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Information quality life cycle in secondary use of EHR data

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A R T I C L E I N F O

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A B S T R A C T

The paper argues that existing research on information quality (IQ) mainly focuses on the primary use of electronic health record (EHR) data, whereas IQ in secondary use of EHR data needs further deliberation. The current view of IQ in a healthcare context is static. It assumes that once the EHR system generates the information product, individual users may act on the information based on their subjective perception of its quality. However, this view ignores the complexities of secondary use of EHR data, in which users are actively involved in (re)generating and communicating the information product. Thus, IQ does not remain static but keeps on transforming through active engagement and interpersonal communication. To contribute to this debate, we conducted a qualitative case study in a Norwegian healthcare context by employing an IQ life cycle model. In conclusion, we enhanced the existing IQ model by (1) adding interpersonal communication, (2) showing the interrelations of the IQ dimensions, and (3) integrating the mechanisms of the transformation process for IQ in secondary use of EHR data. In doing so, we unfold the dynamics of IQ in the secondary use of EHR data.

1. Introduction

The increasing adoption of electronic health records (EHR) systems has become a focused area of research since any compromise of the health information quality (IQ) can lead to dire consequences (Pipino & Lee, 2011; Welzer, Brumen, Golob, Sanchez, & Družovec, 2005). In an EHR context, IQ is referred to as information appropriate for healthcare interventions and processes, encompassing human, social, and technological elements of the context where information is generated, communicated, and used (Cabitza & Batini, 2016).

EHR systems capture patient-level clinical and administrative data. Clinical data includes documentation of clinical services delivered to patients, clinical findings, patient history, clinical orders, allergy details, and laboratory results (Ward, Marsolo, & Froehle, 2014), while administrative data includes demographic, socioeconomic, financial, and logistics data (Davis & LaCour, 2014; Jensen, Jensen, & Brunak, 2012). The use of EHR data can be broadly categorized as primary and secondary (Mann & Williams, 2003). The primary use of EHR data is "to use it to directly support patient care" (Cabitza & Locoro, 2017, p. 187) by aiding clinicians in medical decision making at the point-of-care.

Unlike deterministic use of medical information, where "data shall be used only for the purpose for which they were collected" (van der Lei, 1991, p. 80), secondary use is the reuse of EHR data "for a purpose different than the one for which it was originally collected" (Hripcsak et al., 2014, p. 207) in a non-direct care use (Safran et al., 2007) both within and across organizational boundaries. The secondary use of EHR data holds the potential to fuel a learning healthcare system and ensure quality, safety, and value in healthcare (Krumholz, 2014). Examples of such secondary use of EHR data include service planning, resource allocation, performance monitoring, clinical auditing, and quality management (Cabitza & Locoro, 2017; Hripcsak et al., 2014; Mann & Williams, 2003; Safran et al., 2007). In this paper, however, the definition by Safran et al. (2007) is applied, which excludes the secondary use of EHR data for direct patient care. Furthermore, since the use of data for medical research is out of the scope of this paper, secondary use of EHR data here relates only to the quality management of organizations.

Previous studies show that high-quality information is critical for effective and efficient management of healthcare systems (Richards & White, 2013), in terms of economic costs, organizational planning, quality and safety of care (Liaw et al., 2013), and effective dissemination of information (Champion, Kuziemsky, Affleck, & Alvarez, 2019). Research on IQ in healthcare contexts has focused mainly on the primary use of EHR data (Cabitza & Batini, 2016). This research is often conducted from a technological point of view (Mettler, Rohner, & Baacke, 2008; Mohammed & Yusof, 2013) and includes how IQ issues may cause medical errors (Pipino & Lee, 2011) that lead to adverse events (Mettler et al., 2008). In their literature review, Vuokko, Mäkelä-Bengs,

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Hyppönen, and Doupi (2015) only found a handful of research studies addressing the role of IQ in secondary use of EHR data. This research is limited to quality challenges when data is aggregated to regional or national levels (Cabitza & Batini, 2016), for example, in clinical research (e.g., Weiskopf & Weng, 2013) and healthcare policy planning (Häyrinen, Saranto, & Nykänen, 2008).

