hasRecoInformal and hasRecoToDo (Figure D.5). MessageComponent is the parent of Time, Element, Action, and Subject classes with the following objectProperties: hasTime, hasElement, hasAction, and hasSubject. Preferences are a subclass of the Qualifier class and related to the Goal, Interaction, and ResponseType (subclasses of the Preference class) with the following objectProperties: hasInteractionType, hasResponseType, and hasGoal. Preference class is a questionnaire-based method to receive participant's choices on goal setting, response type for e-coaching, and nature of interaction with the e-coach system.

Preference class has 3 subclasses: ResponseType, Goal, and Interaction. Goal class has 2 subclasses: Daily and Weekly (Figure D.6). Each activity recommendations are either generic or personalized. Thus, recommendation generation depends on the assessment of the health status of the participants, regarding activity measurement and contextual information. Contextual data help recommend participants to plan indoor or outdoor activities based on external weather conditions. Table S1 in Multimedia Appendix 1 [48][49][50][51] summarizes the set of identified recommendation messages used for the test setup (ontology verification) and prepared based on positive psychology [52] and the concept of persuasion [48]. Recommendations generated on day-n will reflect daily activity and contemplate what to perform on the day n+1 to achieve the weekly goal. Preference data are personalized and customizable. All the necessary data for this study and their nature are summarized in Table S2 in Multimedia Appendix 2.

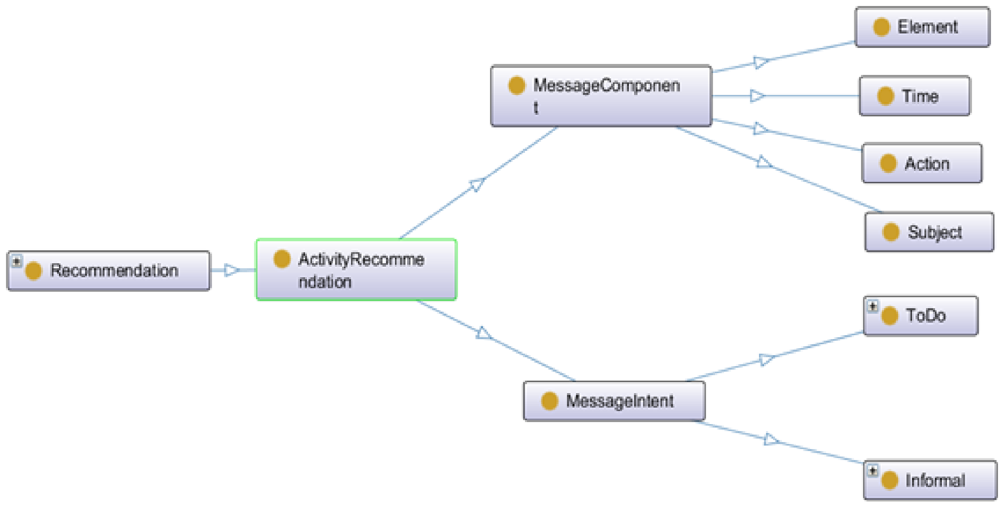

Figure D.5: High-level graphical representation of recommendation using OntoGraf in Protégé.

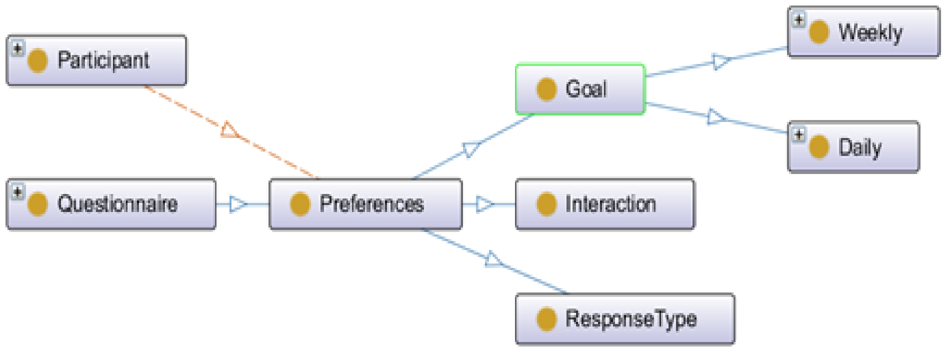

Figure D.6: High-level graphical representation of preferences using OntoGraf in Protégé.

Description logic is the formal knowledge representation of ontology language, which provides a good trade-off between the expressiveness, complexity, and efficiency of knowledge representation and structured knowledge reasoning. We have the following proposition variables and recommended messages with their links to ensure that the paper is fully understood. Now, we need a set of clauses so that specific models can assign these variables to true, which triggers the sending of recommendations. SROIQ Description Logic [53] is the logic that provides the formal basis for OWL2 and has been used as the formal logic for reasoning in this study (Table S3 in Multimedia Appendix 3).

Ontology Verification

Test Cases with Simulated Data

We considered 8 test cases, as described in Table S4 in Multimedia Appendix 4, with simulated data for the proposed ontology verification. In the table, all the data are simulated. Therefore, no ethical approval was required. Cases 1 to 4 were associated with goal type—generic (World Health Organization standard guidelines to stay active for an entire week). Cases 5 to 8 were associated with goal type—personalized. More detailed description of different cases is provided in Textbox 4.6. The primary objective of the test cases was to check whether the daily step goal and daily sleep goal were achieved. The sedentary time and total time of VPA, MPA, and LPA were evaluated as a part of the secondary goal achievement. Daily goal achievement consisted of both primary objective and secondary objectives.

Textbox 4.6: Different test cases and their description.

Goal type: Generic

- Case 1 (11): Daily step goal and sleep goal are achieved.
- Case 2 (10): Daily step goal is achieved; however, sleep goal is not achieved.
- Case 3 (01): Daily step goal is not achieved; however, sleep goal is achieved.
- Case 4 (00): Daily step goal and sleep goal are not achieved.

Goal type: Personalized

- Case 5 (11): Daily step goal and sleep goal are achieved.
- Case 6 (10): Daily step goal is achieved; however, sleep goal is not achieved.
- Case 7 (01): Daily step goal is not achieved; however, sleep goal is achieved.
- Case 8 (00): Daily step goal and sleep goal are not achieved.

Note:

- 1 and 0 are two binary numbers and represent an on-off switch.
- 0 indicates that certain feature is false and 1 indicates that certain feature is true.
- Their combination (00, 01, 10, and 11) represents the following 2 combined features: daily step goal and daily sleep goal.
- The combination produces a total of 2n possible test cases (00, 01, 10, and 11) for each goal type.

For all the test cases, the contextual weather data were considered constant (Table S5 in Multimedia Appendix 5). These test cases were added to the proposed ontology as individuals. SPARQL query processor engine processed the simulated data against certain test cases.

Rule Creation for SPARQL and Rule Execution

Rules were composed of cause (A) and effect (B) to imply A $\rightarrow$ B. For each of the conditions mentioned in Table S3 in Multimedia Appendix 3, the recommendation module performed a SPARQL query every day to determine the type of recommended message to be delivered to each participant, as shown in the Unified Modeling Language sequence diagram (Figure D.7). The execution of each of the predefined semantic rules specified in Table S3 in Multimedia Appendix 3 depended on the performance of the SPARQL queries, and the rules were created according to clinical guidelines [49][50][51]. This study subdivided 12 semantic rules into activity-level classification (n=10, 83%), weather classification (n=1, 8%), and satisfiability (n=1, 8%). The added concepts and rules were relatively easy to follow and use.

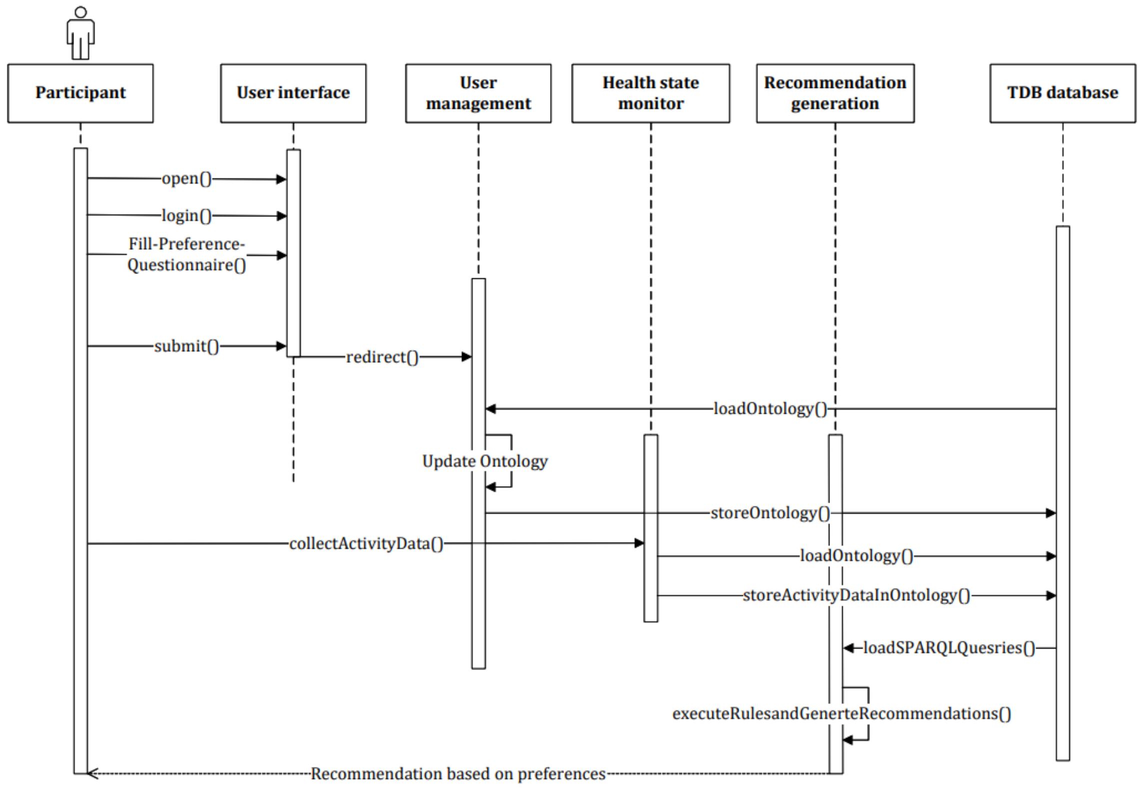

Figure D.7: Unified Modeling Language sequence diagram for personalized recommendation generation and delivery. SPARQL: SPARQL Protocol and Resource Description Framework Query Language; TDB: tuple database.

Observable and measurable parameters related to the activities and context of the individual participants on the time stamp were obtained based on SPARQL queries at preference-based intervals. The rules 1 to 8 in Table S3 in Multimedia Appendix 3 assigned truth values to variables to ensure consistency. We confirmed with HermiT that the correct recommendation message was triggered for specific situations. However, it was necessary to ensure that no variable combination makes the entire formula unsatisfiable; that is, no model can satisfy the process. We confirmed that only 1 message was triggered at a time. In this study, we had a formal guarantee that 2 once a day messages cannot be triggered simultaneously and there cannot be a model output by HermiT every time for every possible variable combination. If we put the different variables used in the first 10 rules (Table S3 in Multimedia Appendix 3) into the propositional variables (Table S1 in Multimedia Appendix 1), we will have an exponential number of possible participants.

As 2 messages cannot be triggered simultaneously to meet the exact requirements, we added a rule (rule 11), and the variable used in the proposal starts once a day. If rule

11 is false, the entire ruleset (deemed as significant conjunction) will be set to false, and then, there will be no model as output, and we will be able to debug our rules if needed. If it is set to true, we will have a formal guarantee that regardless of the true value we put in the rule base, 2 once a day messages will not be triggered at the same time.

Ethics Approval

We have used simulated data for this study. Therefore, participants' data have not been recorded or disclosed.

Results

An e-coach system can use the messages presented in this study (Table S1 in Multimedia Appendix 1) to improve individual activities with proper goal management. Therefore, the e-coach system must access these messages stored in a KB during tailored recommendation generation. Both the asserted and inferred knowledge obtained through the reasoning method will be helpful to determine the most appropriate message.

The TDB database, as shown in Figure D.7, was used as a KB in this study. The test used to verify the performance and reliability of the proposed OntoRecoModel ontology included SPARQL queries and a rule base. In ontology verification, we generated personalized and contextual activity recommendations according to the semantic rules to improve the individual's physical activity to meet their activity goals. We executed all the semantic rules described in Table S3 in Multimedia Appendix 3 and used the Jena ARQ engine to run relevant SPARQL queries on the simulated data for the 8 test cases described in Table S4 in Multimedia Appendix 4. This helped to determine the type of recommendation message that would be generated, and we have presented our findings (rule-based recommendation generation for different cases) in Table D.2. Several individual SPARQL queries are provided in Textbox S1 in Multimedia Appendix 6 as examples, and their results need to be combined to generate personalized recommendations to meet the e-coaching requirements. We achieved 100% precisions in executing SPARQL queries to retrieve the necessary data.

Table D.2: Recommendation generation for participants for Day-(n+1) [n>0].

Case	Activity status on day−n	ToDo	Informal
1	Goal achieved	A-3, A-6, A-8, A-10, and A-12	A-13 and C-1
2	Goal partially achieved	A-2, A-5, A-8, A-10, and A-11	A-14 and C-1
3	Goal partially achieved	A-1, A-5, A-7, A-9, and A-12	A-14 and C-1
4	Goal not achieved	A-1, A-5, A-7, A-9, and A-11	A-14 and C-1
5	Goal achieved	A-4, A-6, A-8, A-10, and A-12	A-13 and C-1
6	Goal partially achieved	A-4, A-5, A-8, A-9, and A-11	A-14 and C-1
7	Goal partially achieved	A-3, A-5, A-7, A-9, and A-12	A-14 and C-1
8	Goal not achieved	A-3, A-5, A-7, A-9, and A-11	A-14 and C-1

Table D.2 shows that participants can receive multiple motivational recommendation messages under To-Do and informal categories. The purpose of the e-coaching is to motivate participants (with motivational recommendation messages) for activities on day n+1 based on the activity progression on day-n so that they can meet their weekly activity goals (generic or personalized) and maintain a healthy lifestyle. Proposition variable A-15 and A-16 (Table S1 in Multimedia Appendix 1) were the determinant of the weekly goal achievement and the delivery of the corresponding recommendation messages.

Discussion

Principal Findings

The recommendation generation module used SPARQL queries and a rule base to generate personalized and contextual activity recommendations. There is no false positive situation based on the proposed ontology. According to the test cases in Table S4 in Multimedia Appendix 4, case 1 and case 5 achieved the daily activity goal; case 2, case 3, case 6, and case 7 achieved partial daily activity goal; and case 4 and case 8 ultimately failed to attain the daily activity goal. After combining the results of SPARQL queries with semantic rules, the related recommendation messages were updated, as shown in Table D.2. The average execution time for all the SPARQL queries was between 0.1 and 0.3 seconds. The semantic rules described in Table S3 in Multimedia Appendix 3 represent the logic behind personalized recommendation message generation. The rule-based binary reasoning (if $\rightarrow$ 1, else $\rightarrow$ 0) helps to interpret the reason behind the delivery of a personal recommendation message.

The reasoning time of the proposed ontology was measured against the following reasoners available in Protégé: HermiT, Pellet, FaCT++, RacerPro, and KAON2; the corresponding processing times are shown in Table D.3. The HermiT reasoner performed the best without reporting any inconsistencies.

Table D.3: Comparative performance analysis of different reasoners available in Protégé.

Reasoner	Approximate reasoning time (seconds)
HermiT	2-3
Pellet	4-5
FaCT++	5-6
RacerPro	4-5
KAON2	5-6

The reading time after loading the ontology into the Jena workspace was approximately 1 to 2.5 seconds, with the OWL_MEM_MICRO_RULE_INF ontology specification (OWL full) in the Terse RDF Triple Language format, in-memory storage, and optimized rule-based reasoner OWL rules. Then, we used the Jena framework to query the ontology classes, predicates, subjects, and individuals in <1, <0.3, <0.4, and <2 seconds, respectively. Each ontology model (complete RDF diagram) was associated with a document manager (default global document manager: OntDocumentManager) to assist in processing ontology documents. All classes that represent the value of the ontology in the ontology API had OntResource as a general superclass with attributes (version information, comment, label, seeAlso, isDefinedBy, sameAs, and differentFrom) and methods (add, set, list, get, update, and delete). We implemented the RDF interface provided by Jena to maintain the modeled ontology and its instances in the TDB and load them back for further processing. Jena Fuseki was tightly integrated with TDB to provide a robust transactional persistent storage layer.

Limitations and Future Scope

As explained in this study, we conducted the overall experiment on simulated data in a modeled e-coaching environment. This concept must be tested after integrating with a real-time activity e-coaching system, in which actual participants will be involved. Here, the personalized recommendation generation is rule-driven and straightforward. In Figure D.2, the health state monitor and prediction module can be upgraded using data-driven ML approaches, followed by annotation of prediction results into the ontology. However, it is the future scope of this study.

In our conceptualized activity e-coaching, the recommendation generation module successfully searched the KB of motivational recommendation messages based on the rules in addition to the SPARQL results. The recommendation messages can be further personalized based on human behavior, liking for sports (eg, soccer), and the concept of reward bank. The components of the activity-related message can be further divided into indoor, outdoor, morning, afternoon, evening, and night activities. If a person has a dog and the e-coach system is aware of it, its recommendation generation module may suggest some activity recommendations involving the dog.

Table D.2 shows that a participant can receive >1 recommendation message. It may lead to a message overloading problem. In future research, the recommendation process can be automated with ML algorithms (eg, time series and regression model) to select an optimal set of recommendations from feasible recommendations. The scope of the proposed ontology can be enhanced by conducting a study on a cluster of trials.

Conclusions

This study created the OntoRecoModel ontology to generate and model personalized recommendation messages for physical activity coaching. The proposed ontology not only semantically annotates recommendation messages, their intention, and components but also models personal preference data, individual activity data, and contextual weather information (required for personalized recommendation generation). Moreover, we successfully verified the use of the proposed ontology in rule-based recommendation generation using the SPARQL query engine. This study also showed a direction to categorize recommendation messages according to the defined ontology rules. Furthermore, reasoning has helped to organize the recommendation messages into multiple aspects. The recommendation message categorization, their semantic annotation, and the ontological

SPARQL queries enable the recommendation generation module to generate them based on preferences, activity data, and contextual weather data.

The OntoRecoModel ontology uses the OWL-based web language to represent the collected data in the RDF triple storage format. The performance of the proposed ontology was evaluated using simulated data from 8 test cases. The structure and logical consistency of the proposed ontology were evaluated using the HermiT reasoner. In future studies, we will recruit actual participants following the inclusion and exclusion criteria to replicate the entire test scenario and assess the effectiveness of the recommendation generation plan for goal evaluation.

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Authors' Contributions

AC contributed to conceptualization, formal analysis, investigation, methodology, obtaining resources, and writing the original draft. AP was involved in funding acquisition and writing the original draft. All authors read and agreed to the published version of the manuscript.

Conflicts of Interest

None declared.

Abbreviations

API: application programming interface
CDSS: clinical decision support system
KB: knowledge base
LPA: low physical activity
ML: machine learning
MPA: medium physical activity
OWL: Web Ontology Language
OWL-DL: Web Ontology Language–Description Logic
RDF: Resource Description Framework
SPARQL: SPARQL Protocol and Resource Description Framework Query Language
SSN: semantic sensor network
SWRL: Semantic Web Rule Language
TDB: tuple database

UiAeHo: University of Agder eHealth Ontology
VPA: vigorous physical activity

Multimedia Appendix

Appendices 1-6[1]:

1. Propositional variables and corresponding recommendation messages.
2. Different data types used in this study and their nature.
3. In-context recommendation conditions and corresponding rules (rule base) for test setup.
4. Description of the test cases.
5. Description of the contextual weather data.
6. Selected list of SPARQL Protocol and Resource Description Framework Query Language queries used in this study.

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Paper E

An automatic and personalized recommendation modelling in activity eCoaching with deep learning and ontology

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An automatic and personalized recommendation modelling in activity eCoaching with deep learning and ontology

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Abstract – Electronic coaching (eCoach) facilitates goal-focused development for individuals to optimize certain human behavior. However, the automatic generation of personalized recommendations in eCoaching remains a challenging task. This research paper introduces a novel approach that combines deep learning and semantic ontologies to generate hybrid and personalized recommendations by considering "Physical Activity" as a case study. To achieve this, we employ three methods: time-series forecasting, time-series physical activity level classification, and statistical metrics for data processing. Additionally, we utilize a naïve-based probabilistic interval prediction technique with the residual standard deviation used to make point predictions meaningful in the recommendation presentation. The processed results are integrated into activity datasets using an ontology called OntoeCoach, which facilitates semantic representation and reasoning. To generate personalized recommendations in an understandable format, we implement the SPARQL Protocol and RDF Query Language (SPARQL). We evaluate the performance of standard time-series forecasting algorithms (such as 1D Convolutional Neural Network Model (CNN1D), autoregression, Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU)) and classifiers (including Multilayer Perceptron (MLP), Rocket, MiniRocket, and MiniRocketVoting) using state-of-the-art metrics. We conduct evaluations on both public datasets (e.g., PMData) and private datasets (e.g., MOX2-5 activity). Our CNN1D model achieves the highest prediction accuracy of 97%, while the MLP model outperforms other classifiers with an accuracy of 74%. Furthermore, we evaluate the performance of our proposed OntoeCoach ontology model by assessing reasoning and query execution time metrics. The results demonstrate that our approach effectively plans and

generates recommendations on both datasets. The rule set of OntoeCoach can also be generalized to enhance interpretability.

Introduction

The collaborative effects of sedentary lifestyle patterns are linked to multiple adverse health outcomes, including increased risk of lifestyle diseases such as obesity, type 2 diabetes, hypertension, depression, and cardiovascular disease [1][2][3][4]. Regular physical exercise positively affects the prevention and management of lifestyle diseases. People who are not physically active have a 20% to 30% increased risk of death compared to those who are physically active[5][6][7][8]. E-health research can improve personal healthcare through information and communication technology (ICT) [9][10].eHealth technologies help collaborate and share health information through digital sensors for ubiquitous monitoring and care. eCoach systems can enable people to lead a healthy lifestyle through ubiquitous personalized health status monitoring (e.g., physical activity, diet, healthy habits) and personalized recommendation generation[11][12][13].

An eCoach system is complex system with many partially connected computerized components interacting through various feedback loops. It creates an artificial entity that can sense, judge, learn and predict the behavior of individuals. It proactively engages in ongoing collaborative dialogue with individuals to support planning and encourage effective goal management through persuasive skills[11]. The eCoach system can generate automatic and customized activity recommendations based on insights from activity sensor data such as that collected using wearable Bluetooth activity devices such as Fitbit, MOX2-5, Garmin, and Actigraph for daily, weekly, or monthly activity goals. The activity coaching process can be face-to-face or technology-driven [11]. Personal coaching with manual activity tracking and generating recommendations is time-consuming and repetitious.

Recommendation technology can be defined as a decision-making approach in complex information environments [14][15][16]. The techniques can be classified as rule-based and data-driven [17]. Solely data-driven recommendation technology with machine learning (ML) and deep learning (DL) models suffers from insufficient data, high computing overhead, lack of interpretability, re-training, personalization, and cold-start problem [17][18]. In contrast, a rule-based recommendation technology uses binary logic in a symbolic form to present knowledge in "IF-THEN or IF-ELSE IF-THEN" rules and infer new knowledge with reasoning. A knowledge base (KB) is retained to store and access such rules and related messages. Rules can be specified differently, such as propositional logic, decision tree, relational algebra, and description logic. Rule-based systems are modular, intelligible, and easy to manage; however, they suffer from symbol grounding problems [17]. Therefore, a hybrid approach may overcome the shortcomings of both data-driven and rule-based recommendation technologies.

Description logics (i.e., formal knowledge representation of ontology language) balances transparency, complexity, and effectiveness of knowledge description and knowledge reasoning. Moreover, semantic web rule language (SWRL) and SPARQL languages also represent description logics in an ontology [3][19][20]. In particular, ontology is a formal description of knowledge in a domain and its relationships according to a hierarchical structure, which can help existing technologies develop new ideas through conceptual modeling or proof-of-concept (PoC) research to address the challenges of semantic processing modeling. Unlike taxonomies or relational database schema, ontologies express relationships and allow users to connect or relate multiple concepts innovatively using the following elements: individuals/objects, classes, attributes, relations, and axioms [3][21]. They follow an open-world hypothetical knowledge representation style using the Web Ontology Language (OWL), Resource Description Framework (RDF), and RDF Schema (RDFS) syntax [3]. In addition, knowledge representation can be optimized by the ontology model, and the ontology reasoning engine can verify the stability of its logic and structure.

A digital activity recommendation system includes a data collection module, data processing and a recommendation generation or decision-making module. Data can be collected over time and analyzed using ML, DL, or rule-based algorithms to generate real-time feedback to achieve individual activity goals. The decision engine recommends changes to a person's behavior, daily routine, and activity schedule. The eCoach feature can show hope and motivation to improve physical activity using wearable activity sensors and digital activity trackers. Various mobile applications for activity monitoring and lifestyle guidance are available online; however, they are too generic and lack proper design guidelines. Furthermore, the existing literature lacks real-time data analysis to generate timely, personalized recommendations through eCoaching. An appropriate eCoach-based personalized referral program can help people stay active and achieve their activity goals. There can be two types of goal types - short-term goals (e.g., weekly) and/or long-term goals (e.g., monthly). Achievement of the short-term goals (STG) contributes to the achievement of the long-term goals (LTG), and the LTG is the sum of the STG. Semantic rules in the ontology may enhance understandability in personalized recommendation generation. Most activity trackers, involving mobile apps and intelligent wearable devices (e.g., smart watches), predict future activity in terms of "steps" as a point prediction either with time-series forecasting, probabilistic approaches, or specific rules. However, point prediction is a very abstract concept. Therefore, in this context, a probabilistic interval prediction approach may be promising.

This study proposes a hybrid personalized recommendation generation concept in intuitive coaching with deep learning and ontology. We have developed an eCoaching prototype system that can perform a collection of activity data from actual participants with wearable activity sensors; process collected activity data with DL models to forecast step count; classify individual activity levels; calculate and compare activity intensity across different weeks with statistical methods; combine the results in an ontology for semantic knowledge representation and thereby generate personalized recommendations with SPARQL query engine against a rule base. The novel major contributions of this work include – 1) the design and development of an ontology model (OntoeCoach) for semantic representation of personal and personalized activity data, 2) the proposal of a novel algorithm that combines the OntoeCoach model with deep learning for hybrid recommendation generation with a person based heuristic configuration, and 3) evaluation of the performance of time-series prediction, classification, and ontology models on both public (i.e., PMData) and private (i.e., MOX2-5 activity) datasets.

The rest of this paper is structured as follows. Section E describes related work and emphasizes the difference between the existing eCoaching concepts and our proposed work in a qualitative way. Section E presents a proposed hybrid recommendation generation approach. Section E provides the activity eCoach prototype system's design. Section E describes the adopted methods to run the experiment. experimental results are discussed in Section E. Section E discusses the principal findings and future scope. The paper is concluded in Section E.

Related Work

We considered the overall activity eCoaching process in related work by classifying it into a data-driven approach and a rule-based approach. As eCoach design approaches and applications in eHealth are broader, therefore, included search results are mainly focused on technology-driven activity coaching for a healthy lifestyle and personalized feedback or recommendation generation.

Data-Driven Approach

The literature search reveals that eCoach concepts with artificial intelligence (AI)-based tailored recommendation generation are still improving. Few studies have examined the use of actionable and data-driven predictive models [30]. Dijkhuis et al. [22] analyzed personalized physical activity guidance for sedentary lifestyles using AI (ML and DL) algorithms at Hanze University. They collected daily step count data to train an AI classifier, estimated the likelihood of reaching an hourly step count goal, and then used a web-based coaching app to generate feedback. Hansel et al. [23] designed and developed a fully automated web-based tutorial program. They used pedometer-based activity or step monitoring to increase their physical activity in a randomized group of patients with type 2 diabetes and abdominal obesity.

Pessemier et al. [24] used raw accelerometer data for individual activity detection, accepted personal preferences to schedule activity recommendations and generated personalized recommendations via tag-based and rule-based filtering. Amorim et al. [25] and Oliveira et al. [26] performed activity monitoring using a Fitbit Activity Sensor in a randomized study. They performed a statistical analysis to find the effectiveness of a multimodal physical activity intervention, including supervised exercise, fitness coaching, and activity monitoring of physical activity levels in patients with chronic nonspecific low back pain. Their research shows that physical activity is vital in managing chronic back pain. In the current study, several ML (e.g., SVM, DT, KNN, PCA, LDA) and DL (e.g., MLP, CNN, RNN, LSTM) models have been used to classify, predict and generate recommendations for health settings [30][22][23][24][25][26][31][32][33][34][35][36].

Table E.1: A comparison between our study and the related studies in a qualitative way.

Study	Hybrid recommendation	Semantic modeling with ontology and ontology tree in decision-making	Interval prediction	Observation with activity sensor	Incorporation of preference data	Logical recommendation generation
Our work	Yes	Yes	Yes	Yes	Yes	Yes
TB Dijkhuis et al.[22],	No	No	No	Yes	No	No
B Hansel et al. [23],	No	No	No	Yes	No	No
TD Pessemier et al. [24],	Yes	No	No	Yes	Yes	No
AB Amorim et al. [25],	No	No	No	Yes	No	No
CB Oliveira et al. [26],	No	No	No	Yes	No	No
D Petsani et al. [27],	No	No	No	No	No	No
NB Den et al. [28],	No	No	No	Yes	No	No
A Chatterjee et al. [3],	No	Yes	No	No	No	No
C Villalonga et al. [29]	No	Yes	No	No	No	No

Rule-based Approach

Rule-based recommendation generation has opened a new direction in eCoaching. Petsani et al. [27] designed and developed an eCoach system for older adults to improve their adherence to physical activity. They followed electronic coaching guidelines set by a human therapist/physician or a trusted person chosen by the user who had access to stored health and wellness data and included or intervened in the coaching process. They concluded that health eCoaching is a complex process that requires careful planning and collaboration across many scientific fields, including psychology, computer science, and medicine. Braber et al. [28] incorporated the eCoaching concepts into personalized diabetes management, where lifestyle data (e.g., food intake, physical activity, blood glucose values) were recorded and integrated into clinical rules to enable customized coaching for better lifestyle recommendations management. Chatterjee et al. [3] focused on the design and development of a meaningful, context-specific ontology ("UiAeHo") to capture unintuitive and raw insights from human-generated health data (e.g., sensors, interviews, questionnaires) using semantic models and unstructured observation metadata to create logical abstractions for rule-based health risk prediction in the eCoaching system. Villalonga et al. [29] designed an ontology-based automated reasoning model to generate personalized motivational messages for activity guidance, taking into account behavioral traits. Therefore, ontologies can be a practical choice for rule-based decision-making with powerful design flexibility within the object-oriented design paradigm.

In state-of-the-art research, the feasibility analysis of DL time-series classifiers and prediction models in physical activity detection is demonstrated to design an ML or DL pipeline. However, this study shows its application one step ahead by applying DL models, statistical methods, and OWL ontology in real-time activity guidance to improve sedentary lifestyles through goal management skills. In particular, this study has utilized the ML and DL concepts in the followings objectives of – 1) an MLP model to classify individual daily physical activity into multiple levels such as sedentary, low physically active (LPA), medium physically active (MPA), and vigorous physically active (VPA), 2) a CNN1D model for univariate "step" forecasting, 3) state-of-the-art statistical methods to calculate weekly activity intensity, 4) mapping the time-series point prediction to an interval prediction, and 5) the creation of an OWL ontology for semantic modeling of personal preferences, activity predictions, and the generation of personalized recommendations with SPARQL against a rule base.

To verify the above objectives, we use sensor data processed by Fitbit Versa and MOX2-5 wearable activity sensors instead of raw signal data (e.g., accelerometer, gyroscope) for personal activity prediction and classification. Moreover, to explain the study's relevance, we proposed an algorithm to annotate the activity prediction outcomes in an ontology for personalized recommendation generation. Semantic annotation can more easily identify causal relationships between data inputs and recommendation results. The above-mentioned study by Pessemier et al. focused on recommendation generation at the "Community" level whereas this work targets activity coaching and recommendation generation at the "Personal" level. To the best of our knowledge, no similar work has been published or made available online, therefore, instead of a quantitative evaluation,

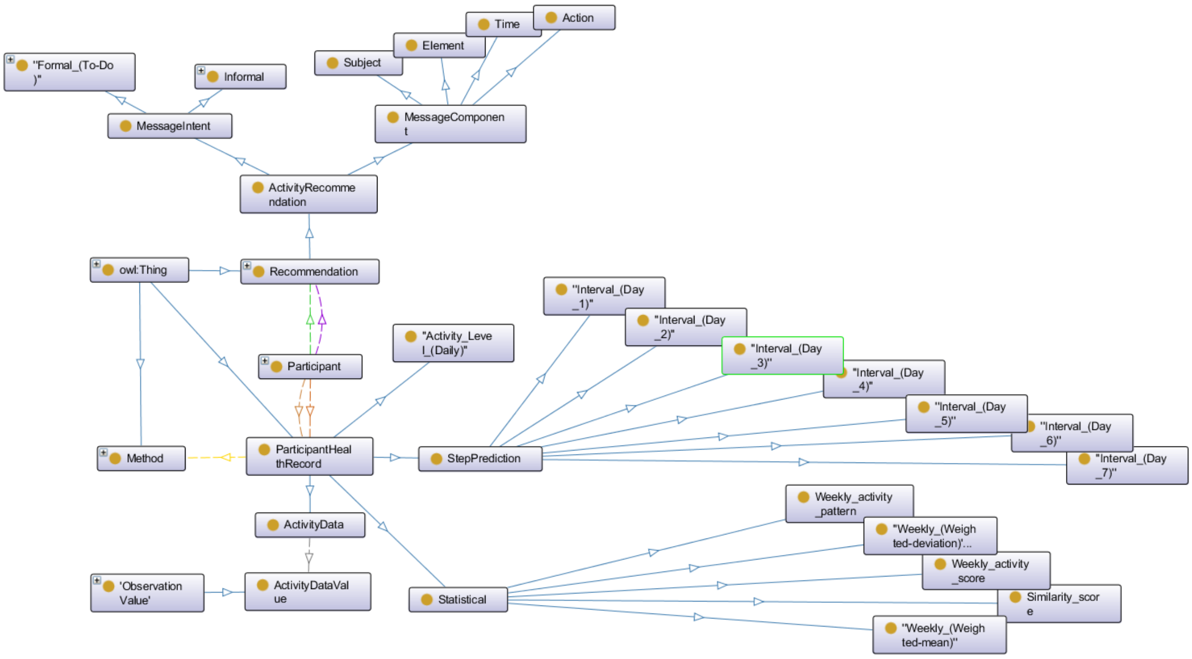


Figure E.1: The high-level structure of the proposed OntoeCoach Ontology.

a qualitative comparison between our study and the related activity coaching studies has been described in Table E.1.

Our present study is the extended version of our previous studies [36][37][38]. In Table E.2, we elaborated on the novelty of this study and how this study differs from our previous studies and added more value, with a qualitative comparison.

Proposed hybrid recommendation generation

In this section, we begin by defining and explaining the OntoeCoach ontology proposed in our research. We then delve into the problem formulation and algorithm. Finally, we conclude this section by presenting the derived time complexity of the proposed model.

Ontology modelling

The proposed OntoeCoach ontology follows the following knowledge representation phases – abstraction or dictionary (L) of mapping rules, abduction phase (B) of hypothesis generation rules, deduction (C), and induction of operator reduction rules for generalization (D). The generated recommendation spanning tree (T) follows a binary structure, and the syntactic knowledge representation of T helps to solve the understandability problem when generating personalized lifestyle recommendations.

Our proposed OntoeCoach ontology is a tree-like hierarchical structure (O_h) with the following properties. Formally, the ontology (O) may be represented as $\Omega = \{C, R\}$, where C is the concept set and R is a relation set. The total levels in an ontology hierarchy is represented by H = Levels (O_h), $0 \leq n \leq H$, where $n \in Z^+$, $n = 0$ and represents the root node. When a model is classifying (O) at a level n, can be denoted as $C_{n,i}$, where i

Table E.2: A comparison between our previous studies and this extended study.

Study	Study focus	Dataset used	Recommendation type	Method focus
A Chatterjee et al. [36]	Conceptualized the idea of weekly activity forecasting with statistical models and a rule-base for personalized rule-based recommendation generation in activity eCoaching.	PMData	Personalized	ARIMA, SARIMA, Kalman Filter, Rule-database
A Chatterjee et al. [37]	Conceptualized the idea of weekly activity forecasting and a rule-base for personalized recommendation generation with Ontology reasoning and querying in activity eCoaching.	PMData	Personalized	LSTM, Ontology
A Chatterjee et al. [38]	Semantic ontology model to annotate the machine learning (ML)-classification outcomes and personal preferences to conceptualize personalized recommendation generation with a hybrid approach in activity eCoaching with a focus on transfer learning approach to improve ML model training and its performance, and an incremental learning approach to handle daily growing data and fit them into the ML models (Support Vector, Naive Bayes, Decision Tree, K-Nearest Neighbour, Random Forest).	Zenodo Fitbit and MOX2-5	Personalized	Standard ML classification models, Ontology
Our work	Design and development of an extended ontology model for semantic representation of personal and personalized activity data, and algorithm development to include time-series forecasting, time-series physical activity level classification, and statistical metrics in the ontology model for hybrid recommendation generation with person-based heuristic configuration and the verification of the algorithm against different datasets with existing and derived metrics.	PMData and MOX2-5	Personalized	Deep learning models, Ontology, Probabilistic Interval Prediction, Statistical Metrics

$\in \{0, 1, ...|C_n|\}$. $|C|$ is number of instances classified as class C. The edge between node $C_{n,i}$ and its parent node $C_{(n-1,j)}$ is defined as E = Edge $(C_{n,i}, C_{(n-1,j)})$. We have re-used the concept and extended our ontology representation with the following four tuples:

$$O = \{O_a, R, I, P\} \tag{E.1}$$

Where O_a is defined as $O_a = \{O_{a1}, O_{a2}...O_{an}\}$, it represents "$n$" concepts or classes and each O_{ai} has a set of "j" attributes or properties $\forall$ $P_i = \{p1, p2...pi\}$ where n, i, j $\in Z^+$. We denote a set of binary relations between the elements of O_a by R. R holds two subsets H for the inheritance relationship among concepts and S for the semantic relationship between concepts with a domain and range. We represent a knowledge base with a set of object instances by I. P represents a set of axioms to model O and it includes domain-specific constraints to model an Ontology with O_a, R, and I. The knowledge (K) in the ontology has been expressed with two tuples, defined as:

$$O = \{Onto_{ActivityReco}, Rules_{ActivityReco}\} \tag{E.2}$$

The components of $Onto_{ActivityReco}$ and $Rules_{ActivityReco}$ are defined as:

$$Onto_{ActivityReco} = \{OA_L, OA_B, OA_C, OA_D\} \tag{E.3}$$

$$Rules_{ActivityReco} = \{RA_L, RA_B, RA_C, RA_D\} \tag{E.4}$$

Where OA_L, OA_B, OA_C, OA_D are the knowledge bases, consisting of lexicon, abduction, deduction, and induction phases for personalized physical activity recommendation. On the contrary, RA_L, RA_B, RA_C, RA_D are rule sets to match with the abstraction, abduction, deduction, and induction interfaces, respectively. OA_B, OA_C, OA_D are representations of properties P of concepts O_a, data or entities (e.g., activity variables), and they follow a simple representation of $P(X|Y)$ or $P(Y|X)$ based on the relational mapping, where, P is attributes or properties in O, and X, Y are components of activity variables.

Rule sets help to explain the logic behind recommendation generation. All rule execution internally follows a binary tree structure, where non-leaf nodes contain semantic rules to be executed (A | $A \rightarrow B$), and leaf nodes have results (B or recommended message). The edges contain decision statements (true or false). For interactively navigating the relationships of our OWL ontology, we implemented the high-level structure of OntoeCoach ontology (see Figure E.1) in OntoGraf using the Protege. The key object properties, domain, range, property, and cardinality of OntoeCoach ontology are described in Table E.3.

The OntoeCoach ontology is the extended version of our previous ontological studies as elaborated in [13][38] and annotates the subsequent data types for reasoning − sensor observation (e.g., activity sensor), personal information, and personal preference data, personalized recommendations, and participant health records (e.g., activity level, step prediction, statistical metrics) in the processed forms. The ontology metrics used in our OntoeCoach design are − a. Metrics (Axiom (n=965), Logical axiom count (n=327), Declaration axiom count (n=310), Class count (n=90), Object property count (n=81), Data property count (n=128) and Annotation property count (n=13)), b. Class axioms (SubClassOf (n=167), EquivalentClasses (n=12), Hidden GCI Count (n=12)), c. Object

Table E.3: Key object properties, domain, range, and cardinalities of the ontoeCoach ontology.

Object Properties	Domain	Range	Cardinality
hasPersonalHealthRecord	Participant	HealthRecord	Some
hasPersonalDataInfo	Participant	PersonalData	Some
hasPersonalPreferences	Participant	Preferences	Some
hasReceivedPersonal Recommendation	Participant	Recommendation	Some
hasHealthStatus	Participant	ParticipantStatus	Some
hasbeenCollectedBy	ActivityData	ActivityDataValue	Some
hasTimeStamp	ActivityDataValue, Questionnaire, Recommendation, ParticipantHealthRecord	TemporalEntity	Some
has Measurement Capability	ActivityDevice	Measurement Capability	Only
hasOutput	ActivityDevice	Sensor Output	Some
observes	ActivityDevice	Property	Only
detects	ActivityDevice	Stimulus	Only
feature of interest	Observation	Feature of Interest	Only
observation result	Observation	Sensor Output	Only
observedBy	Observation	Sensor	Only
is property of	Property	Feature of Interest	Some
hasProperty	Feature of Interest	Property	Some
hasIntervalDay	Participant	StepPrediction	Some
hasActivityLevel	Participant	Activity_Level_(Daily)	Some
hasStatValue	Participant	Statistical	Some

property axioms (SubObjectPropertyOf (n=30), InverseObjectProperties (n=8), ObjectPropertyDomain (n=8), ObjectPropertyRange (n=8), and SubPropertyChainOf (n=2)), d. Data property axioms (SubDataPropertyOf (n=9), DataPropertyDomain (n=25), and DataPropertyRange (n=25)), and Annotation axioms (AnnotationAssertion (n=328)). ”n” signifies counts ≥ 0.

Problem formulation

In this study, the recommendations are generated to maximize weekly individual physical activity levels and to minimize sedentary time. The maximization problem focuses on maintaining a moderate activity level for an entire week (i.e., $\sum$ Days $\in$ (1, 2...n) $\forall$ $n = 7$. We consider multiple expression for the activity maximization problem. We maximize the four parameters – 1) $\sum \text{Moderate}_{Activitytime} > 150$, 2) $\sum \text{GoalScore}_{daily} \geq 21$, 3) $0 \leq \sum \mu_S \leq 32$, and 4) $\text{SimilarityScore}_{weekly} \geq 0$.

These parameters are maximized subject to the multiple conditions such as – 1) $\text{Moderate}_{Activitytime} \geq 21.45$, 2) $\text{GoalScore}_{daily} \geq 3$, 3) $0 \leq \text{PerformanceScore}_{daily} \leq 32$, 4) $C_V \rightarrow P$, 5) $P \rightarrow R$, 6) $\sum P = 1$, and 7) ModerateActivitytime = 2 * VigorousActivitytime.

Table E.4: The "Activity Level" classification rules following the WHO guidelines.

Level (score)	**Rule(s)[a]**
Sedentary (0)	((step <5000) ∧ (VPA*2 + MPA) *7 <90 ∧ LPA ≥ 0)) ∨ (step <5000)
Low physical active (1)	((step >4999) ∧ (VPA*2 + MPA) *7 ≥ 90 ∧ (VPA*2 + MPA) *7 <210) ∨ (step >4999 ∧ step <7500)
Active (2)	((step >4999) ∧ (VPA*2 + MPA) *7 ≥ 210 ∧ (VPA*2 + MPA) *7 <300) ∨ (step >7499 ∧ step <10000)
Medium physical active (3)	((step >4999) ∧ (VPA*2 + MPA) *7 ≥ 300 ∧ (VPA*2 + MPA) *7 <360)) ∨ (step >9999 ∧ step <12500)
High physical active (4)	((step >4999) ∧ (VPA*2 + MPA) *7 ≥ 360) ∨ (step >12499)

*[a] $MPA = 2\,VPA$

Activity goals can be system-defined (i.e., generic goals defined by WHO) or user-defined, as athletes may have different goal plans than ordinary people. According to the World Health Organization, adults (ages: 18-64) should complete at least 150–300 minutes (2.5-5 hours) of moderate-intensity aerobic activity (MPA); or at least 75–150 minutes of vigorous aerobic activity (VPA) or equivalent moderate- and vigorous-intensity exercise to stay active. To calculate each week's individual goal achievement scores, we have added the daily activity scores (see Table E.4). In Table E.4, the right column represents the standard rules to determine the activity level on a daily basis. The left column represents the type of activity level and their numeric representation as a daily score value. Activity eCoach is designed to maximize target scores through continuous activity monitoring and personalized recommendation generation.

For validation, we used rule-based personalized activity recommendation generation and *SPARQL* queries to motivate eCoach participants to stay active by reducing their sedentary time. Ontologies annotate recommendation messages to describe their attributes, metadata, and content information outside the static text form. Recommendation messages can be both formal and informal. Additionally, the rule base helps explain the logic behind recommendation generation through logical *AND*, *OR*, and *NOT* operations.

In this work, the *SROIQ* description logic is used as the formal argument logic (see Table E.5). Table E.6 contains a defined set of recommended messages for OntoeCoach ontology validation based on the used dataset. For each condition described in table E.5, the *RG* module runs a *SPARQL* query to determine the type of referral message sent to the individual daily. This study grouped eight semantic rules into activity-level categories (9) and satisfiability categories (1). The integrated concepts and rules are easy to follow and apply. Custom recommendations are generated using the structure ((rule) IMPLIES (suggestion variable) → recommendation message). In Table E.5, the semantic rules have been created to define relationships and constraints between different entities or concepts within the activity eCoach knowledge representation system. These rules help capture the data's meaning and semantics and enable reasoning and inference capabilities. Here are the steps involved in defining the semantic rules – **a.** *Identify the Entities*: We identified the entities and concepts for which we want to define semantic rules. These entities represent objects, properties, and relationships in the physical activity domain. **b.** *Define the Relationships*: We specified the relationships between the entities, which includes identifying the type of relationship (e.g., "is-a," "part-of," "has-property") and the directionality of the relationship. **c.** *Define Constraints*: We determined constraints or conditions that need to be satisfied for the relationships to hold true. These constraints involve logical operations, comparisons, or other specific criteria. **d.** *Rule Representation Format*: We selected a suitable format or language to represent the semantic rules. Our common formats include formal languages, such as OWL (Web Ontology Language) or RDF (Resource Description Framework), and rule-based languages, such as SPARQL (SPARQL Protocol and RDF Query Language). **e.** *Expression of the Rules*: We expressed the semantic rules using the chosen representation format. This involves writing the rules based on the identified entities, relationships, and constraints. The syntax and semantics of the chosen format will guide the rule expression. **f.** *Validate and Test the Rules*: We validated the semantic rules to ensure their correctness and consistency. We planned to test the rules against sample data or scenarios to verify their behavior and evaluate their effectiveness. **g.** *Refine and Iterate*: We refined the rules based on feedback, domain expertise, or real-world use cases. We iterated the process of rule creation, testing, and refinement to improve the quality and accuracy of the semantic rules. Overall, the creation of semantic rules required a good understanding of the domain, the entities involved, and the desired semantics. Collaboration with domain experts and leveraging existing ontologies or knowledge bases had also been valuable in the rule-creation process.

Measurable parameters related to the activity of a particular participant in a timestamp are obtained at preference-based intervals based on SPARQL queries. Rules (1-9) in table E.5 assign Boolean values to variables, ensuring consistency. We have verified using Ontology Reasoner that the correct recommendation message is triggered for a particular situation. However, it is essential to ensure that no variable patterns would make the entire rule unsatisfactory. We've made sure that only one message is active at a time. Here we have a formal guarantee that neither two "once a day" messages can be active at the same time, nor can there be a model with a reasoner output each time for every possible combination of variables.

Table E.5: In context recommendation conditions and corresponding rules (Rule-base) for test set-up.