In the conventional view, information is often treated as a product, where raw data are manufactured into information products by information systems. In this view, information is the product of a well-defined information production process (Lee, Pipino, Funk, & Wang, 2006; Wang, Lee, Pipino, & Strong, 1998). The manufacturing view assumes that IQ is static and law-like, where the outcomes are predictable.

This view of information is particularly challenging in the secondary use of EHR data for several reasons. Unlike the manufacturing view, the process of obtaining value from EHR data is not well-defined. Instead, it is characterized as ad hoc, with no standards in terms of empirical measures of core processes and a lack of understanding of information needs (Botsis, Hartvigsen, & Weng, 2010; Foshay & Kuziemsky, 2014). Thus, treating information processing as a standardized manufacturing process provides a static view without addressing the process's dynamics.

The information manufacturing view assumes that quality is achieved when the information is "meeting or exceeding consumer expectations" (Kahn, Strong, & Wang, 2002, p. 185). However, quality is often described as a relational concept where multiple actors pass different judgments on quality (Lillrank, 2003). This leads to a paradox between quality and time; defining quality as meeting or exceeding information users' expectations assumes that the information users, including their quality requirements, are identified before the information generation (Lillrank, 2003). In reality, however, information is often the subject of interpersonal communication[1] within health care organizations (Avison & Young, 2007), where the actual use of information often resides outside of the information producer's control (Mettler et al., 2008). Thus, viewing information as a mere technological service provided by the EHR system is insufficient. According to this perspective, to achieve appropriate actions in response to the information, we need to consider both the information and the communication processes (Alenezi, Tarhini, & Sharma, 2015).

Moreover, the manufacturing view of information treats the output information as a fixed product. However, transforming and filtering the information is likely to happen in interpersonal communication (Rogers & Agarwala-Rogers, 1976), thus modifying the information. Hence, we need to take a more balanced (sociotechnical) view of IQ (Mettler et al., 2008; Neely & Cook, 2011) to understand not only how data transform in the information generation process but also how perceptions of IQ in the information use process are affected by the communication processes. Thus, we need to understand the interplay of technical and social processes involved, which is not currently addressed in the IQ literature.

To address the identified gaps, we formulated the following research question: How does IQ transform through secondary use of EHR data? Guided by this question, we conducted a qualitative case study of quality assurance in a Norwegian hospital trust and applied an IQ life cycle approach to analyze the case.

The paper is organized as follows: In the following section, we introduce the study's theoretical background. After that, we present the case description, followed by the research method and findings. Finally, we conclude with a discussion of the theoretical and practical implications of the study.

[1] In this context, the term 'interpersonal communication' denotes communication between a minimum of two parties as defined in Oxford Reference (https://www.oxfordreference.com/view/10.1093/oi/authority.20110803100008269)

2. Theoretical background

In this section, we introduce the theoretical concepts used for the analysis. First, we discuss the concept of IQ in a healthcare context, and then we introduce the concept of the IQ life cycle.