No.	Semantic Rule(s) (R) and Condition
1	(hasActivityLevel == 0) IMPLIES (Sedentary AND hasPhysicalActivityLevel) (hasActivityLevel == 1) IMPLIES (Low_physically_active AND hasPhysicalActivityLevel) (hasActivityLevel == 2) IMPLIES (Physically_active AND hasPhysicalActivityLevel) (hasActivityLevel == 3) IMPLIES (Moderate_physically_active AND hasPhysicalActivityLevel) (hasActivityLevel == 4) IMPLIES (Vigorous_physically_active AND hasPhysicalActivityLevel)
2	((hasSedentaryBouts – daily_sedentary_goal_time as set in goal) >0) IMPLIES (Sedentary_hour_negative) ((hasSedentaryBouts – daily_sedentary_goal_time as set in goal) <= 0) IMPLIES (Sedentary_hour_positive)
3	((hasSteps – daily_step_goal as set in goal) =>0) IMPLIES (Steps_positive) ((hasSteps – daily_step_goal as set in goal) <0) IMPLIES (Steps_negative)
4	((hasMPAMinutes – daily_MPA_goal as set in goal) OR (hasVPAMinutes*2 – daily_VPA_goal as set in goal) =>0) IMPLIES (Activity_minute_positive) ((hasMPAMinutes – daily_MPA_goal as set in goal) OR (hasVPAMinutes*2 – daily_VPA_goal as set in goal) <0) IMPLIES (Activity_minute_negative)
5	((hasWeeklyStepPrediction – weekly_step_goal as set in goal) =>0) IMPLIES (Step_forecast_trend_postive) (hasWeeklyStepPrediction – weekly_step_goal as set in goal <0) IMPLIES (Step_forecast_trend_negative)
6	((hasSteps – daily_step_goal as set in goal) =>0) AND ((hasMPAMinutes – daily_MPA_goal as set in goal) OR (hasVPAMinutes*2 – daily_VPA_goal as set in goal) =>0) AND (hasTotalSleepTime =>(daily_sleep_goal as set in goal *60)) AND ((hasSedentaryBouts – daily_sedentary_goal_time as set in goal) <= 0) IMPLIES (Daily_Goal_achieved)
7	(hasCurrentWeeklyDeviation >hasPreviousWeeklyDeviation) AND (hasSimilarityScore >0) IMPLIES (Weekly_performance_deviation_trend_negative)
8	(hasCurrentWeeklyDeviation <= hasPreviousWeeklyDeviation) AND (hasSimilarityScore == 0) IMPLIES (Weekly_performance_deviation_trend_positive)
9	((hasSteps – weekly_step_goal as set in goal) =>0) AND ((hasMPAMinutes – weekly_MPA_goal as set in goal) OR (hasVPAMinutes*2 – weekly_VPA_goal as set in goal) =>0) AND (hasTotalSleepTime =>(weekly_sleep_goal as set in goal *60)) AND ((hasSedentaryBouts – weekly_sedentary_goal_time as set in goal) <= 0) IMPLIES (Weekly_Goal_achieved)
10	(Sedentary + Low_physically_active + Moderate_physically_active + Vigorous_physically_active + Sedentary_hour_negative + Sedentary_hour_positive + Steps_negative + Steps_positive + Activity_minute_negative + Activity_minute_positive + Step_forecast_trend_postive + Step_forecast_trend_negative + Daily_Goal_achieved + Daily_Goal_not_achieved + Weekly_Goal_achieved + Weekly_Goal_not_achieved + Good_weather + Bad_weather + Weekly_performance_deviation_trend_positive + Weekly_performance_deviation_trend_negative = 1)

Table E.6: Propositional variables and corresponding recommendation messages.

Type	Propositional variable (P)	Description
A-1	Sedentary	Please continue a light activity (e.g., sports 1-3 days/week, a walking goal of 5,000 to 7,499 steps/day).
A-2	Low_physically_active	Please continue more activity (e.g., sports 3-5 days/week, a walking goal of 7,500 to 9,999 steps/ day) OR do a minimum 150–300 minutes (2.5 – 5.0 hours) of moderate-intensity aerobic exercise or minimum 75–150 minutes of high-intensity aerobic exercise or do an equivalent combination of moderate and high-intensity activities in a week to stay physically active.
A-3	Physically_active	Please continue the same or more activities based on your goal (e.g., sports 3-5 days/week, a walking goal of 7,500 to 9,000 steps/ day)
A-4	Moderate_physically_active	Please continue the same or more activities based on your goal (e.g., sports 3-5 days/week, a walking goal of 10,000 to 12,499 steps/ day).
A-5	Vigorous_physically_active	Please continue the same or more activities based on your goal (e.g., sports 5+ days/week, a walking goal of 12,500+ steps/day).
A-6	Sedentary_hour_negative	Please be active for z hr. more as today you were z hr. more sedentary beyond your goal.
A-7	Sedentary_hour_positive	You were very active today and z hr. less sedentary; therefore, you can take that hr. of rest tomorrow.
A-8	Steps_negative,	Please continue x steps more tomorrow to achieve your weekly goal of x1 steps.

Continued on next page

Table E.6 – continued from previous page

Type	Propositional variable (P)	Description
A-9	Steps_positive	You have performed extra x steps today beyond your goal; therefore, you can do x steps less tomorrow, or you can carry out the same pace. You are x1 step behind to achieve your weekly goal (OR) congratulations! You have achieved your weekly target.
A-10	Activity_minute_negative	Please continue more activity of n minutes tomorrow to achieve n1 mins. of a weekly goal.
A-11	Activity_minute_positive	You have performed extra m minutes of activity today beyond your goal; therefore, you can be m mins. of less highly active tomorrow or you can carry out the same pace. You are n1 mins. behind to achieve your weekly goal (OR) congratulations! You have achieved your weekly target.
A-12	Step_forecast_trend_postive	Based on your weekly step forecast trend in this Week-N you can achieve the step goal.
A-13	Step_forecast_trend_negative	Based on your weekly step forecast trend in this Week-N you cannot achieve the step goal. On Week-XX and Week-XY weeks, you were very active. Please try to follow similar activity patterns.
A-14	Daily_Goal_achieved	Good work. Please keep it up tomorrow. You are active and completed the goal for today. Overview: You have performed X steps today. You slept Y hrs. You were sedentary for Z hrs. You were M minutes medium active. You were N minutes highly active.

Continued on next page

Table E.6 – continued from previous page

Type	Propositional variable (P)	Description
A-15	Daily_Goal_not_achieved	You must improve to meet the daily goal. Please stay active tomorrow. Overview: You have performed X steps today. You slept Y hrs. You were sedentary for Z hrs. You were M minutes medium active. You were N minutes highly active.
A-16	Weekly_performance_deviation_trend_positive	Congratulations! You have maintained a good weekly activity pattern.
A-17	Weekly_performance_deviation_trend_negative	Your weekly activity pattern must be improved.
A-18	Weekly_Goal_achieved	Good work. Please keep it up next week. You are active and completed the goal for this week.
A-19	Weekly_Goal_not_achieved	You must improve to meet the weekly goal. Please stay active next week and try to overcome the shortcomings of this week. On Week-XX and Week-XY weeks, you were very active. Please try to follow similar activity patterns.

Let us consider a case, if we put the different variables used in the nine rules as described in Table E.5 to generate respective propositional variables (see Table E.6). In that case, we will have an exponential number of possible participants. A traditional way to ensure the presence of a model negates all our rules and provides the same. Therefore, this formula is not satisfactory. Since two messages cannot be triggered simultaneously, we added a rule (Rule-10) to meet the exact requirement, and the variables used in the suggestion start once a day. If (rule-10) is false, the entire rule set (considered significant conjunction) is set to false, then there is no model as output, and we can debug our rules if needed. When set to true, we have a formal guarantee that no two "once a day" messages will fire simultaneously, regardless of the true value we feed into the rule base. All rule execution internally follows a binary tree (BT) structure, where the non-leaf nodes contain the semantic rules to be executed ($A \mid A \rightarrow B$), and the leaf nodes have the results (B or recommendation message). Edges have decision statements (true or false). In this way, satisfiability and understandability (or explainability) issues are addressed in custom recommendation generation in our Activity eCoach system. The proposed personalized hybrid recommendation generation approach is described in Algorithm 1.

To assess the performance of Algorithm 1 more effectively, we consider its time complexity[39].

Algorithm 2 Hybrid recommendation generation with person-based heuristic configuration

Input: Individual daily activity data *D(t)*; Knowledge base set S ={*semantic rules, activity, variables*}; Recommendation message set R = {*proposition variables, message bodies*}; Preference set P = {*Goal setting, target goal, target activity score, mode of interaction, recommendation delivery time*}; Ontology model *ontologyO*; Duration of eCoaching *DeCo*;

Output: Personalized recommendation message set $L \subseteq R$

1. Days ← 0
2. **while** (Days < *DeCo*) **do**
3. *D(t-1)* ← load (previous day's individual daily activity data)
4. Pre-process *D(t-1)* and split it into set $XY = \{x_{train}, x_{test}, y_{train}, y_{test}\}$, Initialize list{L} = ϕ, $select_C$ ← predict configuration for the time-series classifier model *(C)* with set *XY*, $select_F$ ← predict best configuration for the time-series forecast model *(F)* with set *XY*. *ontologyO* ← Δ_1, Δ_2, Δ_3, Δ_4, Δ_5, Δ_6, Δ_7
5. $\Delta_1 = \sum_{k=1}^{n} \alpha$ {*D(t-1)*} where α is activity pattern vector for different weeks {k = 1...n}
6. $\Delta_2 = \sum_{k=1}^{n} \beta$ {*D(t-1)*} where β is activity score vector for different weeks {k = 1...n}
7. $\Delta_3 = \sum_{k=1}^{n} \gamma$ {*D(t-1)*} where γ is mean for different weeks {k = 1...n}
8. $\Delta_4 = \sum_{k=1}^{n} \delta$ {*D(t-1)*} where δ is standard deviation for different weeks {k = 1...n}
9. $\Delta_5 = \sum_{k=1}^{n} \theta$ {*D(t-1)*} where θ is activity similarity score for different weeks {k = 1...n}
10. $\Delta_6 = \sum_{k=1}^{n} \eta$ {*D(t-1)*} where η is daily activity level for different weeks {k = 1...n}
11. $\Delta_7 = \sum_{k=1}^{n} \zeta$ {*D(t-1)*} where ζ is step interval prediction for different weeks {k = 1...n}
12. result *(ontologyO)* ← execute SPARQL queries on *ontologyO*
13. *activity variables* ← result *(ontologyO)*
14. Formed *proposition variables* based on the results of *activity variables*
15. Update list{L}
16. Generate and deliver L based on P
17. Days ← Days + 1

This analysis helps to understand how the algorithm's effectiveness scales with increasing input size. The time complexity is typically expressed using big O notation, which provides the maximum growth rate of the algorithm's execution time. By analyzing time complexity, we can estimate the efficiency and scalability of the algorithm, compare the performance of different algorithms, and identify any design bottlenecks. In the case of our proposed algorithm, the time complexity is quadratic, denoted as $O(n^2)$, due to the presence of a nested loop. Here, "n" represents the input size, with a value greater than 0. This quadratic time complexity indicates that the running time of the algorithm grows quadratically with the input size.

Activity eCoach system overview

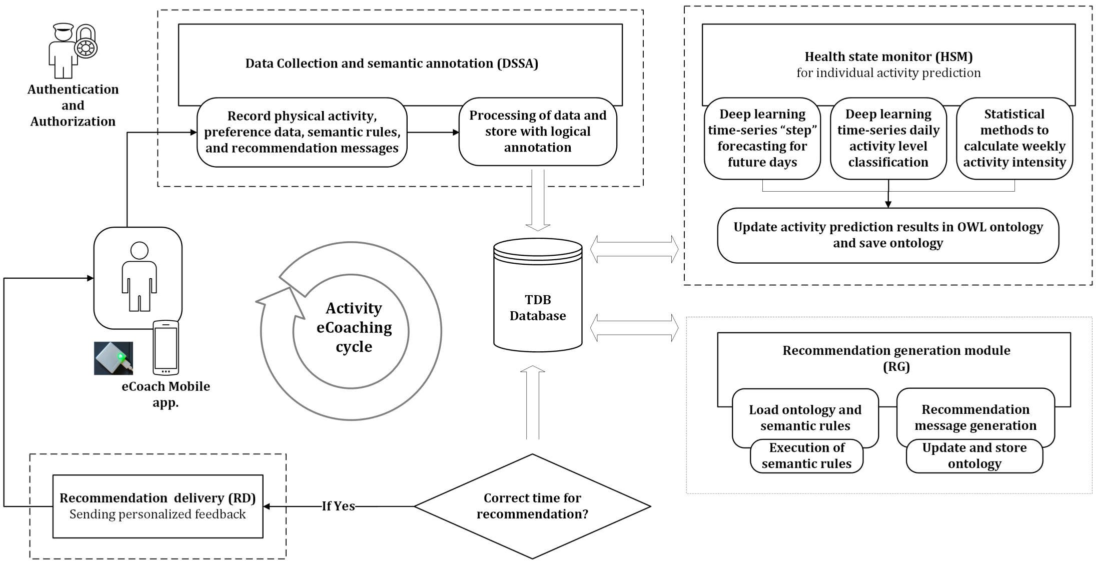


Figure E.2: The data flow in the Activity eCoach system includes all components and their connections. In this, TDB represents a tuple database.

This section describes a model for activity eCoaching. We followed an iterative and incremental approach to design and develop our Activity eCoach that follows a modular design with four primary modules – 1) data collection and semantic annotation (DSSA), 2) health state monitoring (HSM), 3) recommendation generation (RG), and 4) recommendation delivery (RD). The data flow in the activity eCoach prototype system is depicted in Figure E.2.

After collecting personal, person-generated activity and preference data, the DSSA module stores them in a tuple database (TDB) using semantic annotation. Moreover, the DSSA module records pre-defined rulesets and recommendation message set to be generated as a part of personalized recommendation generation and stores them in the database. The rules and recommendation messages can be updated based on the context. We plan to use a standard wearable CE-approved activity sensor (e.g., MOX2-5) for activity data collection. Furthermore, we prepared a set of questionnaires to collect personal preference data for recommendation planning. Personal preference data includes goal settings (such as daily, weekly, or monthly), target goals (such as moderately active or vigorously active), goal scores, interaction types, or recommendation delivery (such as text, audio, or graphics), and the recommended delivery time. Participants can review and update their preference information at any time.

The HSM module consists of the following three submodules – classification, forecasting, and statistical analysis (SA). The classification submodule classifies daily time-series activity data into the following activity levels: sedentary (0), LPA (1), MPA (2), and VPA (3) (see Table E.4). The prediction submodule is responsible for forecasting daily steps for the next 7-days based on the temporal pattern in individual step data. The SA submodule calculates the weighted mean, activity pattern, and similarity score between the weekly achieved activity score and weekly goal score to understand the weekly activity intensity. All the outcomes of the DP module are semantically annotated in OntoeCoach ontology and followed by stored in the TDB. Furthermore, we designed a pipeline to automate the process. An incremental approach helped to keep the DL models updated with real-time, growing activity data.

The RG module runs a scheduler periodically to query and process individual activity prediction results from the TDB database with a SPARQL query engine and a KB. In KB, all the semantic rules are stored for recommendation generation. Some suggestions should be made to the participants of the semantic data source if some specific variables are inferred to be true. Semantic rules consist of propositional variables using (IMPLIES), (OR), (AND), and (NOT) operations. RG modules trigger logical structure rules (A IMPLIES B) or in a logically identical way (NOT(A) or B). Following, individual recommendation data are updated in the OntoeCoach ontology against a timestamp and stored in the TDB. The RD module periodically accesses TDB for personal preference data and generates individual recommendation data to send personalized feedback based on personal preferences. Additionally, it meaningfully displays a reflection of ongoing activity through continuous and discrete personal health data, notifications, and recommended messages.

All the modules follow a microservice architecture. The exposed eCoach interfaces are protected with multifactor authentication and authorization (OAuth2) to allow legitimate users only [40][41][42]. The DC, RG, and RD modules are written in Java (JDK 11+) programming language with SpringBoot Framework. The HSM module is written in Python (V. 3.8.x) programming language with Flask Framework, and Python DL libraries, such as sktime, and Keras. Open-source Apache libraries (such as Jena, Jena Fuseki, and Tomcat 9.x) have been used for ontology implementation and eCoach service deployment.

Materials and methods

This section describes materials and methods that are utilized to run the overall experiment.

Experimental Setup

We used Python 3.8.5-supported language libraries such as pandas (v. 1.1.3), NumPy (v. 1.21.2), SciPy (v. 1.5.2), Matplotlib (v. 3.3.2), Seaborn (v. 0.11.0), Plotly (v. 5.2.1), scikit-learn or sklearn (v. 0.24.2), Keras (v. 2.6.0), and Graph Viz (v. 2.49.1) to process data, build and train deep learning models. We set up a Python environment on a Windows 10 operating system using the Anaconda distribution and installed Jupyter Notebook v. 6.4.5 for development, model analysis, and data visualization. The target system consists of 16 GB RAM and 64-bit architecture. Due to the small size of the dataset, we used the CPU to run the experiments.

Data Collection

We followed ethical guidelines during the collection, processing, and representation of personal and personalized activity data in our activity eCoach prototype system. We focused collection of activity data only for adults (aged: 18-64). The bodybuilders, pregnant women, and persons with severe medical history and chronic illness were excluded from the study. This work includes the following two datasets.

PMData Public Datasets

We used the anonymized PMData public physical activity dataset of *n=15* adult *(male: 12; female: 3)* for model training and testing. The activity dataset was collected from a Fitbit Versa 2 fitness smartwatch to PMSys sports logging smartphone application [43]. We received nearly 114–152 days of recordings from each participant, for a total volume of 2244 recordings. This dataset shows several features related to physical activity, e.g., VPA). However, we chose the “steps” metadata file and excluded sleep-related features since sleep tracking is out of scope. We excluded activity data for participant P_12 from the analysis due to a lack of LPA information.

MOX2-5 Real-Time Datasets

We collected 30–45 days of physical activity data from *n=16* adults *(male: 12; female: 4)* in Grimstad, Norway anonymously, using the wearable activity sensor MOX2-5 (CE certified) [44]. We followed Norwegian ethical guidelines to collect real-time activity data from actual participants with signed consent forms. It produced 539 volume records. With the permission of the Norwegian Study Data Center (NSD), we have collected and evaluated the personal data of the participants in this study following data protection law. The participant’s characteristics are recorded in Table E.7. The features of the MOX2-5 datasets are described in Table E.8.

Feature Selection

Activity data shows steps per minute. Therefore, we turned it into a daily step count for daily step count prediction. We used the Augmented Dicky-Fuller (ADF) hypothesis test [45] with Autolog = “AIC” and Regression = “CT/C” to verify the stationarity of the

Table E.7: Participant characteristics (N=16).

Factors	Mean (μ)	SD (σ)	Min	Max	P_{25}	P_{50}	P_{75}
Age	35.375	±7.03	21	51	30.8	35.5	39.0
Height (cm)	173.5	±8.02	158.5	184.0	167.6	173.3	180.5
Weight (Kg.)	77.0	±16.36	55.0	107.0	65.0	72.0	90.5
BMI	25.38	±3.93	19.41	31.604	22.0	25.8	27.9
Duration (days)	33.6875	±5.41	30	48	30.6	31.0	34.3
Total sedentary seconds	2449171	±1051610.5	590028	4261190	-	-	-
Total VPA seconds	41887.81	±60688.5	112	256896	-	-	-
Total MPA seconds	53231.75	±17965	23402	95730	-	-	-
Total LPA seconds	154647.1	±66540.6	32272	254332	-	-	-
Total steps	366703.3	±87202.25	52551	588132	-	-	-

Table E.8: Attributes of the MOX2-5 datasets.

Attributes	Type	Description
Date	string	Recorded activity date
Time	string	Recorded activity time
Upload Status	character	Indicates uploading status: ‘H’ and ‘L’
IMA	integer	Total activity intensity
Weight-bearing	integer	Total weight-bearing seconds
Sedentary	integer	Total sedentary seconds
Standing	integer	Total standing seconds
LPA	integer	Total low physical activities seconds
MPA	integer	Total moderate physical activities seconds
VPA	integer	Total vigorous physical activities seconds
Steps	integer	Total daily step count

time series data. We used seasonal decomposition to analyze the data’s trend, seasonal and residual components. We transformed non-stationary data into stationary using the differential transformation method. It helped to remove trends and seasonality in time series data. We observed the lag values (X-axis) and correlations (Y-axis) using the 2D autocorrelation (ACF) plots and partial autocorrelation (PCF) with finite lag values (e.g., 25, 50) to plot observations. ACF and PCF have been useful for parameter selection in time series forecasting models. Additionally, we used the forward and backward filling methods to handle missing data.

The relevant features obtained from the MOX2-5 sensor are − time stamp, the intensity of activity (IMA), seconds sitting, seconds bearing weight, seconds standing, seconds LPA, seconds MPA, seconds VPA, and steps per minute. “Step” and “IMA” are the most valuable and robust features of the sensor-based MOX2-5 dataset since other attributes (except timestamp) are almost derived (e.g., LPA, MPA, and VPA are defined as IMA derivative of E.9).IMA has a strong relationship with step count and is primarily

Table E.9: Relation between activity intensity (IMA) AND activity classification.

Activity type	Rule
LPA	$0 \leq$ Activity Intensity (IMA) ≤ 400
MPA	$401 \leq$ Activity Intensity (IMA) ≤ 800
VPA	Activity Intensity (IMA) ≥ 801

used as a measure of activity. For MOX2-5 sensors, sedentary time is the period without physical activity, including leisure and sleep. The relationship between sitting and active (LPA/MPA/VPA) time can be written as Σ(sitting, active, weight-bearing, standing) = 60 seconds. Activity intensity values can be correlated to energy expenditure expressed in metabolic values (METs). It allows the following classification − LPA: 1.5 to 3.0 METS, MPA: 3.0 to 6.0 METS, and VPA: 6.0 or more METS.

Shapiro–Wilk normality test method [2] uncovered that the individual data sample and their columns did not look like a Gaussian distribution. Normality testing is a hypothesis testing method using P-value $> \alpha = 0.05$ (i.e., the sample looks like a Gaussian distribution) and P-value $< \alpha = 0.05$ (i.e., the sample does not look Gaussian) [2]. The α indicates the confidence interval. For feature selection, we used Spearman's correlation analysis, which reveals the strength of the linear relationship between features according to the value of the correlation coefficient (r) [2]. We removed functions that strongly depend on the value $|r| > 0.72$. SelectKBest using chi-square, ExtraTreesClassifier, and Principal Component Analysis (PCA) facilitates feature ranking and feature selection in two datasets [4][46][47]. PCA uses the variance ratio of the eigenvalues of the eigenvectors to the total eigenvalues. The selected temporal activity data are continuous for both datasets. We have eliminated participant data that is less than a month old, redundant, noisy, incomplete, or missing. For prediction, we considered univariate daily steps from two datasets.

Data Labelling for Classification

The activity level characteristics represent the following five categories | Sedentary (0), Low Physical Active (1), Active (2), Moderately Physical Active (3), and High Physical Active (4). Activity level feature class creation rules are defined in the Table E.4, where we derived the feature class based on the sedentary, LPA, MPA, and VPA following activity references for adults [5][8][48][49]. Features, such as age, gender, and weight are not in the scope of this study. The class distributions for both datasets are depicted in Figure E.3.

Deep Learning Time-Series Classifier

The architecture of the time-series classifier we developed is inspired by standard, well-known MLP architectures based on the fully connected neural network (FCNN) style. Since our dataset is small, we employed a decent number of neurons in each layer based on common heuristics (e.g., validation loss, hidden units are a fraction of the input). The entire sequential structure of the model we developed consists of six fully connected dense

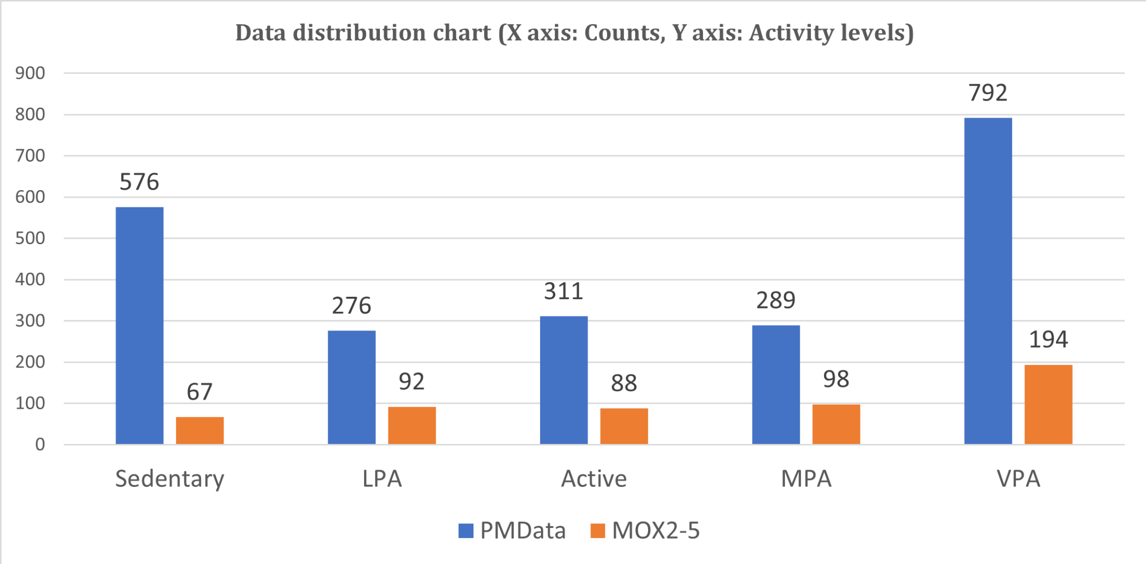


Figure E.3: The comparison of the distribution of classes for the public PMData and the private MOX2-5 datasets.

layers, an input layer $\in R^{32}$, followed by a hidden layer $\in R^{32}$, then, three hidden layers $\in R^{16}$ followed by an output layer $\in R^{5}$. The input dimension of the input layer is five. Due to the limited number of functions and data, regularization and dropout layers are not used. We checked; however, L1 and L2 regularizers could not help much to improve the model performance.

For the first five layers, we chose the rectified linear unit (ReLU) activation function over other linear and nonlinear functions because ReLU does not have the zero gradient problem and generally leads to faster convergence [50]. We used the SoftMax activation function in the last layer to classify the data according to the probability distribution.

We used the categorical_crossentropy loss function in model compilation because we one-hot encoded the predictor class variables. Also, we used the ADAM optimizer because it is computationally efficient and consumes less memory. The ADAM configuration parameters are α (the learning rate), β_1 (the exponential decay rate of the first moment guess), β_2 (the exponential decay rate of the second moment guess), and ϵ (very Small numbers to prevent division by zero). In Keras, the default ADAM configuration is α=0.001, β_1=0.9, β_2=0.999, ϵ=1e-08 and Decay=0.0, and this experiment also uses the same configuration. We used validation split = 0.05, verbose = 0, and the callback of ReduceLROnPlateau to reduce the learning rate and improve the model's performance. We recorded loss histories to compare training and test losses over multiple epochs.

Deep Learning Univariate Time-Series Forecasting

CNNs are primarily designed and developed to process two-dimensional (2D) image data. However, CNNs can automatically extract and learn features from one-dimensional sequence data, such as patterns in univariate time-series data. The traditional, well-known CNN architecture inspired the univariate predictive model we developed. Since our dataset is small, we kept a reasonable number of neurons in each layer based on common heuristics (e.g., validation loss, hidden units are a fraction of the input). The model's overall structure consists of the following five layers—two CNN1D layers, one MaxPooling1D layer, one flattening layer, and one dense seed layer. A Conv1D layer consists of 3D input and output tensors of shape (Batch, Steps, Channel) and (Batch, new_{steps}, Filter), respectively. The output shape changes depending on padding or stride selection. The batch dimension is the number of samples in the dataset, which is called "None" because it is not fixed. We performed linear convolution operation using Keras Conv1D plane with input parameters filter $kernel_{size}$ and padding.

Due to the limited number of functions and data, the dropout layer is not used. MaxPooling1D blocks sample input data, parameters, and computed convolutions needed to control overfitting. The flattened layer takes compressed input from a MaxPooling1D block and converts the data into 1D linear vectors for input to the following dense layer. We used the standard MaxPooling1D parameter defined in the Keras library [51]. We kept the kernel size of the CNN1D layer as 3. We used a sequential model with two CNN1D layers, a MaxPooling1D layer, and a flattened and dense output layer with an output size of 1. We chose the ReLU activation function for the first two CNN1D slices to avoid vanishing gradients and achieve faster convergence.

We used public PMData and private MOX2-5 datasets for model training, testing, and cross-validation. Before training, we processed our active dataset with MinMaxScaler (μ = 0 and σ = 1) with features ranging between 0 and 1. We then calculated a timestep value as the difference between the training set's length and the training data's size. The time steps are valued as n_steps, n_features = 1. The input form of the initial CNN layer consists of the following two input parameters: n_steps and n_features.

We used the mean squared error (MSE) loss function to compile our CNN1D model because we performed one-hot encoding on the predictor class variables. Also, we used the ADAM optimization function because it is computationally efficient and consumes less memory. Adam optimization is a stochastic gradient descent method based on adaptive first and second-moment estimation. We used the standard ADAM configuration parameters available in Keras. We used validation split = 0.05, verbose = 0, and the callback of ReduceLROnPlateau to reduce the learning rate (α) and improve the model's performance.

We compared our developed CNN1D model with other baseline predictive models such as autoregressive (AR), LSTM, and GRU. We evaluated each model for 200 epochs with a stack size of 50. We used 100 neurons for the LSTM and GRU base models, the ADAM optimizer, and the MSE loss function for model compilation. The AR time series base model was improvised with residual error minimization (REM) to verify how our model solves the traditional REM problem in time series step data. We created a lag value of 50 for the PMData dataset and 14 for the MOX2-5 dataset. We consider two datasets with AR window lengths 5.

Interval Prediction over Point Prediction

In predictive inference, a prediction interval estimates a gap in which future observations will have some probability of falling, assuming what has already been observed [52][53].

Prediction intervals are often used in prediction analysis. In this study, we used the concept of step forecasting. The prediction interval, which gives the gap to maintain a specific probability value, can be written as −

$$\widehat{Y}_{T+h} \pm c\sigma_h \tag{E.5}$$

c changes with coverage probability. In 1-step interval prediction, $c$is 1.28 (80% prediction intervals where forecast error values are normally distributed). σ_h estimates the residual standard deviation in the h-step forecast distribution ($h > 0$). Residual standard deviation (RSD) statistically describes the difference between the standard deviation of observed values and the standard deviations of estimated values. We used a well-accepted Naïve forecast method to statistically derive "σ_h" under the assumption of uncorrelated residuals.

Ontology Processing

In Figure E.2, the TDB database acts as a KB. All the messages as described in Table E.6 are stored in the KB. The RG module in Figure E.2 is used to access these messages during tailored recommendation generation based on SPARQL query execution, followed by implementing the rules in Table E.5. The rules are also stored in the KB. The asserted and inferred knowledge obtained from the reasoning method helped determine the most suitable recommendation message. Ontology models are associated with a document manager, OntDocumentManager to assist in processing ontology documents. All classes that represent the value of the ontology in the ontology API have OntResource as a general superclass. We have implemented the RDF interface provided by Apache Jena to persist the designed and developed OntoeCoach ontology and its instances in the TDB and load them back for further processing. Jena Fuseki is tightly integrated with TDB to provide a robust transactional persistent storage layer. The reasoning time of the OntoeCoach ontology is measured against the following reasoners available in the Protégé: HermiT, KAON2, Pellet, RacerPro, and Fact++.

Performance Evaluation

We utilized multiple state-of-the-art metrics to evaluate and compare the performance of the classifier, forecasting, and OntoeCoach models.

Classification

The performance of DL-based multi-class classification models was evaluated against discrimination analysis. Multiple metrics such as classification report, confusion matrix, precision, recall, specificity, accuracy score, and F1 score were estimated [2]. A confusion matrix is a 2-D table (*actual* versus *predicted*) and both dimensions have four options, namely, *true positives (TP)*, *false positives (FP)*, *true negatives (TN)*, and *false negatives (FN)*. TP is an outcome where the model estimates the positive class accurately; TN is an outcome in which the model correctly predicts the negative class; FP is an outcome where the model estimates the positive class inaccurately; and FN is an outcome in which the model predicts the negative class incorrectly. The corresponding equations are −

$$Precision = \frac{TP}{TP + FP} \tag{E.6}$$

$$Recall = Sensistivity = \frac{TP}{TP + FN} \tag{E.7}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{E.8}$$

$$F1\text{-}score = \frac{2 \times Recall \times Precision}{Recall + Precision} \tag{E.9}$$

A higher value from the above expressions represents a better performance of a model, and this applies to all performance metrics. On the other hand, *bias* is an error due to erroneous assumptions in the learning algorithm, and *variance* is an error from sensitivity to small fluctuations in the training set. While high bias leads to under-fitting, high variance results in overfitting. *Accuracy* and *F1-scores* can be misleading because they do not fully account for the sizes of the four categories of the confusion matrix in the final score calculation. In comparison, the *MCC* is more informative than the *F1-score* and *Accuracy* because it considers the balanced ratios of the four confusion matrix categories (i.e., *TP, TN, FP*, and *FN*). The *F1-score* depends on which class is defined as a positive class. However, *MCC* does not depend on which class is the positive class, and it has an advantage over the *F1-score* as it avoids incorrectly defining the positive class [53]. The *MCC* is expressed as follows [38].

$$MCC = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{E.10}$$

Forecasting

The performance of each time-series forecasting model was evaluated with root mean squared error (RMSE). MSE informs how close the regression line is to a set of points. It calculates "errors" from the points to the regression line and squares them to eliminate negative signs. The squared root of MSE gives more weight to a significant difference with no bias [45]. The RMSE can be expressed as (y_i represents the predicted value and x_i represents the expected value) −

$$RMSE = \sqrt{(\frac{1}{n})\sum_{i=1}^{n}(y_i - x_i)^2} \tag{E.11}$$

Additionally, we have used other metrics such as Forecast Bias (FB), RSD, and model execution time in seconds (sec.). FB can be positive or negative. A nonzero mean forecast error value indicates the tendency of the model to overpredict (negative error) or underpredict (positive error). Therefore, the average forecast error is also called FB. If Forecast Error = 0, the forecast has no errors or perfect predictive power. Overpredict if forecast variance < 0, the model is unbiased if forecast variance ≈ 0 [45].

Statistical

We developed new four statistical metrics beyond the existing ones. 1) activity pattern vector (APV) – a weekly activity pattern vector of length 7 that contains an activity level score for a given week. Thus, it can also be termed as an activity level vector (ALV), 2) similarity score (SC) – a weekly similarity score is a difference between the summation of the weekly activity pattern vector and weekly goal vector. If SC ≥ 0, then it signifies that the participant has achieved a weekly goal, 3) weighted mean (μ_S) – standard mean calculation with weighted mean calculation to determine personal activity intensity on a weekly basis and thereby use the information in activity recommendations (e.g., based on the progress, the activity on Week-2 will likely match the action performed; however, your activity was very good on Week-3). We calculated a weighted mean on an individual weekly activity dataset to calculate weekly activity progression with a defined non-negative weight point set: $\{0, 2, 4, 6, 8\}$ that represents sedentary, low active, active, medium active, high active, 4) standard deviation (σ) – weighted mean values to calculate deviations in weekly activity intensities.

We evaluate these statistical metrics using the following steps. *Step 1* – load individual activity datasets for the last few weeks, *Step 2* – calculate the weekly mean of the following activity features F: Sedentary time, LPA, MPA, VPA, Steps, *Step 3* – calculate weekly activity level score based on the activity level classification results, APV, *Step 4* – SC = Σ APV (W_i) - Σ GoalScore (W_i), where W_i signifies a week, *Step 5* – calculate performance score against APV with the following rule: Performance Score (S) = Σ activity level on day-n * activity weight point ($point_i$), *Step 6* – μ_S = Calculate the mean of S on weekly basis (= S/7), *Step 7* – predict or calculate activity intensity of the corresponding week based on µ score and prepare a weightedMeanList, and *Step 8* – calculate deviation in between weekly activities and prepare a deviationList.

Ontology

Our proposed ontology model was evaluated against the following two matrices, reasoning time and query execution time. Protégé provides a list of reasoners, such as HermiT, Fact++, Pellet, KAON2, and RacerPro, to check the logical and structural consistencies. We compared mean reasoning time and selected the best reasoner for our ontology. Besides, we captured the SPARQL query execution time in Protégé. We loaded the ontology file in "TTL" format into the Jena Fuseki server for cross-verification in SPARQL query execution time. We used the Apache Jena Framework to query each ontology class, predicate, subject, and object.

Ethical approval and consent to participate

In this project, for handling personal health and wellness data, we received approval from the Norwegian Centre for Research Data (NSD) (797208) and we obtained ethical approval from the Regional Committees for Medical and Health Research Ethics (REK) (53224). For this study, participation has been voluntary, and informed or signed consent has been obtained from all the participants. Moreover, we have not disclosed any identifiable data of the participants using numbers, text, or figures.

Results

We performed the entire experiment on PMData and MOX2-5 datasets for verification. The volume of the PMData dataset was more than the MOX2-5 datasets.

Correlation Analysis and Feature Ranking

The correlation matrix of the features selected from the PMData and MOX2-5 datasets are depicted in Figure E.4 and Figure E.5, respectively. The resultant $|r|$ value helps to understand the strong association between the features, followed by preparing the final feature set to run the entire experiment. We found that the duration_score, deep_sleep_in_minutes, resting_heart_rate, and sleep_duration features produced a very high correlation in the PMData dataset. Whereas IMA, standing, and Weight-bearing features produced a very high correlation in the MOX2-5 dataset.

Moreover, we prepared the final feature set for daily activity level classification, with the most relevant features, such as Steps, sedentary, LPA, VPA, and MPA, based on the adopted feature analysis methods, such as SelectKBest, PCA, and ExtraTreeClassifier. The selected features are presented in Table E.10 for both datasets based on their ranks. Table E.10 reveals that in both the datasets, the "Step" feature has achieved the highest rank against the used methods.

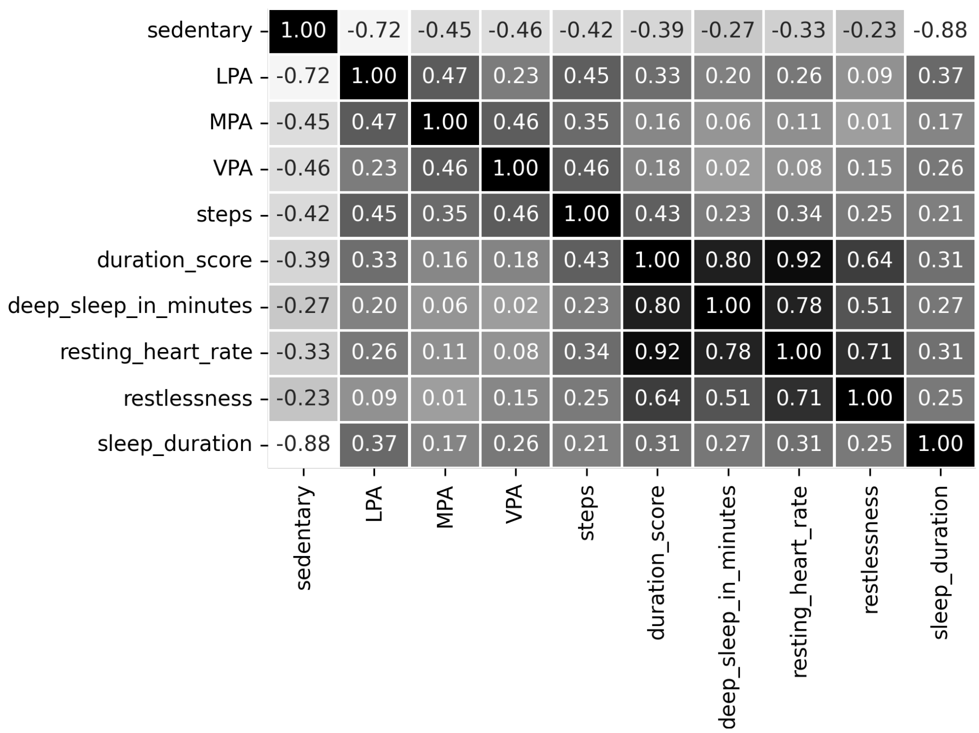


Figure E.4: The feature correlation in the PMData datasets.

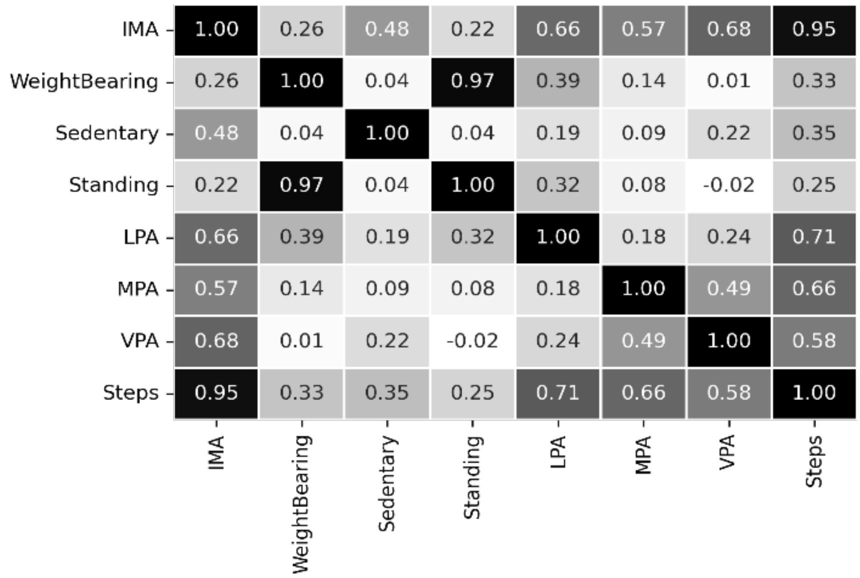


Figure E.5: The feature correlation in the MOX2-5 datasets.

Table E.10: The feature ranking in datasets against different methods.

Method	Datasets and rankings
SelectKBest	PMData: steps, sedentary, LPA, VPA, MPA and MOX2-5: steps, sedentary, LPA, VPA, MPA
PCA	PMData: steps, VPA, MPA, LPA, sedentary and MOX2-5: steps, VPA, MPA, LPA, sedentary
ExtraTreesClassifier	PMData: steps, VPA, sedentary, LPA, MPA and MOX2-5: steps, LPA, MPA, VPA, sedentary

Classification Performance

The performance of our developed time-series classifier and other state-of-the-art time-series classifiers, such as Rocket, MiniRocket, and MiniRocketVoting, was evaluated for both PMData (see Table E.11 and MOX2-5 (see Table E.12) datasets. The proposed MLP classifier model has outperformed other baseline state-of-the-art classifiers for both PMData and MOX2-5 datasets with an accuracy score of 97.0% (precision=97.0%, recall=97.0%, F1-score=97.0%), and 74% (precision=71.0%, recall=72.5%, F1-score=71.0%), respectively. The MLP model has produced the best performance on selected features in the low-volume activity datasets.

We compute the model loss for both datasets. The loss value indicates how well the model performed after each optimization iteration. It is a value representing the sum of the errors in our developed MLP classifier model. Loss measures how well (or poorly) our model performs. The “Model Loss” with categorical entropy to compare training and test sets over epochs for both the datasets have been depicted in Figure E.6 together with the confusion matrices in Figure E.7 to describe the weighted average precision, recall, and accuracy score for both datasets against our developed MLP classifier.

Results in Figure E.6 and Figure E.7 show that MLP model loss in training and testing

Table E.11: Classification results on PMData datasets.

Models	Precision	Recall	F1-score	Accuracy	MCC
Our MLP model	97.0%	97.0%	97.0%	97.0%	94.0%
Rocket	51.0%	56.0%	52.0%	56.0%	54.0%
MiniRocket	66.0%	52.0%	58.2%	58.2%	54.2%
MiniRocketVoting	45.0%	52.0%	48.5%	49.0%	46.0%

Table E.12: Classification results on MOX2-5 datasets.

Models	Precision	Recall	F1-score	Accuracy	MCC
Our MLP model	74.0%	71.0%	72.5%	71.0%	69.0%
Rocket	56.0%	42.0%	48.0%	48.0%	45.0%
MiniRocket	58.0%	45.0%	50.2%	51.0%	49.0%
MiniRocketVoting	39.0%	44.0%	41.3%	42.0%	41.0%

data converges for both datasets without showing any abruption or divergence. The confusion matrices provide insight not only into the incorrect classifications of developed MLP classifiers but also into the types of mistakes made. According to the confusion matrices, the performance of the MLP classifier increases with more training data. Therefore, misclassification rates are less in PMData datasets as compared to MOX2-5 datasets. Similar precision and recall scores signify that FP = FN, and their similarity with accuracy tells that our developed MLP model is balanced. However, this may vary from cases and datasets. DL models improve their learning with an increased volume of data. The evidence has been captured in Table E.11 and Table E.12. The proposed MLP classifier has outclassed its nearest best-performing MiniRocket classifier with ≈ 46% and 27.5% accuracy improvement for PMData and MOX2-5 datasets, respectively.

Table E.13: Mean step forecasting results on PMDATA datasets.

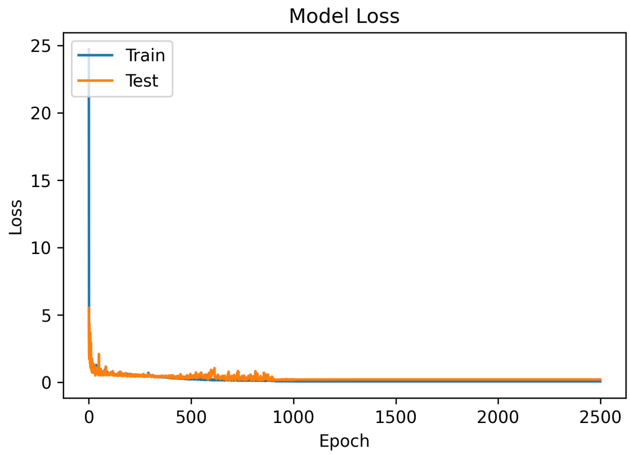
Models	RMSE	| FB |	RSD	ET (sec.)
Our CNN1D	1520.9	222.54	1534.0	88.0
AR with REM	5936.5	223.4	1475.6	144.0
Vanilla LSTM	4537.3	234.0	4574.7	149.2
Stacked LSTM	4541.7	244.0	4580.4	232.6
Bidirectional LSTM	4369.7	369.0	4411.0	211.8
Vanilla GRU	4488.3	223.5	4526.6	146.8
Stacked GRU	4518.6	125.0	4515.0	234.2
Bidirectional GRU	4367.4	224.6	4434.3	219.3

Table E.14: Mean step forecasting results on MOX2-5 datasets.

Models	RMSE	| FB |	RSD	ET (sec.)
Our CNN1D	1742.7	246.3	1796.3	88.0
AR with REM	3753.1	150.0	3956.4	143.0
Vanilla LSTM	3831.5	128.4	3951.0	157.3
Stacked LSTM	3788.7	111.0	3907.2	199.3
Bidirectional LSTM	3687.9	138.0	3801.7	192.0
Vanilla GRU	3930.9	104.8	4052.9	152.0
Stacked GRU	3877.1	185.3	4007.1	205.5
Bidirectional GRU	3703.9	117.5	3819.4	209.3

Table E.15: Statistical analysis of last four weeks' activity data for P-1 in MOX2-5 data.

Week(s)	Mean sedentary time (sec)	Mean LPA time (sec)	Mean MPA time (sec)	Mean VPA time (sec)	Mean steps	APV	Goal Score (GS)	SC = (ΣAPV - ΣGS)	Accumulated score (AC) = Σ (APV * P)	Mean weekly activity score (S)	Weekly ($\|SD\|$) of activity performance
Week-1	2146.0	5935.0	1239.0	55.0	11706	[3,3,3,4,4,2,4]	[3,3,3,3,3,3,3]	+2	Σ [18,18,18,32,32,8,32] = 158	22.5	0.0 (margin of error: ± 0.0)
Week-2	81838.0	3799.0	1008.0	164.0	8861	[4,4,4,2,0,0,0]	[3,3,3,3,3,3,3]	-7	Σ [32,32,32,8,0,0,0] = 104	14.9	3.8 (margin of error: ± 2.7)
Week-3	91305.0	2551.0	316.0	0.0	4649	[0,0,0,0,0,1,0]	[3,3,3,3,3,3,3]	-20	Σ [0,0,0,0,0,2,0] = 2	0.3	9.2 (margin of error: ± 5.3)
Week-4	940.0	3240.0	682.0	383.0	7256	[1,1,3,2,1,1,1]	[3,3,3,3,3,3,3]	-11	Σ [2,2,18,8,2,2,2] = 36	5.1	8.6 (margin of error: ± 4.3)



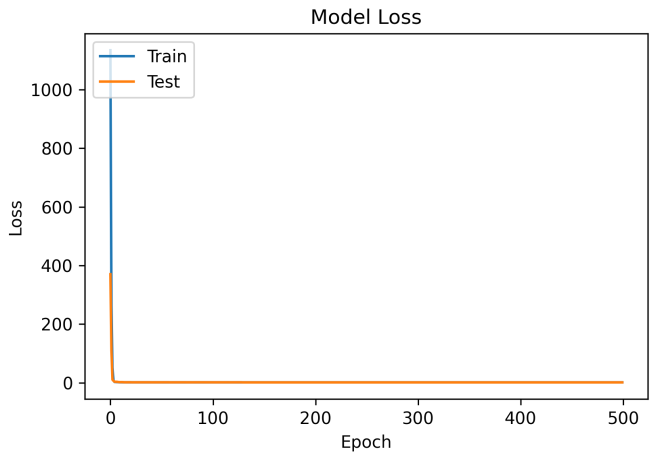


Figure E.6: Model Loss of our proposed classifier in PMData (a) and MOX2-5 (b) datasets.

Prediction Outcomes

The mean performance analysis against forecasting matrices between our CNN1D-based univariate "Step" forecasting model and other existing DL forecasting models has been compared in Table E.13 and Table E.14 for both datasets. Our developed CNN1D model reduces the RMSE error, improves forecast bias, and balances residual standard deviation for both datasets. Forecasting results in both tables show that our developed CNN1D has outperformed other baseline time-series forecasting models against state-of-the-art evaluation matrices. Its close competitors are bidirectional LSTM and GRU models. We found that the CNN, LSTM, and GRU effectively manage residual errors, and produce better results than AR with REM technique.