2.1. Information quality in the context of EHR

IQ is a multidimensional concept (Ge & Helfert, 2007; Illari & Floridi, 2014), where dimensions are defined as characteristics of the information (Ge & Helfert, 2007). Examples of such dimensions are accuracy, relevancy, reliability, completeness, and timeliness (see Appendix C for complete definitions). Numerous frameworks and models have tried to capture the concept, without reaching a consensus about classifications of quality dimensions (Price, Shanks, & Neiger, 2008) or defining the concept itself (Batini, Cappiello, Chiara, & Maurino, 2009). However, the most adopted definition of IQ is "fitness for use" (Neely & Cook, 2011, p. 82; Sadiq & Indulska, 2017) or "fit for purpose" (Embury & Missier, 2014, p. 257). This definition implies that information considered appropriate for one user may be inadequate for another. Thus, IQ is contingent upon the context of use, where subjectivity influences the perception of usefulness. Accordingly, IQ in a healthcare context is defined as information that is appropriate for health interventions and processes (Cabitza & Batini, 2016). The definition encompasses human, social, and technological elements of the context where information is generated, communicated, and used (Cabitza & Batini, 2016). As mentioned in the previous section, EHR systems typically capture patient-level clinical and administrative health data, which is often categorized into primary and secondary use (Mann & Williams, 2003). Framing IQ in this context has been recognized as a challenging task because of the multitude of users, the heterogeneity and ambiguity of the data, and the diverse and multi-level use of EHR data (Cabitza & Batini, 2016). There are IQ frameworks that attempt to address existing challenges in the secondary use of EHR data. For example, Johnson, Speedie, Simon, Kumar, and Westra (2015) suggested an applied ontology (Johnson, Speedie, Simon, Kumar, & Westra, 2016), consisting of four high-level data quality dimensions, i.e., correctness, consistency, completeness, and currency. Similar, Kahn et al. (2016) proposed a three-dimensional framework of conformance, completeness, and plausibility. Since the process of obtaining value from secondary use of EHR data is characterized as ad-hoc and often supplemented with third-party tools (Foshay & Kuziemsky, 2014), viewing information as an output of a well-defined manufacturing process (Lee et al., 2006; Wang, 1998; Wang et al., 1998) provides a static view without addressing the dynamics of the process. For example, when human actors manually export data from EHR systems and manipulate this data in external tools, it is insufficient to view information as the output of a technological manufacturing process performed by the EHR system.

Furthermore, since the information output of this process is subject to interpersonal communication (Avison & Young, 2007; Mettler et al., 2008), viewing information as a technological service provided by the EHR system is insufficient. For example, service or media quality dimensions, such as accessibility and access security (Wang & Strong, 1996), do not cover the characteristics of person-to-person interactions. Additionally, information, including its quality dimensions, changes in organizational communication through transformation, and filtering (Rogers & Agarwala-Rogers, 1976). This suggests that IQ is transforming throughout the process of secondary use of EHR data. In the following section, we describe our perspective on IQ from a life cycle perspective.

2.2. IQ life cycle

The IQ life cycle model suggested by Liu and Chi (2002) captures IQ through a sequence of processes, including collection, organization, presentation, and application of data. The processes represent the interaction between users and information. In each process, quality