Statistical Analysis and Interval Prediction

Based on the proposed weighted mean calculation method, we showed the weekly activity score (S), similarity score (SC), and standard deviation (SD) calculation for participant-1 or P-1 from the MOX2-5 datasets in Table E.15. For example, we considered the activity data of P-1 for the last four weeks. We can use the same method for other participant data. The mean sedentary, LPA, MPA, and LPA times are measured in seconds. SC

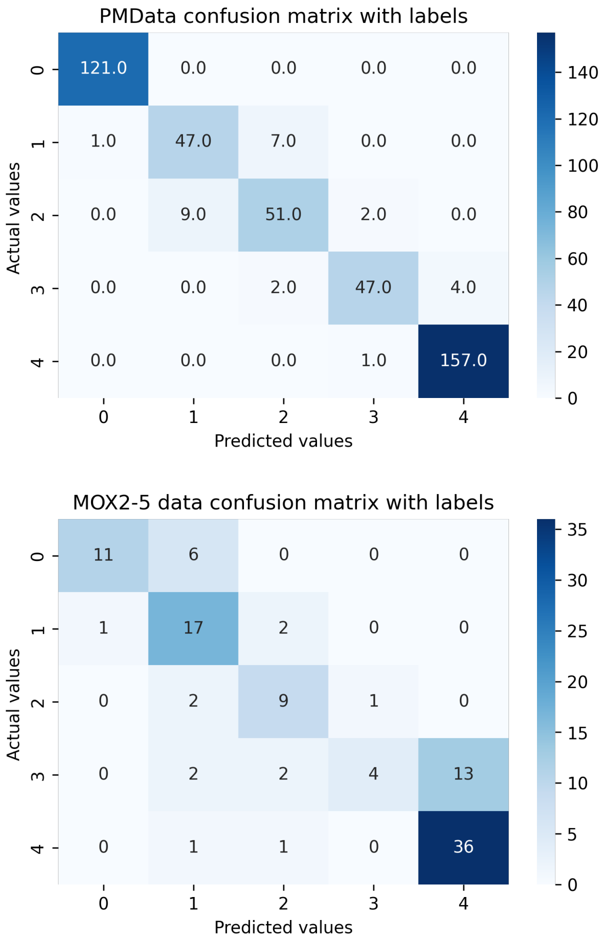


Figure E.7: The confusion matrix in the classification of PMData (a) and MOX2-5 (b) datasets with a weighted average precision, recall, and accuracy score.

signifies that P-1 has failed to achieve weekly goals for the last three consecutive weeks and therefore needs proper recommendation planning to stay motivated in the following weeks. The S and SD value state that the activity performance has significantly dropped after Week-1.

Moreover, we used our CNN1D model for the next seven days' step forecast for P-1 based on its temporal step data analysis. We calculated the RSD value $\approx$ 1271.0 for the step data of P-1. Using the Naïve-based interval prediction method, we have shown a direction to calculate the 1-step interval prediction of activity steps on top of the point prediction (see Table E.16). The mean predicted steps for the following week (Week-X) produced a value of 4576.0 ($\approx$ (3520.0 + 5171.0 + 4855.0 + 4979.0 + 5071.0 + 4508.0 + 3928.0)/7) which tells that the upcoming week (or Week-X) can be a match with Week-3. Therefore, the daily activity performance must be improvised.

Query Execution and Recommendation Generation

We generated personalized activity recommendations during ontology verification according to the semantic rules to improve individual physical activity levels to meet activity

Table E.16: Step and interval prediction for Week-X for P-1 in MOX2-5 datasets.

Week-x	Predicted step points (SP)	80% interval step prediction with c = 1.28, σ_h = 1271.0
Day-1	3520.0	[1893, 5147]
Day-2	5171.0	[3544, 6798]
Day-3	4855.0	[3228, 6482]
Day-4	4979.0	[3353, 6605]
Day-5	5071.0	[3445, 6697]
Day-6	4508.0	[2882, 6134]
Day-7	3928.0	[2302, 5554]

Table E.17: Performance comparison of different ontology reasoners available in Protege.

Reasoner(s)	Average reasoning time (sec.)
HermiT	1-2 sec.
Pellet	2-4 sec.
Fact++	3-4 sec.
RacerPro	2-3 sec.
KAON2	3-4 sec.

goals. We executed the semantic rules and used the Jena ARQ engine to run relevant SPARQL queries on the used datasets. Query results have been combined to create tailored recommendations to meet the eCoaching requirements. For instance, in Week-3, participant P-1 failed to achieve WHO's generic activity goal to stay active. Therefore, based on the semantic rule, he received recommendation messages A-19 and A-17. Based on the step forecast results with our developed CNN1D model, P-1 received recommendation message A-13 for the following week. On Week-3, the set of daily classified activity levels or APV is [0, 0, 0, 0, 0, 1, 0]. Therefore, for activity level 0, P-1 received A-1, A-7, A-8, A-10, and A-15, and for activity level 1, P-1 received A-2, A-7, A-8, A-10, and A-15.

We utilized the OWL_MEM_MICRO_RULE_INF specification (OWL-full) to investigate the ontology structure in Jena in the TTL format and approximated the reading time to 1.0-1.5 sec. Moreover, we used In-memory storage, optimized rule-based reasoner OWL rules, and the Jena framework to query the ontology class, ontology, predicate, subject, and object of each sentence in <1.0 seconds, <2.0 seconds, and <2.0 seconds, respectively. The reasoning time of the OntoeCoach ontology has been captured in Table E.17. The HermiT reasoner performed the best without any inconsistencies.

Discussion

This work presents a novel deep learning and ontology-based personalized Recommendation modeling and includes comprehensive and multiple levels of comparisons to better appreciate the performance of the proposed approaches. From the classification and forecasting results on both datasets, we found that DL models for time-series prediction and classifications can be effectively designed and developed. Further, we integrated these models into the OntoeCoach model for hybrid personalized recommendation generation.

According to the evidence in Table E.11 and Table E.12, an increased volume of MOX2-5 datasets could improve our model performance in this multi-class classification problem. In both datasets, model loss for training and testing converges. Due to the higher volume in PMData as compared to MOX2-5 datasets, our MLP classifier took more epochs for convergence. We compared the result of our proposed MLP classifier with traditional ML classifiers, such as Support Vector Machine with linear and non-linear kernels, Decision Tree, K-nearest neighbor, Naïve Bayes, Linear Discrimination Analysis, and our model outperformed these ML classifiers on PMData datasets. We planned to perform a similar comparison on MOX2-5 datasets in our future study with increased data.

Across both datasets, CNN1D outperformed other forecast models and produced high-speed output. We tried to increase the efficiency of the CNN1D model with more hidden layers, neurons, variations in filters, and dropout layers; however, we could not succeed. A limited volume of datasets can be a strong reason behind this. We also noticed that CNN, LSTM, and GRU models have different hyperparameters in terms of filter dimension, the number of filters, and hidden state dimension, and they internally work differently. CNN1D generally manipulates the spatial correlation in data and performs well when capturing the neighborhood information in data.

Future step prediction for individuals combined with the estimated S-value for the previous weeks can be a good direction for generating tailored recommendations. Similar studies are missing in the literature. Figure E.8 shows a visual approach to present the interval step prediction in the ActiCoach smartphone application to motivate individuals to personal activity monitoring to reach their activity goals.

The average SPARQL queries' execution time was captured between 0.1 seconds – and 0.4 seconds (sec). The semantic rules described in Table E.5 represent the logic behind personalized recommendation message generation. The rule-based binary reasoning (If $\rightarrow$ 1, else $\rightarrow$ 0) helps to interpret the formation of a personal activity recommendation message. A complete data-driven approach to personalized recommendation generation in healthcare is still critical due to false-positive scenarios. Therefore, prediction modeling followed by an annotated ruleset can add more value to personalized health recommendations. To solve the cold-start problem in recommendation generation, we recorded data for an initial two weeks to identify the activity patterns in an individual before starting DL-based data processing and followed by a recommendation generation.

Our modular eCoach system design can integrate other ML and DL classifiers, predictors, and statistical methods (e.g., daily activity frequency, regular activity frequency, graded activity frequency, and distribution of daily activity patterns). In that case, we only need to update respective models and techniques. The concept of ontology supports new branching to integrate new ideas or pruning if some ideas are unnecessary. The KB and RMT can grow or shrink on demand based on future studies' efficacy evaluation. Furthermore, this type of design approach can support similar activity sensors (e.g., Actigraph).

This study proves an integrated concept for hybrid personalized recommendation gen-

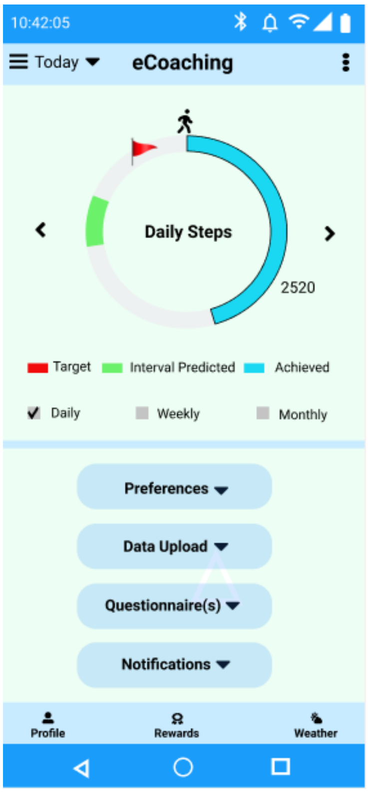


Figure E.8: Visualization of daily step count, target step count, and predicted interval.

eration in activity eCoaching, combining time-series classification and forecasting results with semantic ontology to generate rule-based customized recommendations. However, a longitudinal study on a cluster of controlled trials could evaluate its practical efficacy. More state-of-the-art time-series models (classification and forecasting) for performance comparison, stability analysis, and more activity attribute support with the growing activity data can be included. The recommendation generation performance could improve by using density-based spatial clustering, sessions, criteria, similarity score, reward maximization, fuzzy logic, entropy, and community-based heuristic approaches. In the current approach, a person can receive multiple recommendation messages. Thus, the scope of the solution can be increased with meta-heuristic methods to select an optimal set of recommendations from a feasible recommendation set and make the selection dynamic with personal behavioral patterns.

Collaborative filtering, [54] well-established recommendation method to generate recommendations to filter out items based on the user similarity score. It defines an optimal search space that includes users with the closest preference score. The similarity score helps to create profile rankings. Our model-based exercise recommendations are filtered based on personal preferences and short- and/or long-term goal achievement. The tree structure of the semantic ontology explains the binary logic or rules behind specific recommendation generation. The process is highly individualized; thus, the notion of group similarity is not included in recommendation generation. In the future, we will extend this research to group-based meta-heuristics by incorporating ideas from collaborative filtering.

The proposed Activity eCoach system demonstrates its significance in real life by offering personalized guidance, support, and motivation to individuals aiming to enhance their physical health and overall well-being. Our physical activity eCoaching system could offer multiple benefits and use cases in the real world, as demonstrated by real-life examples (a-j). These could directly contribute to the sustainable development goal of the nation, e.g., the United Nations' Sustainable Development Goal (SDG) 3 [55]. **a.** *Personalized Approach*: Our activity eCoaching offers a personalized approach to fitness and wellness. It takes into account individuals' unique characteristics, goals, preferences, and constraints, allowing for tailored recommendations and strategies that align with their specific needs. This personalized approach enhances engagement and increases the likelihood of successful behavior change. **b.** *Accessibility and Convenience*: Our activity eCoaching provides accessibility and convenience to individuals. With the use of mobile applications, online platforms, and wearable devices, individuals can access coaching support and resources anytime, anywhere. This flexibility eliminates geographical barriers and time constraints, making it easier for people to engage in fitness activities and receive guidance, regardless of their location or schedule. **c.** *Continuous Support and Accountability*: Our activity eCoaching provides continuous support and accountability. Coaches can monitor individuals' activity progress, track their activities, and provide timely feedback and encouragement. This ongoing support helps individuals stay motivated, overcome obstacles, and maintain consistency in their fitness journey. **d.** *Goal Setting and Progress Tracking*: Our activity eCoaching facilitates goal setting and progress tracking. Activity eCoache system works with individuals to set realistic and achievable goals, breaking them down into manageable steps. Regular tracking of progress allows individuals to visualize their achievements, identify areas for improvement, and make necessary adjustments to their routines. **e.** *Education and Guidance*: Our activity eCoach system can provide evidence-based information, answer questions, and address concerns, empowering individuals to make informed decisions about their health and well-being. **f.** *Behavior Change Support*: Our activity eCoaching focuses on behavior change strategies and techniques. eCoaches help individuals develop new habits, overcome barriers, and adopt healthier lifestyles. They provide guidance on setting realistic expectations, managing setbacks, and sustaining long-term behavior change. **g.** *Motivation and Engagement*: Our activity eCoaching enhances motivation and engagement. Through personalized feedback, progress updates, goal achievements, and interactive features, individuals are motivated to stay active and engaged in their fitness routines. Recommendation and rewarding features further enhance motivation and create a sense of community. **h.** *Health Monitoring and Risk Management*: Our activity eCoaching can incorporate health monitoring features to track vital health signs, heart rate, sleep patterns, and other relevant health indicators. This may allow identifying potential health risks, providing early intervention, and promoting overall well-being. **i.** *Integration with Other Healthcare Services*: Our activity eCoaching can be integrated with other healthcare services, such as telemedicine or electronic health records, to ensure a comprehensive approach to individuals' health management. eCoaches may collaborate with healthcare providers, share relevant data, and align coaching strategies with medical recommendations. **j.** *Long-Term Sustainability*: Our activity eCoaching aims to promote long-term behavior change and sustainability. Providing ongoing support, education, and personalized strategies, eCoaches help individuals develop healthy habits that can be sustained beyond a specific program or intervention.

Conclusion

To improve an individual's physical activity levels through wearable activity sensors and digital activity trackers, eCoach capabilities may be encouraging. Through continuous monitoring and personalized recommendation generation, eCoach can motivate participants to achieve their physical activity goals to maintain a healthy lifestyle. This work proposes a new theoretical concept for generating personalized activity recommendations in eCoaching using a hybrid approach. The idea of univariate time series forecasting exists; its application to the ontology of activity eCoaching and interval forecasting is novel. This study reveals a method for examining and using projection, classification, statistical, and recommendation models with semantic rule bases to design and develop a prototype eCoach system to generate interpretable and personalized campaign recommendations to manage campaign goals.

Data availability

The corresponding author AC can be contacted for the datasets and codebase.

Abbreviations

- eCoach: Electronic coaching
- ICTs: Information and Communication Technologies
- ML: Machine Learning
- DL: Deep Learning
- SWRL: Semantic Web Rule Language
- SPARQL: SPARQL query protocol and RDF Query Language
- PoC: Proof-of-Concept
- OWL: Web Ontology Language
- RDF: Resource Description Framework
- RDFS: RDF Schema
- KB: Knowledge Base
- AI: Artificial Intelligence
- LTG: Long-term Goals

- STG: Short-term Goals
- LPA: Low Physical Activity
- MPA: Medium Physical Activity
- VPA: Vigorous Physical Activity
- SVM: Support Vector Machine
- NB: Naive Bayes
- KNN: K-Nearest Neighbour
- DT: Decision Tree
- PCA: Principal Component Analysis
- LDA: Linear Discriminator Analysis
- MLP: Multi-Layer Perceptron
- CNN: Convolution Neural Network
- RNN: Recurrent Neural Network
- LSTM: Long Short-Term Memory
- GRU: Gated Recurrent Unit
- ReLU: Rectified Linear Unit
- RMSE: Root Mean Squared Error
- AR: Auto Regression
- TDB: Touple Database
- NSD: Norwegian Study Data Center
- REK: Regional Committees for Medical and Health Research Ethics
- SDG: Sustainable Development Goal

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Author Contributions

A.C. and Y.K.M. formulated the concept and designed the methodology. A.C. performed and analyzed the experiments and data. A.P., M.R., and Y.K.M. provided additional suggestions relevant to the experiments and analysis. A.C. and Y.K.M. wrote the paper. All authors reviewed and edited the paper.

Competing interests

The authors declare no competing interests.

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Paper F

ProHealth eCoach: User-Centered Design and Development ... Activity Recommendations

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ProHealth eCoach: user-centered design and development of an eCoach app to promote a healthy lifestyle with personalized activity recommendations

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Abstract – **Background**: Regular physical activity (PA), healthy habits, and an appropriate diet are recommended guidelines to maintain a healthy lifestyle. A healthy lifestyle can help to avoid chronic diseases and long-term illnesses. Monitoring an automatic personalized lifestyle recommendation system (i.e., automatic electronic coach or eCoach) considering clinical and ethical guidelines, individual health status, condition, and preferences may successfully help participants to follow recommendations to maintain a healthy lifestyle. As a prerequisite for the prototype design of such a helpful eCoach system, it is essential to involve the end-users and subject-matter experts throughout the iterative design process. **Methods**: We used an iterative user-centered design (UCD) approach to understand the context of use and to collect qualitative data to develop a roadmap for self-management with eCoaching. We involved researchers, non-technical and technical, health professionals, subject-matter experts, and potential end-users in the design process. We designed and developed the eCoach prototype in two stages, adopting different phases of the iterative design process. In design workshop 1, we focused on identifying end-users, understanding the user's context, specifying user requirements, and designing and developing an initial low-fidelity eCoach prototype. In design workshop 2, we focused on maturing the low-fidelity solution design and development for the visualization of continuous and discrete data, artificial intelligence (AI)-based interval forecasting, personalized recommendations, and activity goals. **Results**: The iterative design process helped to develop a working prototype of the eCoach system that meets the end user's requirements and expectations towards an effective recommendation visualization, considering diversity in culture, quality of life, and human values. The design provides an early version of the solution, consisting of wearable technology, a mobile app following the "Google Material Design" guidelines, and web content for self-monitoring, goal setting, and lifestyle recommendations in an engaging manner between the eCoach app and

end-users. **Conclusions**: The adopted iterative design process brings in a design focus on the user and their needs at each phase. Throughout the design process, users have been involved at the heart of the design to create a working research prototype to improve the fit between technology, end-user, and researchers. Furthermore, we performed a technological readiness study of ProHealth eCoach against standard levels set by European Union (EU).

Key Contributions to the Literature

- This study proposes ProHealth eCoach to promote a healthy lifestyle with personalized activity recommendations using an iterative design process.
- The foremost principle of this eCoach system is to reinforce positive behavior through persuasive strategies, such as self-monitoring of behavior, self-management, personalization, goal setting, reminder, rewards, personalized recommendation generation, and effective presentation.
- Based on insights from a series of design workshops, we envisage PA as the basis for a healthy lifestyle and the development of the eCoach system. However, regardless of the design and development of multiple PA apps in the App Store and Playstore, it remains unclear how to design and develop an engaging and effective PA coaching app.

Background

Chronic illness associated with modifiable lifestyle factors will be accountable for the highest death rates worldwide [1][2][3][4][5][6][7]. Lack of physical activities, improper dietary habits, excess consumption of tobacco and alcohol are severe risk factors for chronic diseases, such as obesity, overweight, hypertension, diabetes type II, cardiovascular diseases (CVDs), osteoporosis, and several types of cancer [1][2][3][4][5][6][7]. The World Health Organization (WHO) recommends for adults aged 18–64 years at least 150-300 minutes of moderate-intensity aerobic exercise or at least 75-150 minutes of high-intensity aerobic exercise or an equivalent combination of medium and high-intensity exercise throughout the week [6][7]. Furthermore, according to WHO, adults should include at least 400 grams or five servings daily of fruits, vegetables, legumes (i.e., lentils and legumes, nuts, and whole grains (i.e., unprocessed corn, millet, oats, wheat, and brown rice) in their healthy dietary plan [8]. Previous studies have shown that an active and healthy lifestyle can reduce the risk of chronic disease and improve the health-related quality of life and psychological condition of people suffering from chronic illness [1][2][3][4][5][6][7]. Healthy lifestyle management can be supported by self-management, motivation, coaching, regular monitoring, goal setting, goal evaluation reminders, and contextual personalized recommendation generation. Persuasive approaches such as eCoaching can empower people to manage a healthy lifestyle with early risk predictions and appropriate individualized recommendations. The intended eCoach system is a set of computerized components that constitutes an artificial entity that can observe, reason about, learn from and predict a user's behaviors in context and over time, and that engages proactively in an ongoing collaborative conversation with the user to aid planning and to promote practical goal striving with persuasive techniques [9].

mHealth Interventions and Factors for Physical Activity Behavior

There exist multiple challenges in developing a mHealth mobile app, such as the involvement of different stakeholders, consideration of needs and preferences of end-users from diverse backgrounds, time, technical limitations, and practical implementation of behavioral coaching theories in the app design [10]. To develop an effective mHealth intervention, the following popular frameworks have been suggested – Integrate, Design, Assess, and Share framework (IDEAS), Medical Research Council (MRC) framework, and behavioral intervention technology (BIT) model [10]. Moreover, interventions should identify target behavior and factors responsible for behavior change [10]. The notable PA behavior factors are - goals, motivation, habits, emotions, perceived risks, and contextual influences [10]. The challenge in developing a mHealth mobile app lies in applying PA behavior factors. Literature shows different existing models [10], such as capability, opportunity, motivation, and behavior (COM-B) model, self-determination theory, socio-ecological models, goal-getting theory, behavior economics, Fogg's behavior model (FBM), and just-in-time (adaptive) interventions (JITAIs). Sporrel et al. [10] expected that the individual ability and motivation have a high chance of engaging in physical activity, and if the participant receives personalized recommendations at such a moment, s/he will participate in the physical activity with enthusiasm.

Aim of the Study

The design and development of a health eCoach system require integration between technologies (e.g., mobile phone, computer, wearable and non-wearable sensors, tablet), concepts, and strategies from interdisciplinary domains (health informatics, computer science, software engineering, persuasive technologies, networking, and human-computer-interaction (HCI)), and of users' preferences and requirements in an engaging manner. The UCD approach [11][12][13][14][15] may solve such an integration challenge by positioning the end-users centrally for designing, developing, testing, and evaluating an eCoach prototype. It may promote interactive digital services and applications with Internet-of-Things (IoT) connected sensors and actuators to open new opportunities for HCI [16][17]. A user-centered design framework integrates a wide range of practices around understanding the needs, requirements, and limitations of end-users [7][10]. It can improve strategic decisions and increase the effectiveness of individual projects and services [10]. The United States Food and Drug Administration (FDA) recently required human factors design and evaluation practices for a wide range of medical technologies [18].

Our research focuses on health prevention by reinforcing healthy habits (e.g., regular physical activity) using an intelligent eCoach system to generate meaningful and personalized lifestyle recommendations automatically. We plan to collect data (personal and activity data) from a healthy group of adult participants, both male and female, over a defined period, followed by the analysis of the time-series data in regard to the impact of lifestyle recommendations on the reinforcement of positive habits of the participants. Also, we plan to collect personal preferences with a self-reporting form and activity data through a wearable activity sensor with minimal burden to the participants. A key goal is to develop a roadmap for self-management with eCoaching that accelerates development, generates best practices, and raises public awareness.

We began with a broader perspective of the ProHealth eCoach system that explored potential designs and development for self-management of behavior (physical activity, nutrition, and habits) focusing on obesity as a study case with the following research questions (RQs):

RQ1: What are the opportunities of an "eCoach application" in eHealth?
RQ2: What type of goal setting will be needed for self-management of behavior for a healthy lifestyle?
RQ3: Which feedback from an eCoach to the users would have an effective impact on the motivation for self-management of their behavior?
RQ4: How should the feedback be presented, and what information should be visualized and how?

Later, we primarily focused on self-management of physical activity for activity coaching. To achieve this, we set the following RQ:

RQ5: How to visualize continuous and discrete data, personalized recommendations, and activity goals in an eCoaching application for physical activity?

We approached the above RQs by conducting two design workshops over one year. These workshops actively involve everyday participants and subject-matter experts in information and communication technologies, health informatics, computer science, nursing, information systems, and HCI. We designed these sessions to explore the challenges and opportunities of eCoaching in self-monitoring, self-management, recommendation generation, and feedback visualization to motivate users to improve their healthy lifestyles. In this paper, we present the methods and results of the workshops, critical insight, and the working research prototype, demonstrating the results of this research as a starting point for digital health monitoring, self-management, and HCI innovation.

Related Work

This section presents existing background knowledge applicable to current research. Different research groups have conducted different studies related to UCD strategies for technologies that support behavior change in daily life. We considered systematic literature search with the following search string pattern: ((design strategies OR user-centered design) AND (behavior change OR lifestyle) AND (persuasive technology or persuasive strategy) AND (smartphone application OR mobile application OR web-based application) AND (goal-setting or self-management) AND (visualization OR recommendation OR feedback OR notifications)) on the following electronic databases – Scopus, EBSCOhost, ACM, Science Direct, AMIA, JMIR, IEEE, Google Scholar, and Springer. A subset of these articles is cross-referenced between portals, especially Google Scholar and PubMed. Related search keywords were identified using terms of MeSH (Medical Subject Headings), synonyms, relevant articles, and self-determined search terms. We used EndNote (V. X9), DOAJ, Sherpa/Romeo, and Microsoft Excel (MS Office 365 V. 16.x) to efficiently search, collect, and select related articles. We included articles that are peer-reviewed, full-length, and written in English. The UCD design approach and its application domain in eHealth is broad. Therefore, the search results have been selective and are further refined to focus on UCD methods, behavioral intervention, lifestyle, and personalized recommendations (see Table F.1). From the literature search, the UCD approaches can be classified as follows: iterative, non-iterative (sequential), and other approaches.

Table F.1: A qualitative comparison between our study and the related studies.

Study	UCD Approach and/or Method	Behavioral intervention and purpose	Personalization approach
Our study	Iterative approach	Activity coaching to reduce sedentary behavior	Preference-settings, self-monitoring, interval prediction, and recommendation visualization
[19]	Iterative approach	To deliver rehabilitation strategies in chronic conditions	Self-management report generation
[20]	Iterative approach	Rural eHealth nutrition education for low-income families	-
[21]	Iterative approach and collaborative engagement	For elderly decision-making towards care location	-
[22]	Iterative approach	Prototyping for a clinical ecosystem	-
[23]	Iterative approach	To support obese and overweight adolescents with a future focus on healthy lifestyle and economic advantage	Feedback presentation

Continued on next page

Table F.1 – continued from previous page

Study	UCD Approach and/or Method	Behavioral intervention and purpose	Personalization approach
[24]	Iterative approach	Nutritional intervention for healthy lifestyle	Recommendation generation, reminder design
[7][18]	Non-Iterative approach and Shah's methodological framework	Physical activity for primary care for patients with chronic obstructive pulmonary disease or type-2 diabetes	Goal-setting and general feedback generation
[25]	Non-iterative approach	To enhance the physical activity level	Goal management, rewards, and self-monitoring
[26]	Non-iterative approach	Proposed and validated the design strategies for persuasive technologies	-
[27]	Non-iterative approach	To design and develop a technology-mediated therapy tool for adults with mental illness	-
[28]	Structured method	For independent and safe elderly living	-
[29]	Participatory design approach	For the self-management of food, exercise, mood, and social values	Graphical representation (e.g., picture and text)
[30][31]	Evidence-based approach	Remote patient monitoring and early detection of health risks	-
[32]	Behavioral engagement	Behavioral improvement by reducing alcohol consumptions	Daily notification generation and feedback visualizations
[33][34]	-	Highlighted the importance of self-management for developing the gradual human behavior change intervention strategy	-

Iterative Approach

Richardson et al. [19] adopted an iterative UCD approach to developing a web-based app for delivering rehabilitation strategies (e.g., self-management support and services) with enhanced accessibility, availability, and affordability for people/participants with chronic health conditions. They developed a prototype with close consultation with rehabilitation experts and performed usability tests, heuristic evaluations, and a target group analysis. Atkinson et al. [20] adopted an iterative UCD approach to developing a rural eHealth nutrition education website for low-income families so that low-income women can use the prototype effectively. The UCD approach focused on – the identification of user content needs, identification of access concerns, content confirmation, and determination of the functionality, usability, and acceptability study to make the look and feel of the website better. Garvelink et al. [21] adopted a three-cycle (iterative) UCD approach for elderly decision-making toward care location. The cycle consisted of the following steps – cycle 1: ideation and requirement gathering on home-care service delivery and the development of the prototype based on the input from the end-users, cycle 2: usability testing with end-users and re-design, and Cycle 3: final refinement with a linguist, graphic designer, and end-users. The result shows a successful design and development of a decision guide system for the elderly population with a fully collaborative approach. Pais et al. [22] performed an iterative UCD study to develop a proof-of-concept prototype for a clinical ecosystem that can integrate, and store health and wellness data generated by commercially available mobile apps in Gestational Diabetes Mellitus (GDM) care. The UCD approach helped them gather end-user requirements and refine them further in successive iterations to meet the expectations of end-users. LeRouge et al. [23] performed a qualitative user-centered design study to design a technology-mediated nutritional program to support obese and overweight adolescents with a future focus on money savings (or economic advantage), healthier dietary planning, good societal impact, and enhanced self-efficacy. They divided the UCD approach into two iterations – early-stage prototype usability analysis and semi-structured interviews with health professionals and end-users. The result produced good reflections on existing theories about personalized behavior change and design requirements for feedback presentation (e.g., vivid colors, semirealistic images, cooking sounds, multimedia, and gaming). Mummah et al. [24] conducted an iterative UCD approach to design "Vegethon" to perform a theory-based smartphone app-based nutritional intervention with an IDEAS framework to enhance vegetable consumption. The key findings were – a focus on self-monitoring, the inclusion of challenges, simplified features (e.g., weekly reporting), goal setting, recommendation framing, effective recommendation generation, reminder design, and evaluation.

Non-Iterative Approach

Van der Weegen et al. [7] and Verwey et al. [18] conducted a user-centered design study to develop a smartphone-based monitoring and feedback generation tool to simulate patients' physical activity with lifestyle diseases. They followed Shah's methodological framework in three iterations for medical tool development. The study demonstrated how the user-centered design approach helped integrate concepts, such as literature findings, tool architecture, goal setting, feedback generation, feedback visualization, data sharing, and consequences of a smartphone app and mature it further with iterations. Munson et al. [25] performed a user-based study with their developed mobile phone app, “GoalPost”, and “GoalLine” to better understand the impact of goal setting, rewards, self-monitoring, and sharing of goals, goal progress on enhancing the physical activity level. The study found that the generation of secondary and primary objectives and non-judgmental reminders were effective among participants; however, rewards must be designed more effectively for more participant engagement. Consolvo et al. [26] proposed and validated the design strategies (e.g., abstract, reflective, unobtrusive, public, aesthetic, positive, controllable, trending, and comprehensive) for persuasive technologies using a user-based study to motivate and help people/participants in improving their daily negative behavior with technology design. Lederman et al. [27] adopted a three-month user study to design and develop a technology-mediated therapy tool for adults with mental illness, including psychoeducation, therapist moderators, social networking, goal-based analysis, and HCI approaches. They found that an effective engagement of end-users with automated system behavior and the development of therapeutic alliances are essential for mental health therapy and self-determination theory.

Other Approaches

Harte et al. [28] successfully derived a structured methodology (three-phase method) with the UCD approach to design and develop a health system, namely “Wireless Insole for Independent and Safe Elderly Living (WIISEL)” for elderly care with fall-risk prediction. In phase 1, they focused on creating use case documents using storyboarding, paper prototypes, mock-ups, and user interviews. Phase 2 focused on expert usability inspections (e.g., heuristic evaluations, prototype reviews, and feedback generation). In Phase 3, they did classical user testing with user experience to improve the final WIISEL prototype. Kim et al. [29] performed a user-centered participatory design approach to design and develop an iOS application for the self-management of food, exercise, mood, and social values in the form of pictures and texts for obese or overweight adults. The study showed promising results in enhancing self-awareness towards a healthy lifestyle and behavioral change, effective engagement, and self-reporting to manage the factors that impact obesity or overweight. McCurdie et al. [30] and Bruce et al. [31] adopted a UCD evidence-based approach to develop a mHealth consumer app to enhance healthcare delivery and clinical outcomes with remote patient monitoring and early detection of health risks to avoid severe damages. Their research reveals the importance of a user-centered/patient-centered approach in achieving user engagement (or user evaluation) to enhance the effectiveness of behavioral interventions. Bell et al. [32] explored how user engagement can improve the research and development of a behavior change app iteratively. They performed a behavioral engagement longitudinal observational study on a group of participants using their “Drink Less” behavior change app for alcohol reduction and explored parameters, such as frequency, amount, depth, and duration of the study with a simple data visualization tool to understand user psychology to improve the app further. Branford et al. [33] also emphasized the importance of privacy, trust, and experience, as well as opportunities to provide healthcare and empower people to manage their health and well-being in a way more suited to their lives and values to design and develop HCI-based digital health technologies effectively. Araújo-Soares et al. [34] highlighted the importance of self-management for developing the gradual human behavior change intervention strategy in chronic diseases. Interventions that address risk factors and support behavioral changes to effectively self-manage chronic disorders can significantly impact health and well-being and reduce the cost of providing medical care for the elderly with chronic diseases [34]. Self-management is a complex task, including adherence to therapy, changing multiple health behaviors, and regular contact with healthcare providers [34]. Interventions often include additional components to establish and maintain harmony and participation through interpersonal communication methods or functions, such as gamification in digital health interventions [34]. The development of healthy behavior change interventions determines the best combination of these characteristics and the transparent reporting of these decisions [34].

Therefore, an iterative UCD approach has been essential to address the users' health requirements and technological needs throughout development and to design and develop personalized care applications in the healthcare domain to increase their acceptability, credibility, and effectiveness. Human behavior is crucial for customized care, particularly in chronic illnesses [35]. It requires the effective engagement of end-users, proper recommendation generation, and presentation. The state-of-the-art of this research is input to the design and development of an initial working prototype of an eCoach mobile app that can recommend, and motivate participants with personalized recommendation messages and its meaningful presentation. Our mobile app design follows the standard "Google Material Design" guidelines. The design provides usable themes, material guidelines, system icons, and color palettes to craft an intuitive eCoach app. In this study, our focus of eCoaching has been physical activity coaching; however, its scope is not limited to that.

Many e-coaching apps offer personalization features in the market. However, they are missing to have multiple generic eCoaching components. The motivation of this study is to design and develop an initial workable research prototype using an iterative design process for personalized recommendation generation and meaningful representation. Moreover, we provide a further innovative direction to research how AI technology could be utilized for effective recommendation generation. A qualitative comparison between our study and the related studies has been made in Table F.1 based on the following three parameters: UCD approach and/or method, behavioral intervention and purpose, and personalization approach.

Methods

We have followed the Standards for Reporting Implementation (StaRI) for this comprehensive UCD study (see Additional file 1). All methods have been carried out in accordance with relevant guidelines and regulations in the "Ethics approval and consent to participate" section under Declarations.

User-Centered Design Approach

A standard UCD is an iterative process with four phases: understand the context of the user, specify user requirements, design solutions and thereby, evaluate design against requirements. The aim of the UCD process is to capture and address the whole user experience with an explicit understanding of the users, tasks, and environments [11][12][13]. We have used such an iterative design process to shape the eCoach prototype design with the end-users. Therefore, the user's context and expectations from a computerized system must be well understood to increase the accomplishment rate in functional testing, acceptance testing, usability testing, and credibility testing. To facilitate UCD from the beginning, we involved subject-matter experts with a background in HCI, health informatics, and computer science in gathering knowledge on the design approach's needs, demands, and restrictions. We conducted a preparation meeting before design workshop 1 to exchange experts' knowledge, thoughts, and ideas from their experience. These experts delivered feedback on the importance of methodology selection, use case design, identification of the background of participants to be recruited as end-users to avoid design biases, fair distribution of participants among different groups, time planning for conducting a digital workshop, potential distractions in digital workshops, challenges with effective engagement, questionnaire design, comprehensibility of the questionnaire and required consent for participant recruitment. We identified the importance of a moderator who can moderate the digital group discussions and involve all participants in each group.

We planned the entire process to be user-friendly and interactive. The future objective of using this eCoaching app is to perform a usability study followed by a longitudinal study on a controlled group of participants to verify the practical effectiveness of using this app toward a healthy lifestyle with self-management, self-motivation, and self-correlation. Therefore, in our study, end-users are a potential subset of actual eCoach participants for our future studies. We aimed at involving end-users in the early eCoach design phase to understand their thinking and expectations to avoid further design conflicts. The working domain and the area of expertise of each end-user can be diverse. Therefore, we decided to recruit participants from the following occupations – student, researcher, health professional, educationalist, and IT professional to bring diversity to the workshops. Our study targeted participants with standard body mass (BMI) ranges [18.5 – 25 kg/m2] as well as obese and overweight [25 – 35 kg/m2]. The initial selection criteria are described below:

Exclusion criteria:

- Participants who do not have wif-fi or wireless broadband (BB) at home.
- Participants with postcode outside Southern Norway.
- Partciapnts with severe medical history (illness, hospitalization) conditions) of last year and severe chronic health issues that may interfere with appropriate data collection.
- Participants with food allergies.

- Underweight (BMI < 18.5).

Inclusion criteria:

- Participants registered to general practitioner (GP).
- Age group 18-64 with targeted BMI range.
- Participants having wif-fi or wireless BB at home.
- Participants in South-Norway.
- Participants motivated for self-monitoring and data collection.
- Participants without a prescribed major chronic condition or current disease episode.
- Can speak, write, and read English in an understandable way.

We agreed to adopt an "iterative" UCD approach [7][11][12][36]. The adopted strategy follows iterative stages (identify end-users and their context, concept development, design, and prototype development to establish the recognized concept in the mobile app) as depicted in Figure F.1. We decided to start the workshop with an introductory presentation of the objective, and the motivation for conducting such a project, to give the participants a high-level overview. The entire workshops have been conducted digitally using Zoom due to the COVID-19 pandemic. All the video and audio recordings were maintained following the data security and privacy guidelines set by the Norwegian Centre for Research Data (NSD) [37].

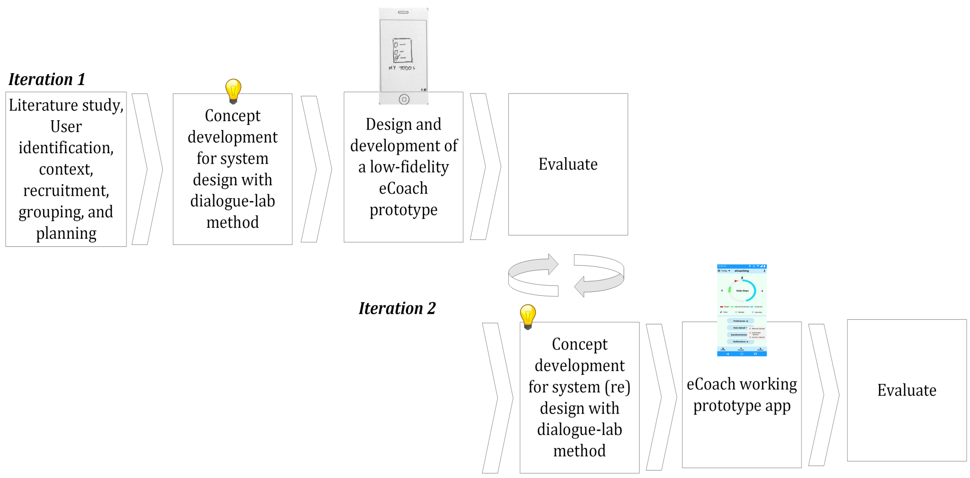

Figure F.1: Adopted process for the iterative-user-centered eCoach prototype design and development.

At the end of workshop 1 (iteration 1), the research team collected all user needs and preferences. An engineering team helped translate the needs into initial technical solution requirements. The initial solution was developed based on continuous interaction and feedback generation between the engineering team and the research team. Afterward, the initial solution was utilized in workshop 2 (iteration 2) to gather feedback on the gap between the technical solution and the user requirements (particularly regarding the visualization of physical activity recommendations). The result of the second iteration helped us to mature the design and the technical solution.

Workshop 1 –Design and End-Users

User identification, Context, Recruitment, Grouping, and Planning

We ran workshop 1 to apply eCoaching for an obesity and overweight risk target group to promote a healthy lifestyle through behavior monitoring and personalized recommendation generation. The aim of eCoaching was healthy and obese (or overweight) participants in good health, men and women between 18-64. A primary objective of this workshop was to focus on the study's goal (i.e., develop a roadmap for self-management with eCoaching that accelerates development, generates best practices, and raises public awareness). During the workshop, we explored the opportunities and challenges of eCoaching with participants and experts on the first four RQs. The workshop structure was based on the dialogue-labs methods from Lucero et al. [17], which facilitate the generation of participants' ideas by stimulating their creative thinking through a sequence of design activities.

Eight end-user volunteers (7M; 1F) aged 18–64 (student (1), research scholar (1), health professional (1), educationalist (4), IT professional (1)) and four experts (4M; 0F) aged 18–64 participated in the workshop along with three facilitators from the research team. The workshop was executed online (via the videoconferencing tool "Zoom") at the University of Agder, Norway. We divided the end-users randomly among four groups headed by one expert (E). We created a Zoom breakout room for each group to discuss and exchange their thoughts with experts. We asked each group to present their ideas using a shared online whiteboard.

We then gave a 20-minute slide-deck presentation using images, the concept of eCoaching, and a brief introduction of the project with objectives and motivation. We split volunteers randomly into four groups (2 × 4 people, 1×4 experts) and these groups took part in two activities. In each group, experts kept advocating the reasoning of the participants by asking incitement questions. We created two Flyers as props for conducting workshop 1. Flyer 1 includes workshop design and development details, which we shared with potential end-user groups before the workshop. Flyer 2 includes detailed activities of the workshop for experts.

Task 1 (30 minutes): We distributed RQ1 and RQ2 to all four groups and brainstorm with groups in the first 20 mins. Then we asked groups to present their ideas to other groups in the last 10 mins.

Task 2 (30 minutes): Like Task 1, we distributed RQ3 and RQ4 to all four groups and brainstorm for in the first 20 mins. Then we asked groups to present their ideas to other groups in the last 10 mins.

Concept Development for System Design

In this workshop, we have integrated the identified behavior change strategies and technologies in the eCoaching prototype design to stimulate a healthy lifestyle (physical activity, proper diet, and healthy habits) corresponding to users' context and needs (overweight and obesity risk management).

In the preparation phase, we discussed user and context description, our literature findings, and the study's objective with experts to plan and create tasks for workshop 1. We provided the users with a high-level conceptual idea about the health eCoach system and its objective in the obesity study case without disclosing too many details about the research and engineering thoughts. It helped end-users to brainstorm their ideas regarding the targeted research questions. Workshop 1 helped us develop general use cases to describe the interaction between the eCoach prototype system to be developed and the end-users in a stepwise approach. After the experts' focus group discussions and result presentations, we created the first draft of a user requirement document to modify it further in the next iteration to reduce the design, development, and user expectation gaps. The researchers and the engineering team worked on the first draft to do a feasibility (technical and financial) check to ensure no significant issues were missed. We created an eCoach prototype app as an initial solution based on the first draft of user requirements, to improve it further based on the feedback from end-users in the next iteration.

Evaluation of the ProHealth eCoach as A Low-Fidelity Prototype

The low-fidelity eCoach prototype for activity monitoring as an outcome of Workshop 1 was presented to the end-user groups in Workshop 2 to receive valuable feedback. The feedback consisted of three choices – passed (5), failed (0), and further scope of improvement (3). We demonstrated the following to evaluate the prototype –

- Selection of activity sensor, it's wearing, and its connection establishment process with the app for the collection of data.
- Information to be collected for authentication on the login page.
- A set of preference data to be collected in the form of a questionnaire.
- Prepared questionnaire set for the feedback or survey, and reporting of technical problems during study in progress.
- Layout, content, icon, and color selection for the following pages: homepage/login page, data upload, preferences, questionnaire, notification, and reward generation.
- Visualization layout for daily, weekly, and monthly activity patterns.

We used Figma app view, basic web page view, and PowerPoint for the demonstration. We received feedback for email id-based login instead of long a unique user identifier or UUID-based login, different modes of data upload from the activity sensor, refining questionnaires sets and their design, uniform layout design, and selecting a standard color with appropriate icons for each eCoach views and concepts, and an integrated circular layout for visualizing activity patterns over time. Overall, we received an average feedback rating of 3.0 out of 5.0. All the feedback or comments were addressed in the initial eCoach working prototype app.

Workshop 2 – (Re)Design and End-Users

User identification, Recruitment, Grouping, and Planning

We created two Flyers as props for conducting workshop 2. Flyer 2 includes workshop design and development details, which we shared with potential end-user groups before the workshop. Flyer 2 includes detailed activities of the workshop for experts.

We ran workshop 2 to bring together different types of users, such as non-technical, technical, subject-matter experts, familiar participants, and people from cross-domains, to join a creative process for making the eCoach prototype attractive, persuasive, easy to use, and suitable for daily use. A key goal of this workshop was to generate ideas to improve the quality of personalized feedback, the visualization of self-monitoring data and recommendations, and goal setting. During the workshop, we explored the opportunities and challenges of eCoaching with participants and experts regarding the RQ5. The structure of this workshop was also based on the dialogue-labs methods from Lucero et al. [17], which facilitate participants' generation of ideas by stimulating their creative thinking through a sequence of design activities.

We host the workshop online (via Zoom) at the University of Agder, Norway. Nine end-user volunteers (8M; 1F) aged 18–64 (student (2), research scholar (2), health professional (1), educationalist (2), IT professional (2)) and four experts (3M; 0F) aged 18–64 participated in the workshop along with three facilitators from the research team. We divided the end-users randomly among four groups headed by one expert (E). We created a Zoom breakout room for each group to discuss and exchange their thoughts with experts. We asked each group to present their ideas using any virtual whiteboard.

We then gave a 5-minute slide-deck presentation using images, and a brief introduction of the project with objectives and motivation. We split volunteers randomly into three groups (3 × 3 people, 1×3 experts), and these groups took part in the respective activity. In each group, experts kept advocating the reasoning of the participants by asking incitement questions.

Task 1 (30 minutes): We distributed three sub-research questions under RQ5 to all three groups and brainstorm with groups in the first 15 mins. Then we asked groups to present their ideas to other groups in the last 15 mins. We then gave a 5-minute slide-deck presentation using images, and a brief demonstration of the initial version of eCoach app.

Task 2 (30 minutes): Like Task 1, we distribute the topic of "feedback generation and presentation" to all three groups and brainstorm for in the first 10 mins. Then we asked groups to present their ideas to other groups in the last 10 mins. In the end, we did a plenary discussion for 10 mins.

Concept Development for System (Re)Design

Workshop 2 (iteration 2) helped us to collect users' input for the improvement of the quality of goal settings, motivational status visualization from self-monitoring, personalized feedback generation based on artificial intelligence (AI) technology and recommendation visualization. The focus of this workshop - was on personal preferences. In this context, we reformulated RQ-5 and prepared the following sub-questionnaires for preference(s): **Goal setting:**

- What goals do you want to set for activity coaching (e.g., nature of goals)?
- How to inform about goals (e.g., direct vs motivational)?
- How to set the goals (e.g., generic vs personalized)?

Response Type and Coaching:

- What goals do you want to set for activity coaching (e.g., nature of goals)?

Interaction Type:

- How do you want to interact with the eCoach?
  - Mode (style, graph)
  - Frequency (e.g, hourly, quarterly, once, twice)
  - Medium (e.g., audio, voice, text)

We divided the topics of discussion, such as "Goal Setting", "Response and Coaching", and "Interaction" between three groups led by experts. End-users were motivated to draw an intended design for the data presentation and recommendation visualization to use online worksheets. This workshop helped us to narrow down the scope of eCoaching from a broad area of behavioral coaching to only physical activity coaching to reduce sedentary behavior. Collected feedback from the end-users and experts provided ideas to (re)design the initial holistic eCoach prototype towards the development of an activity coaching mobile app based on selective considerations.

Evaluation of Functional Design of the Initial Working eCoach Prototype App

We invited the same end-users and observers to evaluate the functional design and working of the initial eCoach prototype app with a heuristic approach and provide feedback. We handed over the prototype to each group to do hands-on functional testing under our lab settings, and the outcomes are noted in Table F.2 as a form of feedback. The feedback consisted of three choices – passed (5), failed (0), and further scope of improvement (3). We received a rating of ≈ 4.1 out of 5.0 with further improvement scope in layout design to give the app a sophisticated view.

Table F.2: Feedback results of functional testing on the initial working ProHealth eCoach prototype.

Feedback	Choice
Simple email-based login	Passed
Simple connection with activity sensor	Passed
No problem with using the activity sensor	Passed
Successful collection of data with sensor	Passed
Successful collection of data with questionnaire	Passed
Page layout design	Further scope of improvement
Proper color in page design and icons	Further scope of improvement
Easy to navigate	Passed

Data Capture and Analysis

During the design workshops, researchers collected data with text notes (using Notepad++, Google Docs, and digital Sticky Notes), video, and images. We prepared two separate folders (for two iterations) in Microsoft Teams to store the materials safely with access control rules. At the end of the first workshop, materials from respective folders were assembled and analyzed to understand themes and categories. Also, we discussed and refined our understanding with the research team. We synthesized the most general scenarios and interaction styles. We used Workshop 1 as input to the next workshop. The data from Workshop 2 helped to refine the design and implementation of the working research prototype of eCoach system.

Results

This section describes in detail the results from (a.) workshop 1 (iteration 1), (b.) workshop 2 (iteration 2), and subsequently, (c.) the overall design considerations based on the workshops to develop a working research prototype of eCoach for personalized activity recommendation generation.

Workshop 1

Iteration 1: Scenario Design

From workshop 1 we identified end-users and their context and, followed by, developed a concept (user requirements) based on the focus group discussion to answer the identified research questions as described in Additional files 2-5.

Despite the initial briefing by our team about the motivation of a health eCoach app, all groups suggested that eCoaching must be user-friendly, accessible, effective, evidence-based, predictive, transparent, and accurate. In goal settings, end-users are told that goals could be open, flexible, adjustable, specific, measurable, attainable, relevant, shareable, and real-time. One group suggested considering cultural aspects, social traits, and individual preferences regarding coaching or motivating. The other two groups suggested the inclusion of key performance indicators (e.g., an overall health index computed by combining several health parameters to forecast health status and update the timely progress indicator) in automatic lifestyle coaching.

All groups suggested that long-term goals must consist of multiple short-term goals, daily goals must be different from long-term goals, and personal preference based. An individual will be motivated if rewards, performance comparisons, constructive motivational feedback, and personal preferences are incorporated into eCoaching. One group suggested including gamification, mood assessment, and iconography to convey feedback without requiring much cognitive involvement from the user. The other two groups ideated to consider a progress evaluation graph or report, fitness status evaluation, goal comparison, timing feedback, reminder design, and high-level contextual information in feedback generation to motivate participants in self-management.

Discussion: Concept Design for Personalized Recommendation Generation

The discussion opened a broad scope for the eCoach system to promote a healthy lifestyle. Usability, credibility, and effectiveness were identified as essential factors to determine the performance of an eCoach system. According to the discussion, the needed data collection for activity, nutrition, and habit is necessary without burdening the participants. Personalized goal setting, health risk prediction, goal evaluation, and evidence-based contextual real-time tailored recommendation generation are essential features for health eCoaching. Goals must be intelligent, customizable, personalized, and context-driven in goal setting. Iterative recommendation generation based on health status adjustment, reminder design, adjustable preferences, progress evaluation, rewarding, realistic feedback generation, and an appropriate information visualization may motivate participants to self-monitor and manage their goals. Recommendation generation can be combined with personalized mood assessment feedback to determine the satisfaction level of participants. The eCoach app must exhibit beyond state-of-the-art innovation to be better than existing apps to manage individual behavioral change. This workshop helped to refine the questionnaire set in the eCoach prototype design and development for meaningful, personalized recommendation generation.

End-user's remark on personalized recommendation generation –
"My FITBIT scares me a bit because it constantly tells me that I sleep too little. It is perceived as annoying bullying and I cannot set up that I do not want all this feedback. My experience is that I like to see that I have been active from week to week, and I probably think that I am more conscious and that it motivates me to make the right choices".

We created a basic initial eCoach prototype for personalized activity coaching given by the participant's discussion and design to capture the high-level plan for goal management and tailored recommendation generation in activity coaching and interactions predicted across groups. Researchers involved in workshop 1 created an eCoach prototype over the next month using data and objects of the workshop. The prototype was further modified based on the outcome of Workshop 2.

Workshop 2

Iteration 2: Scenario Co-(re)Design

We started the workshop with a group discussion focusing on preference(s) and motivation. The selected topics were – goal setting, response and coaching, and interaction type.

According to group-1, goals can be generic as well as personalized. In our eCoaching, personalized goal management will be more meaningful than the existing market apps. They addressed that goal setting is an essential aspect of eCoaching. Goals can be set up by a doctor, a nurse, or a person. Thus, a contextual consideration is necessary for the eCoach design and development. As suggested, goals must be broken down into more detailed, specific goals linked to the more significant life priorities of social and competitive perspectives. Group 2 indicated that motivations could be - user-based, situational-based, and environmental-based. An evidence-based personalized recommendation generation strategy will be very relevant to our eCoaching. According to Group 2, the selection of an appropriate target group, presentation of data, selection of the device, type recommendations, and innovative motivational feedback presentation are essential in our automatic activity coaching with the choice of feedback generation frequency. Group 3 highlighted that interaction type is highly related to "user type" and their "emotional state or perspective". The interaction design in our eCoaching must be two-way, adaptable, ubiquitous, easy to comprehend and visualize, accessible, customized, and personalized.

Discussion: Preference Settings for Personalized Recommendation Planning

From workshop 2 we gathered end-user feedback on the personal preference settings (goal settings, response type for coaching, and interaction type) for personalized recommendation generation and visualization in a health eCoach app based on the focus group discussion to address the RQ5 and its sub-questions. In this workshop, we narrowed the scope of holistic behavioral coaching for managing body weight to only activity coaching to reduce sedentary time.

In goal setting, the goals can be personalized or generic. The generic goals in activity coaching can be general activity guidelines set by the WHO [6,7]. In contrast, athletes or obese or overweight people who want to stay active or reduce their weight to a normal range can set the goal, differing from WHO's generic guidelines. The personalized activity goals can be multiple types (e.g., weight reduction, staying active, body fat level, proper sleeping) and need prioritization. Besides the selection of goal types, goal setting is also essential. A question may arise who will set the goals: a doctor or a trainer or the person himself? However, it depends on the context. Goal scoping in context is also an essential factor in effective coaching. Therefore, it should be broken down in a more readable, detailed, and specific way to link to the purpose. Besides, in successful goal management, social or community perspective (e.g., doing activities together) and/or competitive views (e.g., ranking, rewards) should be addressed. Overall, goals shall be "SMART": specific, measurable, attainable, relevant, and time-bound.

Motivation is the desire to act to achieve a goal. It is a critical factor in setting and achieving goals. Motivation is one of the driving forces behind human behavior. It includes the desire to continue working towards meaning, a purpose, and a life worth living. In eCoaching, motivation is an essential factor in daily life activities. Motivation differs from person to person based on the context (e.g., feedback generation to motivate a blind participant differs from a non-blind or color-blind participant). Participants can be encouraged with personalized, evidence-based, and contextual recommendation generation and its purposeful presentation (e.g., graphs, selection of colors, contrasts, visual aspects of movements, menus, adjustable with device type). Charts can produce a visible reflection of time-bound activities; however, app developers should consider the device's battery usage.

Interaction is an action that occurs due to the mutual influence of two or more objects. The concept of two-way effects is essential in interaction, not one-way causal effects. The factors associated with a good interaction design are – two-way interaction (e.g., having a diologue), ubiquitous interaction (e.g, interaction at home, outside, office or in running or walking), opportunistic (e.g., triggered automatically), adapted to the situation (e.g., former activity the user was doing at the same place, time frame, adaptive in some way based on user's instructions (e.g., visual, audible)) or, interaction preferences (e.g., user needs to see anything, only hear something, feel something, emotional needs, understanding (e.g., complexity), and motivated), visualization of graphs (e.g., what will you use the graphs/voice for?), frequency of interaction (e.g., hourly, twice/thrice per day, per day, weekly, bi-weekly, monthly), accessibility (e.g., voice, chart or graph, text to speech, text), situation awareness (e.g., situation awareness, multimodal interaction), usable and accessible following the international standards, culturally adapted following the cultural conventions, error reduction by design (e.g., redundancy), and personality (e.g., type of user and their action). Notification generation and presentation are a part of interaction and can be persistent or not. In notification design, a balance should be maintained between relevance, persistence, and disruption.

End-user's remark on motivation –
*"I wish to expend 7*X (X¿0) calories per week. I can spend more than X calories on a day when I am highly motivated. Then, it would be nice if the system saves the extra calorie expenditure in a virtual energy bank that I can expend on a lower motivated day or treat myself to my favorite food (e.g., a chicken burger)."*

"The app should generate contextual recommendations to motivate. Example – I am highly interested in soccer, and the app knows it. While I am walking or running, the app can track if any soccer event is progressing nearby and can recommend me with a message like If you walk or run X kilometers, then you have a chance to enjoy an exciting soccer game."

End-user's remark on feedback generation –
"Daily feedback would be better, instead of every minute or hour."

"Personalized activity recommendation should be presented in the form of specialized graph or chart based on activity, goal setting, and goal achievement to motivate participants."

"Feedback could be internal or external. Internal feedback should be generated through the device or eCoach app. External feedback can be generated from external sources."

End-user's remark on interaction –
"Graphs: for someone without academic background or low graphical literacy, how do they understand? May other forms of interaction from the eCoach app."

"Think of presentation of graphs: understand the level of literacy when having visual text. It is widespread. It is important to think very clearly about various questions. What is the goal of the graph? What type of information is needed? How can they adapt to different levels of literacy (e.g., visual numeric literacy)? Is it possible to have different shapes and forms and screen sizes?"

"One notification every one hour may be too disruptive."

We presented the initial activity eCoach prototype in workshop 2. We received participants' feedback to improve the quality of goal setting, the motivational status of visualization, personalized feedback, and recommendations. The overall design and modular implementation of the ProHealth eCoach prototype are described in the following subsection.

Design and Development of the ProHealth Coach Prototype

Here, we describe the high-level design consideration for the ProHealth eCoach prototype. Workshop 1 has given an overview of the necessary data to be collected from the participants relevant to our research's goal. Workshop 2 helped with preference setting, recommendation generation, and visualization. Our developed ProHealth eCoach app consists of the multiple modules described in Table F.3, and the corresponding data considered for prototype design is shown in Table F.4. The software architecture of the ProHealth eCoach app development is depicted in Figure F.2. Please refer to the video (see Additional file 6) to see the demonstrators in action.

On a conceptual level, the activity eCoaching framework consists of – a. high-level components (e.g., activity monitoring, sleep monitoring, monitoring based on self-reports) and b. low-level components (e.g., step prediction, sleep trend analysis, determination of good goal, effective feedback generation for behavioral motivation) as depicted in Figure F.3.

Participants can select single or multiple high-level component blocks for eCoach-based self-monitoring and recommendation generation. In the framework, a semantic ontology can be used to transform distributed, heterogenous health and wellness data (e.g., sensor, self-reported questionnaire) into meaningful information, including health state prediction [3]. We have considered activity monitoring based on time-series data

Table F.3: Multiple modules of the activity eCoaching app.

Module	Purpose
Data Sharing	For user log-in, personalized configuration for activity sensors.
Data Collection	For the collection of sensor data, contextual weather data, and self-reporting questionnaire data.
Preference Settings	For collecting user preferences and persist them. Users can set long-term or short-term physical activity goals, or the system can suggest them for a system-defined goal set. Users can edit and change the goals when they want. The level of goals gradually increases with the progress of individual performance.
Monitoring	For AI or rule-based prediction of the health state of the participant and compare it with pre-set user goals to generate personalized recommendations. This module also monitors contextual weather data that helps in contextual recommendation generation.
Recommendation Visualization	For visual reflection of activity in progress and displaying future predictions to motivate individuals.
Rewards	For classifying the user's progress to reach the personalized goal at the end of a pre-set period into three groups – well done up to the mark and must be improved.
Notification or Reminders	For generating personalized reminders adaptively based on the context, preferences, and health state. It can be an audio notification or a push notification with precise and dynamic content.
Problem Reporting	For addressing technical problems confronted by end-users.

Table F.4: Data considered to design the activity eCoaching app.

Data type	Nature of data	Data
Activity data	Wearable sensory data	Timestamp, steps, low physical activity (LPA), medium physical activity (MPA), vigorous physical activity (VPA), sedentary, weight-bearing, standing.
Contextual data	External sensory data	Timestamp, city, country, weather code, status, description, temp, real_feel, pressure, humidity, visibility, wind_speed.
Goal data	Questionnaire-based preference data	Generic (e.g., system defined) or personalized.
Response data	Questionnaire-based preference data	Recommendation data for activity.
Interaction data	Questionnaire-based preference data	Mode (e.g., style, graph), frequency (e.g., hourly, quarterly, twice a day, daily, bi-weekly, weekly, monthly), medium (e.g., text).

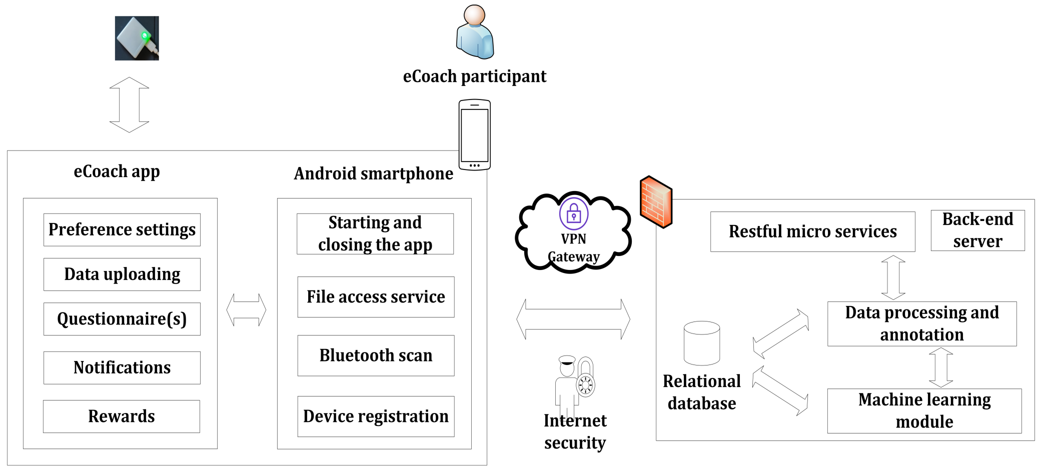

Figure F.2: The software development architecture of activity eCoaching app.

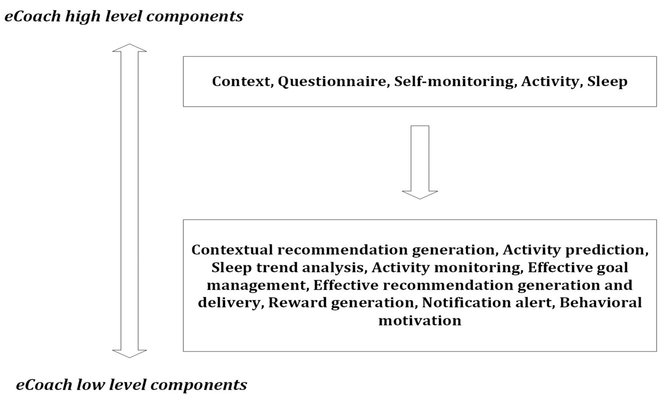

Figure F.3: Components of the activity eCoaching framework.

processing with deep learning networks [38]. Here, we presented activity prediction as a set of numbers or intervals and used its visualization for motivational purposes. However, the usability study and the efficacy evaluation of the eCoach app for behavioral motivation are the future scope of research. In our design consideration, the eCoach system has access to contextual weather data, activity sensor data, and questionnaire data. The overall modularized eCoach app design and its implementation are described below, addressing ideas and concerns.

Data Sharing

The login has been kept as simple and secure as possible. We have planned to collect person-related and activity data without personal identity disclosure. Only authorized users can access the eCoach system. Each participant has been provided with a unique user identifier (UUID), and they will be able to access the system with a personal email-id and modifiable password. The system is further protected with the "eduVPN" network. Activity data can only be shared with the researchers to create meaningful information out of raw data. Sharing data through social media or any other means is prohibited by NSD rules. The simple log-in interface of the eCoach app is depicted in Figure F.4.

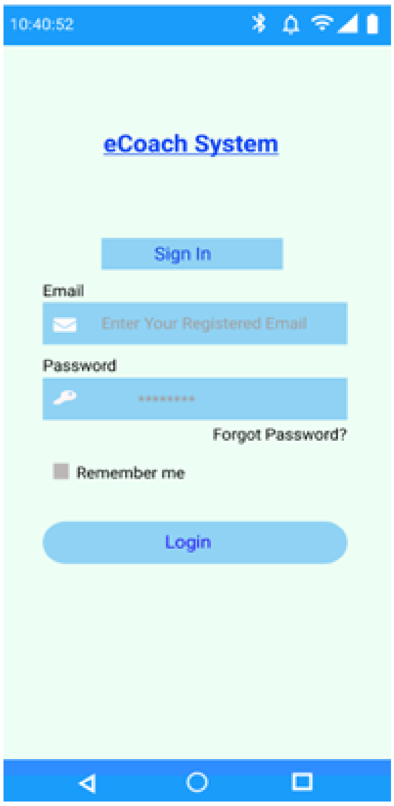

Figure F.4: Simple log-in page for the eCoach prototype system.

Data Collection with eCoach System Prototype

The data collection has been divided into four parts –

- Activity data collection with wearable Bluetooth enabled (BLE) low-energy activity device,
- Questionnaire for daily weight reporting (to analyze over a period of time whether activity coaching has an impact or not!), feedback (or survey), and the reporting of technical problems (without personal identity disclosure) during the study in progress,
- Personal preference settings (goal settings, response, and interaction), and
- Contextual weather data collection with OpenWeather representational state transfer (REST) application programming interface (API) against API Key validation.

We used the MOX2-5 medical-grade (CE certified) accelerometer-based low-energy activity sensor for continuous monitoring [39][40]. The device flawlessly measures and transfers high-resolution activity data, such as activity intensity, weight-bearing, sedentary, standing, low physical activity (LPA), medium physical activity (MPA), vigorous physical activity (VPA), and steps for every minute. The collected data is well suited for physical activity classification (LPA, MPA, VPA) and posture detection (sedentary, (such as sitting or lying), standing, and weight-bearing). The recommended wear locations of the device are thigh, hip, arm, or sacrum. We used the publicly downloadable

Android MOX2 mobile app to capture individuals' activity parameters into the smartphone's download folder. We then used our developed eCoach app to periodically transfer the activity data to the eCoach backend server tagged with the unique user-id, following the Android secure file access policy. Participants had the following two options to upload their activity data from their smartphone to the remote eCoach server – automatic (to upload data automatically after every regular interval) or manual (if automatic data upload fails due to technical problems). The personal health, wellness, and questionnaire data are sent from eCoach app to a remote eCoach server via a REST API (HTTP POST) to store them in a Postgres database in line with General Data Protection Regulation (GDPR) and Norm for information security and privacy in health (NORMEN) guidelines. No disclosable personal identifier has been collected with the questionnaire, complaint, or feedback (survey) data.

The MOX2-5 activity sensor is a 3-dimensional accelerometer with a 25-100 Hertz sample rate (dimensions 35 x 35 x 10 mm). Its sensitivity is 4 mg/LSB. Maastricht Instruments had developed it. It is dust and waterproof gives a battery backup for seven days, and is built with a rechargeable "Lithium Ion125 mAh". The current version of the MOX2-5 activity sensor is not suitable for classifying activities into the following detailed activity classes: cycling, swimming, rowing, and skiing. Therefore, the participants must report them manually as questionnaire data in the latest version of the eCoach app. The MOX2 sensor-based and questionnaire data collection interfaces of the eCoach app are depicted in Figure F.5 and Figure F.6. The daily weight reporting data will help to analyze if regular physical activities or behavioral motivations impact gradual weight change. It can be a helpful direction in obesity and overweight case studies with eCoaching.

Preference Settings

We have designed interfaces for the questionnaires to collect personal preference data, such as goal setting, response, and interaction (see Figure F.7). There are two goal types – system-defined general goals for staying active following the guidelines of WHO and person-defined goals (as athletes might want to get coached towards specific training goals). The duration of the goal period can be 4-12 weeks or more based on personal preferences. The goal-setting can be short-term (e.g., daily, weekly) or long-term (e.g., biweekly, monthly). The eCoach system should encourage end-users to reach their long-term goals with the generation of tailored recommendations and the achievement of short-term goals.

In our eCoach app, we have considered the following pre-selected default values for the preference settings, and the graphical user interface (GUI) design are depicted in Figure F.7.

- Goal Type: Generic or Personalized
- Goal Period: 4 weeks
- Response Type: Representation of steps, VPA, MPA, LPA, sedentary bouts, future step prediction, and interval prediction value

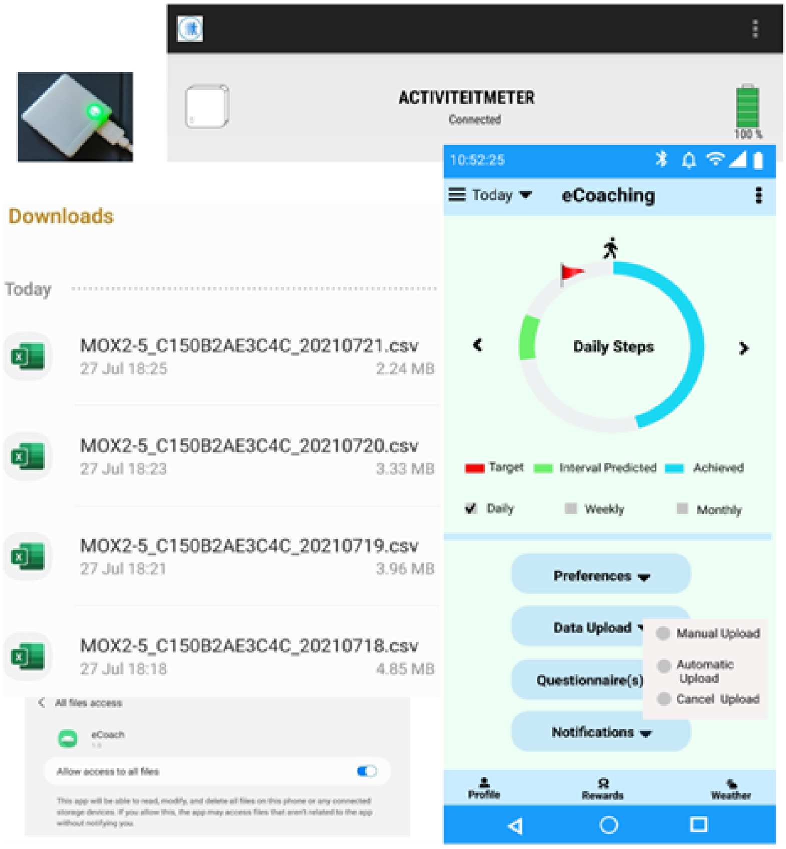

Figure F.5: Sensor-based data collection interfaces in the eCoach prototype app.

- Interaction Mode: Graph, Text, Audio
- Interaction Frequency: Regular interval, Daily, Weekly
- Interaction Medium: Text (e.g., push notification), Audio

All the preference and physical activity data are recorded in a relational database using semantic annotation. Individuals are always allowed to view and update their preference data. A hybrid (data and rule-driven) health state monitoring component is responsible for analyzing physical activity progress and followed by the generation of recommendations to reach personal activity goals (see Figure F.8).

Monitoring and Recommendation (Feedback) Visualization

The app keeps track of an individual number of steps, duration of VPA, MPA, and LPA (in minutes per day), and sedentary bouts until the monitoring period gets over. Participants can actively monitor or track the number of exercises they have performed over the day or week based on their preferences. They will have the option to see their historical performances as well. At the end of the eCoaching session, they can report notes on their satisfaction with using the app. In UCD workshop 2, end-users showed interest in simplified metrics. Therefore, the eCoach app provides numerical feedback on the activity performed on simplified graphs. Here, feedbacks are of two types to motivate participants – indirect visual feedback and direct (e.g., textual pop-up notification generation). The

Figure F.6: Options for questionnaire-based data collection and historic or current notification visualization interfaces in the eCoach prototype app.

participant receives daily as well as cumulative feedback at the end of the session to view their progress towards the goal.

In our activity eCoaching app, we have considered a hybrid health state monitoring component. During health state assessment, the module can predict the activity pattern of the participants (e.g., steps), automatically for the next "n" days (n>0) based on the temporal pattern in data. It can help participants identify which kind of activities they should perform to reach their long-term goals. Temporal analysis of data (e.g., deviation in activities) helps to analyze the pattern in human activities and generate evidence-based tailored recommendations to motivate participants (e.g., comparative statistical analysis in activity data between weeks W1, W2, and W3 helps to determine if any deviation or improvement in performance or in which week the participant was more active). These recommendations can be contextual with the inclusion of weather information (e.g., tomorrow morning, the weather is sunny, and the temperature is between 15–18 degrees Celcius (C). Therefore, you can plan to walk for one hour or perform similar activities).

We have formatted activities in minutes per day or steps per day instead of calories, which is inaccurate and difficult to understand for the users how calories relate to the activity goal. Moreover, for estimating future activity in terms of "steps" based on time-series monitoring data processing using deep learning-based forecasting, we focused on probabilistic interval prediction rather than abstract point prediction. A prediction interval gives an interval within which we expect to remain with a specified probability.

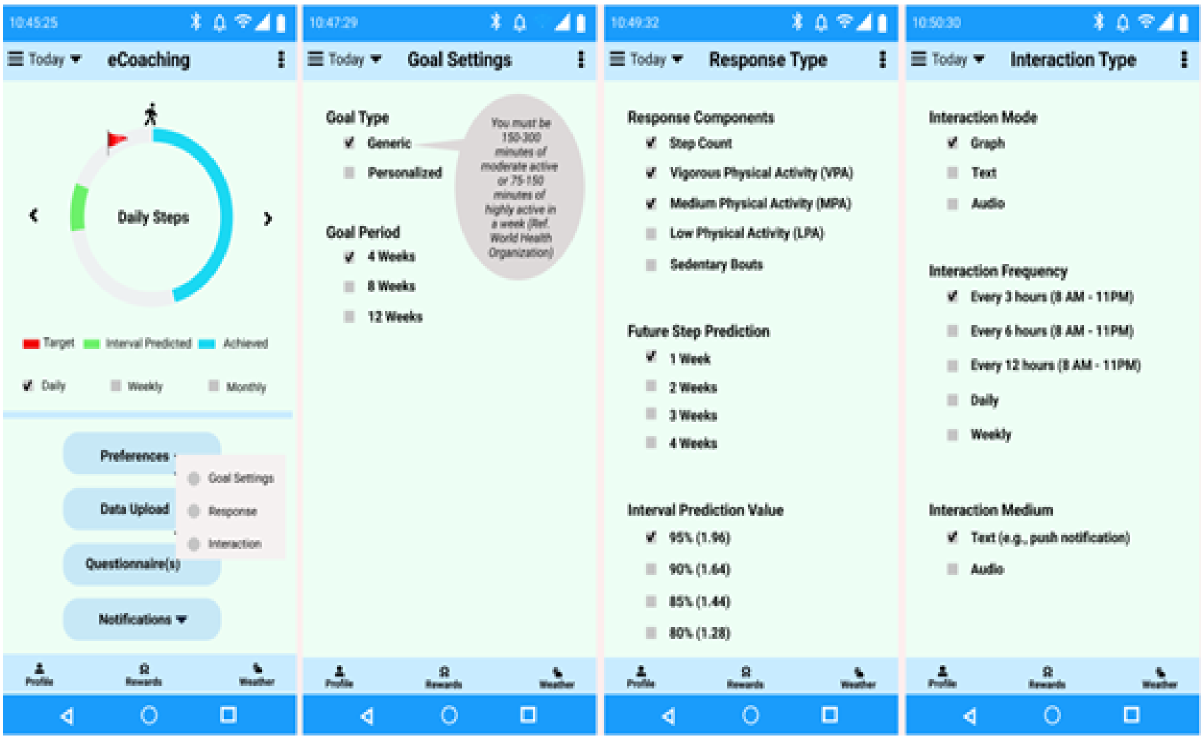

Figure F.7: Representation of preference settings in the eCoach prototype app.

A prediction interval can be written as,

$$\widehat{Y}_{T+h} \pm c\sigma_h$$

Where “c” depends on the coverage probability, and in one-step interval prediction its value is 1.96 (95% prediction intervals where forecast errors are normally distributed). ”σ_h” is the estimation of the standard deviation in the h-step forecast distribution (h>0). However, deep learning-based forecasting implementation, calculation of residual errors in temporal step data, and h-step prediction interval calculation are beyond the focus of this paper. By default, we have used c = 1.96. However, participants can choose the value of “c” up to 1.28 (80% interval).

In UCD workshop 2, end-users agreed to visualize their activity intensity simplified and briefly. Therefore, we had not considered infantile animations, which sound like feedback when a goal is achieved, as they might cause unnecessary interruptions. We have prioritized weekly performance evaluations rather than daily performances, as participants can be active and maybe less active on the next day. A balance of activities must be maintained to achieve the short-term weekly goals to reach long-term monthly goals. We have shown a sample recommendation visualization screen in Figure F.9. In the figure, the daily step count has been represented with a target daily step count based on the goal settings, deep learning-based step prediction, and its extension with naïve-based interval prediction. The nature of step prediction is dynamic and depends on the steps achieved.

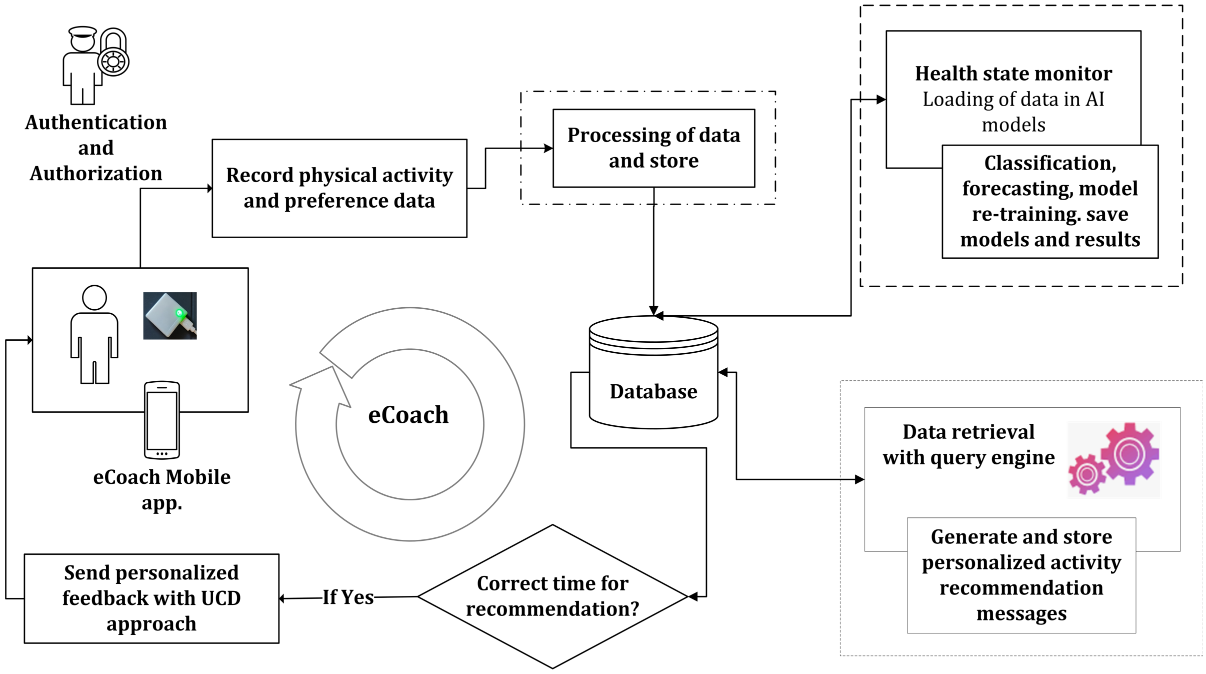

Figure F.8: The continuous process of personalized data collection, decision-making, and personalized hybrid recommendation generation combining AI results and query rules.

Notification

The recommendation module generates personalized and contextual recommendations based on the predicted health state. Recommendations can be direct (for example, pop-up notifications or alerts) or indirect (for example, activity status visualization). Instant notifications can contain two types of messages: (a.) formal To-Do (for instance, "You need to complete another 1500 steps in the next three hours to reach your daily goal") and (b.) informal motivational notifications (e.g., "Good job, keep going! You have achieved targeted steps."). In the activity eCoaching framework, the messages are annotated in a semantic ontology. To inform the user about activity in progress, we have used the indirect approach for recommendation visualization, and to give direct instant notifications, we have considered pop-up text alerts. The participants can select the notification frequency as part of the app preferences. By default, we have considered activity notifications every three hours between 8 AM and 11 PM; however, the user can modify that. These notifications are timely alerts. It will help participants to stay on the right track, either with motivational messages or with activity improvement suggestions. Notifications have been kept short, understandable, and positive. We have depicted sample push notification generation screens in Figure F.10.

Rewards

We have considered a simple emoji and a textual message to represent individuals' short-term (e.g., daily to weekly) and long-term (e.g., bi-weekly, monthly) goals. We have used three emojis to classify individual progress to reach a personalized goal into three groups – well done [10 credit points], up-to-the-mark [5 credit points], must be improved [0 credit

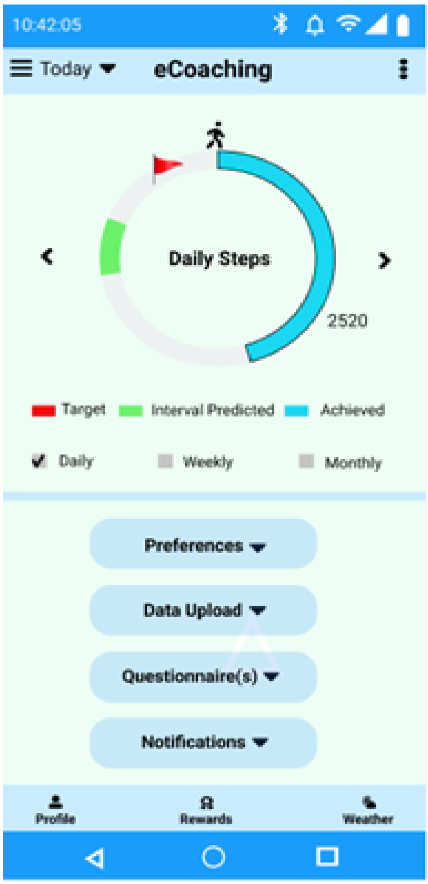

Figure F.9: Visualization of daily step count, target step count, and predicted interval.

points]. All the credit points can be reimbursed against “Foodbank”, as ”reward” means that the user can eat a bit more if he has trained more. We will decide to offer a list of potential food items in the “Foodbank” against the weekly accumulated credit achieved. It is a motivation to do more activity. In the future, we will enhance the reward generation with demographic clustering and profile ranking methods to motivate participants. We have depicted a sample personalized weekly reward generation in Figure F.11.

Discussion

Principal Findings, Innovation, and Technology Readiness

eCoach features [9] (such as recommendation, personalization, interaction, co-creation, goal management, automation, and persuasion) utilize a combination of wearable activity sensors and digital activity trackers with improving physical activity. An intelligent eCoach system can generate automatic, meaningful, evidence-based, and personalized lifestyle recommendations to achieve personal lifestyle goals. Real-time analysis of data to create customized recommendations on time is crucial in eCoaching. From the literature search point of view, the concept of eCoach in the healthcare field is still in its infancy. The associated studies can be classified into the following two categories: “What to coach” and ”How to coach” In fact, in the original eCoach concept, data collection,

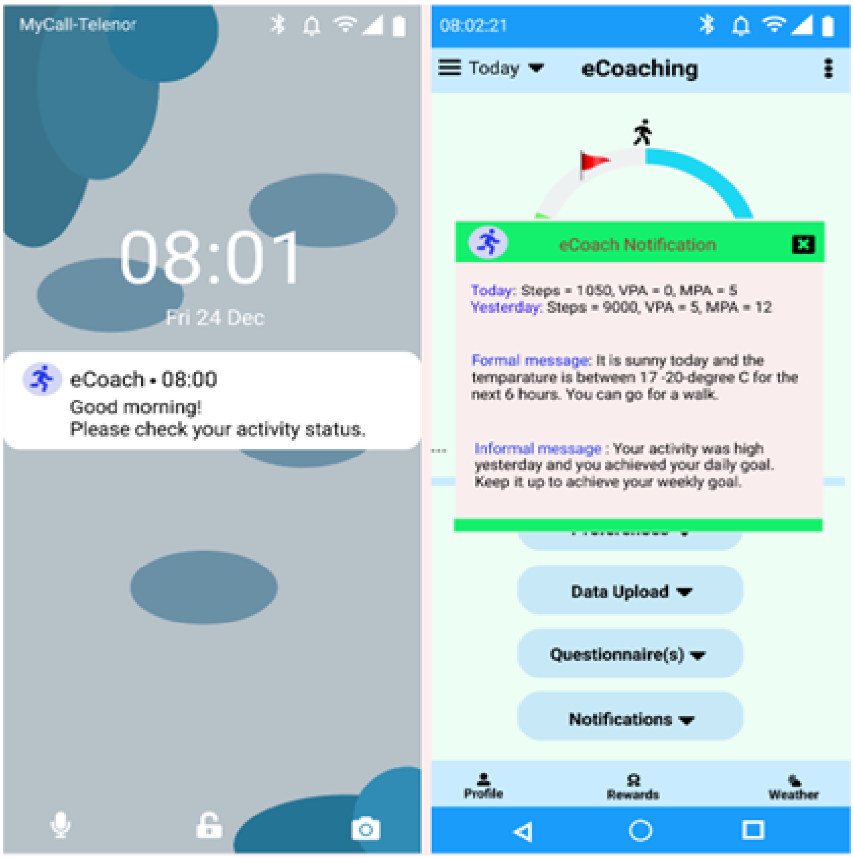

Figure F.10: A sample notification at 8 am. and its visualization in the eCoach app.

and processing is used to determine the "WHAT to coach", in terms of the content of recommendations (direct or indirect), including the calculation of predicted activity, and the resulting gap to the set goal. The "HOW to coach" addresses the HCI related to turning human coaching into automatic, digital coaching, including aspects of persuasive technologies and motivational messages. Integration of recommendation technology with machine learning algorithms and its visualization appropriately to motivate participants is another challenging task in an eCoach design and its development, and this has been addressed in this paper.

This study presents a detailed overview of the rationale, characteristics, user-centered design, and development process of a health eCoach app for the self-management of physical activity to reduce sedentary behavior or to stay active. Proper utilization of the activity eCoaching concept with positive psychology may open a direction for self-management of weight. Our intended eCoach app aims to increase individual participants' apparent abilities and motivation with monitoring and feedback generation and to trigger participants to engage in physical activities at the right time by leveraging self-maintained persuasive strategies. In the design and development of this app, the research team collected user needs and preferences, and an engineering team interpreted them into technical requirements, specifications, and technical solutions. This app allows changing behavior and habits by increasing self-knowledge, self-monitoring, self-awareness, and self-effectiveness. Personalized preferences are set, and tailored evidence-based contextual feedback are generated based on the degree of goal achievement. The UCD approach pro-

Figure F.11: An example weekly reward generation screen in the eCoach app.

vided an understanding of the needs of end-users to make the design of our eCoach app successful. The main requirements for the app design and development as derived from the UCD approach were –

- Data sharing must conform to the GDPR regulations and ethical guidelines [41][42].
- Data comes from heterogeneous sources. There must be a method to annotate data.
- Selection of appropriate medical grade activity sensor that can measure activity accurately. Data collection should not create an additional burden on the participants. Proper placement of the sensor so that it does not create any nuisance.
- Settings of preferences based on individual needs.
- Feedback or recommendations must be direct or indirect. Recommendations should be personalized, evidence-based, contextual, periodic, comprehensible, subtle, brief, and simplified.
- Simple rewarding mechanism to motivate participants.

We integrated the Semantic Sensor Network (SSN) ontology and selected concepts from Systematized Nomenclature of Medicine - Clinical Terms (SNOMED-CT) into our ontology model used in the eCoach Framework to annotate data [3][43][44][45]. However, the ontology design and its implementation are beyond the scope of this paper. In the open discussions (design workshops), end-user groups were not agreed on all requirements. Questions were raised about using the MOX-2 device for activity monitoring as there are different activity monitoring mechanisms in the market, such as Apple, Samsung, and other consumer devices (e.g., Fitbit, Actigraph, smart-watches). Maastricht Instruments, a spin-off company of the Maastricht Hospital, and supplier of the MOX-2 activity monitoring device, has informed us about the following:

- Apple, Samsung, or similar service providers utilizes the sensors in the smartphone. People do not wear the smartphone at the same body location all day, so this poses difficulty in accurately assessing physical activity. On the other side, higher-level activity information is possible, such as including location information from the smartphone.

- Maastricht Instruments validated Fitbit, and the like in elderly populations, and they saw a high variability. Furthermore, it is never known when the manufacturer replaces the algorithms or sensors in the device, so it is tricky to do clinical trials with such devices (over longer durations).

- Most consumer devices are not suitable for use in medical applications. Maastricht Instruments has proven the performance of their MOX-2 device in several published studies on elderly and diseased populations [18].

- Actigraph is in the same category of devices as the MOX; however, MOX2-5 is cheaper to use for clinical trials.

Our concept of eCoaching is novel and in contrast proves the hypothesis that - “in eCoaching, automatic generation of personalized recommendation is possible”. Here, we collected design requirements from the end-users to develop an app that can generate an effective individualized recommendation for a sedentary lifestyle and turn it into a behavioral motivation for an effective human-eCoach-interaction. In the eCoach system, the concept of transforming distributed, heterogenous health and wellness data (e.g., sensor, questionnaire) into meaningful information with semantic ontology is inventive. Here, we used AI-inspired recommendation technology, processing of medical-grade sensor data, anomaly detection in data and its removal, residual error minimization to improve the time-series prediction, and probabilistic interval prediction rather than abstract point prediction for motivational recommendation visualization to make the solution pioneering. Moreover, the adoption of persuasive strategies in the app design has made the concept innovative. In Table F.5, we have performed a qualitative comparison between our ProHealth eCoach and commercial activity tracking smartphone apps (e.g., Fitbit, Actigraph, MOX2-5, Pedometer, Garmin, and smartwatches (e.g., Apple, Samsung, Huawei)) regarding eCoach components identified in the literature search [5][9]. Traditional activity-tracking smartphone apps focus more on data capturing and its representation; however, they suffer from the UCD approach, adequate data, data protection, data consistency, proper documentation, guidelines, and ethical approvals. Table F.6 describes technological readiness levels (TRLs) of ProHealth eCoach against standard levels set by EU [46][47].

Table F.5: A qualitative comparison in regard to the generic eCoaching components.

Persuasive eCoaching components	Addressed in commercial activity tracking mobile apps including smartwatches?	Addressed in ProHealth eCoach?
Intervention	No	Yes
Personalization	No	Yes
GInteraction	Yes	Yes
Co-creation	No	Yes
Goal-settings and evaluation	No	Yes
Automation	No	Yes
Persuasion	No	Yes
Goal-based personalized recommendation generation	No	Yes

Limitations and Future Scope

We plan to overcome certain limitations of this study in our future work. The restrictions are summarized as follows – First, we have presented the design and development of an eCoach prototype (i.e., ProHealth eCoach) for activity coaching. However, we have not performed its usability testing for the heuristic evaluation of the eCoach prototype. Second, in activity monitoring, the scope can be extended to sleep monitoring rather than only step prediction and visualization along with daily step count and total minutes of VPA, MPA, and sedentary bouts. Third, this study has not evaluated recommendation generation's credibility, reliability, and effectiveness and its presentation (direct and indirect) towards motivational, and behavioral change. Following usability evaluation, we will recruit participants of similar interests in efficacy evaluation of the recommendation generation. Fourth, constraints, such as poor internet connectivity, battery lifetime due to BLE and background processing, budget, time plan, and technological limitations should be overcome.

Fifth, the sensor cannot distinguish the types of activities, such as swimming, skiing, or cycling. Therefore, a questionnaire should be designed to overcome its reporting. Sixth, the scope of recommendation generation and turning it into a behavioral motivation is extensive. Here, we have not evaluated concepts, such as what is a good goal? How to generate effective feedback for behavioral motivation? Future studies can compare actual participants' feedback and activity trends to modify goal settings and gradually tailor them. Likewise, recommendations can be presented to participants in different ways, such as visual (e.g., graph, chart), audio, text (e.g., pop-up notification or on-screen messages), or any combination. In our future study, we can recruit different people to compare the conceptual basis of effective recommendation presentation for behavioral motivation. Seventh, besides only activity monitoring and recommendation generation, the incorpo-

Table F.6: Achieved TRLs by our ProHealth eCoach.

Number(s)	Technology readiness levels	Achieved (Yes/No)?	Comment(s)
TL-1	Basic principles observed	Yes	-
TL-2	Technology concept formulated	Yes	-
TL-3	Experimental proof of concept	Yes	-
TL-4	Technology validated in lab	Yes	-
TL-5	Technology validated in relevant environment (industrially relevant environment in the case of key enabling technologies)	No	We will evaluate this in our future usability study.
TL-6	Technology demonstrated in relevant environment (industrially relevant environment in the case of key enabling technologies)	No	We will evaluate this in our future usability study.
TL-7	System prototype demonstration in operational environment	No	We have designed and developed an initial version of the eCoach prototype; however, integration and scalability testing must be performed in the production environment.
TL-8	System complete and qualified,	No	Usability evaluation must be performed on a group of participants for further model improvement and qualification.
TL-9	Actual system proven in operational environment (competitive manufacturing in the case of key enabling technologies; or in space)	No	The system will be operational after efficacy evaluation of the eCoach app. on a group of controlled trials.

ration of nutrition assessment and the tracking of habit can allow eCoach app to change behavior for a healthy lifestyle in obesity cases. Eighth, improvement in AI prediction to classify between meaningful (effective) and bad (inefficient) recommendations with a process of continuous learning from individual data and performance trends, and following, personalized recommendation generation with obtained knowledge. Ninth, here we have discussed eCoaching for personalized physical activity monitoring with tailored recommendation generation, self-monitoring, motivation, and goal management. However, eCoaching can be broad in controlling other behavioral changes, such as habit, nutrition, depression, chronic pain, and cognitive decline. Therefore, the eCoaching concept can be promising in preventing chronic illnesses, such as diabetes type II, obesity and overweight, mental health, and cardiovascular rehabilitation. Tenth, recommendations in an eCoach system can be rule-based, data-driven, or hybrid. An appropriate selection of recommendation generation methods is essential in eCoaching to generate contextual and meaningful personalized and group-level recommendations. The adoption of explanation methods in recommendation generation will make eCoaching more attractive and trustworthy to its participants. Eleventh, behavior is a slow but gradual change. To evaluate the practical efficacy of eCoaching toward behavior change, self-management, credibility, and motivation, a proper longitudinal study plan is necessary for two groups (one group without eCoaching and one group with eCoaching) of controlled trials with a minimum group size of 50 participants following inclusion and exclusion criteria, to compare the outcomes with statistical methods. Furthermore, future work focuses to understand the importance of socio-demographic characteristics such as age, gender, ethnicity, education level, etc. of the enrolled individuals to achieve a high level of generalized findings. It also helps to categorize individuals into different subgroups to obtain effective support to control their lifestyle and behaviors for more generalized purposes.

Conclusions

In this study, the design and implementation process of an activity eCoach monitoring and personalized recommendation generation app is described as the preparation of a mHealth intermediation to encourage the self-management of PA. It demonstrates a user-centered design process's consideration to make it suitable for end-user, technology, healthcare professionals, engineers, and researchers. The main principle of this eCoach app is to change an individual's sedentary behavior through self-monitoring, preference setting, personalized recommendation generation, and presentation. The app connects three technologies – an accelerometer-based medical-grade activity sensor, an Android mobile app, and an internet application. The eCoach app design directs to an innovative approach with the adoption of the following concepts – persuasive strategies, ontology-based data annotation, hybrid recommendation technology, interval prediction, and the incorporation of medical-grade activity sensors. Following the user-centered design, the usability and efficacy evaluation of the eCoach app will be engaged in the lab environment and a cluster of a controlled trial, respectively.

Declerations

Ethics Approval and Consent to Participate

For our project, we received ethical approval from the Norwegian Centre for Research Data (NSD) (#797208) and the Regional Committees for Medical and Health Research Ethics (REK) (#53224). Written informed consent was obtained from all the workshop participants. All the data (e.g., video, audio, text) collected in the workshop were stored following the ethical guidelines without personal identity disclosure. We have not performed any sort of human intervention in this study.

Consent for Publication

Not Applicable.

Availability of data and materials

All data generated or analyzed during this study are included in this published article and its supplementary information files.

Competeting Interests

The work is original and not submitted elsewhere. The authors don't have any conflict of interest. In its extended work, we will take it forward for usability evaluation in the usability laboratory of the UiA-eHealth center, Grimstad, Norway to perform an efficacy evaluation on a cluster of a controlled trial.

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Author's Contributions

AC: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Workshop arrangement, writing - original draft, writing - review & editing, Visualization. **AP:** Writing - review & editing, Supervision. **MG:** Workshop arrangement, writing - review & editing, Supervision. **SM:** Workshop arrangement, writing - review & editing, Supervision. **NP:** Visualization. **YKM:** Conceptualization, Methodology, Writing - original draft, writing - review & editing, Supervision.

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Author's Information

We have mentioned the same in the Title Section.

List of abbreviations

PA: Physical Activity
eCoach: Electronic Coach
mHealth: Mobile Health
UCD: User-Centered Design
CVDs: Cardiovascular Diseases
WHO: World Health Organization
IDEAS: Integrate, Design, Assess, and Share
MRC: Medical Research Council
BIT: Behavioral Intervention Technology
COM-B: Capability, Opportunity, Motivation, and Behavior
FBM: Fogg's Behavior Model
JITAI: Just-In-Time (Adaptive) Interventions
HCI: Human-Computer-Interaction
IoT: Internet-of-Things
USA: United States of Amderica
FDA: Food and Drug Administration
RQ: Research Questions
GDM: Gestational Diabetes Mellitus
WIISEL: Wireless Insole for Independent and Safe Elderly Living
NSD: Norwegian Centre for Research Data
AI: Artificial Intelligence
REK: Regional Committees for Medical and Health Research Ethics
SMART: Specific, Measurable, Attainable, Relevant, and Time Bound
LPA: Low Physical Activity
MPA: Medium Physical Activity
VPA: Vigorous Physical Activity
UUID: Unique User Identifier
BLE: Bluetooth Enabled
REST: Representational State Transfer
API: Application Programming Interface
GDPR: General Data Protection Regulation
NORMEN: Norm for information security and privacy in health

GUI: Graphical User Interface
SSN: Semantic Sensor Network
SNOMED-CT: Systematized Nomenclature of Medicine - Clinical Terms
BMI: Body Mass Index

Supplementary Information

Additional file 1. StaRI checklist for completion.
Additional file 2. The outcome of the focus group discussion for RQ-1 in Workshop 1 (appendix-1.xlsx).
Additional file 3. The outcome of the focus group discussion for RQ-2 in Workshop 1 (appendix-2.xlsx).
Additional file 4. The outcome of the focus group discussion for RQ-3 in Workshop 1 (appendix-3.xlsx).
Additional file 5. The outcome of the focus group discussion for RQ-4 in Workshop 1 (appendix-4.xlsx).
Additional file 6. Here, we have attached a video demonstration of the activity eCoach app's a high-level working as a supplementary ProHealth eCoach.mp4 file (2.46 minutes or min). The navigation windows are mentiond as follows –

- Feature navigation (0.04 seconds or sec)
  - Login (0.09 sec)
  - Visualize step count (0.19 sec)
  - Navigate preferences (0.26 sec)
  - Navigate data upload (1.06 min)
  - Navigate questionnaire(s) (1.15min)
  - Navigate notifications (1.24 min)
- Notification and reward visualization (1.36 min)
- Data collection with MOX2-5 activity sensor (1.55 min)

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