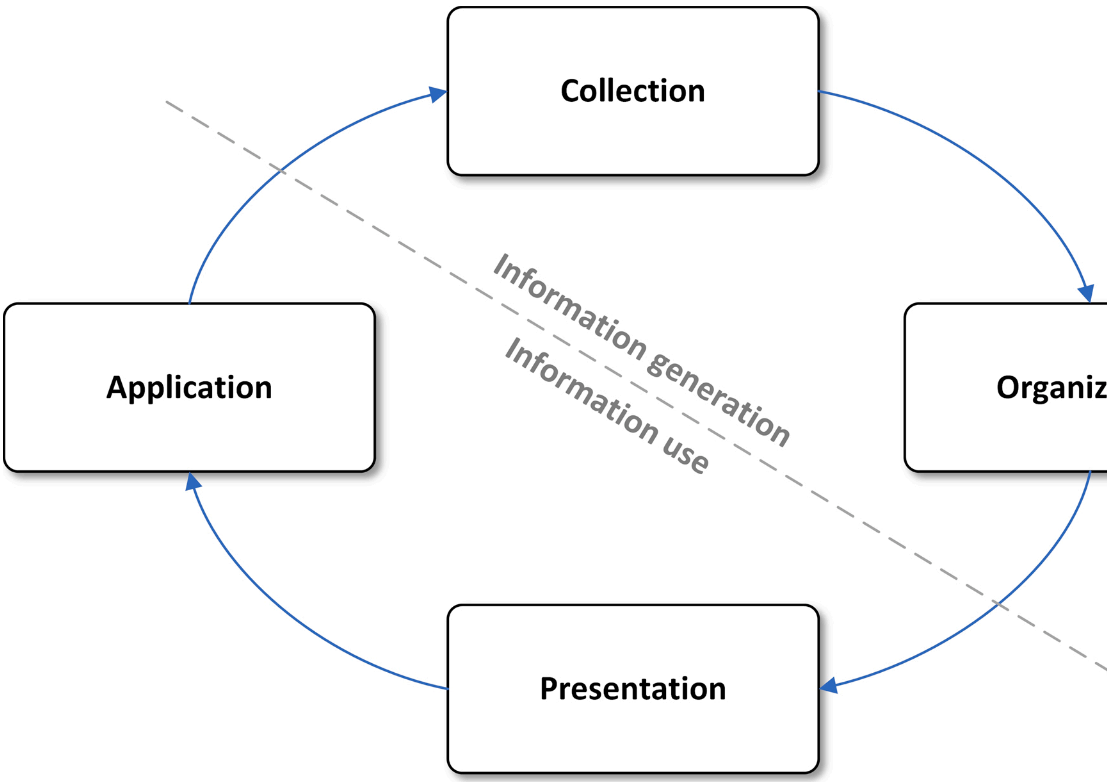

Fig. 1. IQ model, adapted from Knight (2011).

dimensions are integrated into the data and consequently transform the data into a new state (Knight, 2011). Knight (2011) grouped the processes into two overarching processes: information generation and information use. As illustrated in Fig. 1, the *information generation* process comprises the data collection and data organization subprocesses, whereas the *information use* process comprises the data presentation and data application subprocesses.

One of the limitations of Knight's (2011) model is placing information presentation in the information use process. We argue that it should be included in the information generation process, since designing an information product is the final stage in generating information. To avoid confusion between collecting data for primary use and extracting existing data for secondary use, we also renamed the data collection process as *data extraction*.

Furthermore, we argue that the two processes of information generation and information use do not capture the complexity of interpersonal communication involved in the IQ life cycle in secondary use of EHR data. The importance of interpersonal communication in creating a shared understanding (common ground) has been studied extensively within the primary use of clinical health data such as handoff information at the point of care (Collins et al., 2012). However, there is a lack of studies that explicitly focus on interpersonal communication in secondary use (i.e., use of EHR data in non-direct care). In addressing this knowledge gap in the existing perspectives of IQ (Avison & Young, 2007; Mettler et al., 2008), we introduce communication quality, characterizing the transmission of information between human actors. Communication quality is defined as "the characteristic of an interaction process among humans (but incl. computers as intermediaries) to meet or exceed their expectation with regard to the exchanged messages and with regard to the process of doing so" (Eppler, 2006, p. 351). Characteristics of interpersonal communication, or communication quality dimensions, include reciprocity, honesty, fairness, authenticity, timeliness, and balance, along with being targeted, having feedback possibilities, and without distortion and interruptions. Although communication impacts the application of information, to our knowledge, Eppler's research represents the only example of connecting communication quality to IQ research. Integrating communication quality captures how social interactions may influence IQ. As depicted in Fig. 2, our conceptual model is based on the insight from the existing literature (Eppler, 2006; Knight, 2011). We use this model to guide our data analysis process.

In the subsequent sections, after describing our case, we will use this conceptual model to frame our case analysis. The IQ dimensions identified in each process are listed in Appendix C.

3. Case description

Sørlandet Hospital Trust (SHT) is a large public hospital trust in Norway, providing healthcare services at a specialist level to more than 300,000 inhabitants in urban and rural areas. The trust consists of three hospitals and several psychiatric institutions and addiction treatment facilities. The hospital's annual budget is approximately $700 million, and the trust employs more than 7,000 in different medical divisions, service departments, and administration throughout the region. The trust is organized hierarchically, with a CEO reporting to the board of trustees, and administrative directors (e.g., CFO and CTO) and medical directors reporting to the CEO. The directors of the medical divisions are responsible for specific disciplines, such as surgery, medicine, and psychiatry. The divisions comprise different departments that are further sectioned into units. Some units are again divided into teams, based on a division of labor. Formally, the team level is not in the management line, since unit managers are responsible for HR at the operational level. The line of management at SHT is depicted in Fig. 3.

The division of psychiatry and addiction treatment is one of six medical divisions within SHT. The division consists of eight departments—a hospital-based department of adult psychiatry, four district psychiatric institutions, a department of psychiatry for children and adolescents, a department specializing in psychosomatics, and a department for substance abuse and addiction treatment. The division employs over 2,000 employees and is localized in 14 facilities in the region. In this study, we focus on the secondary use of EHR data for

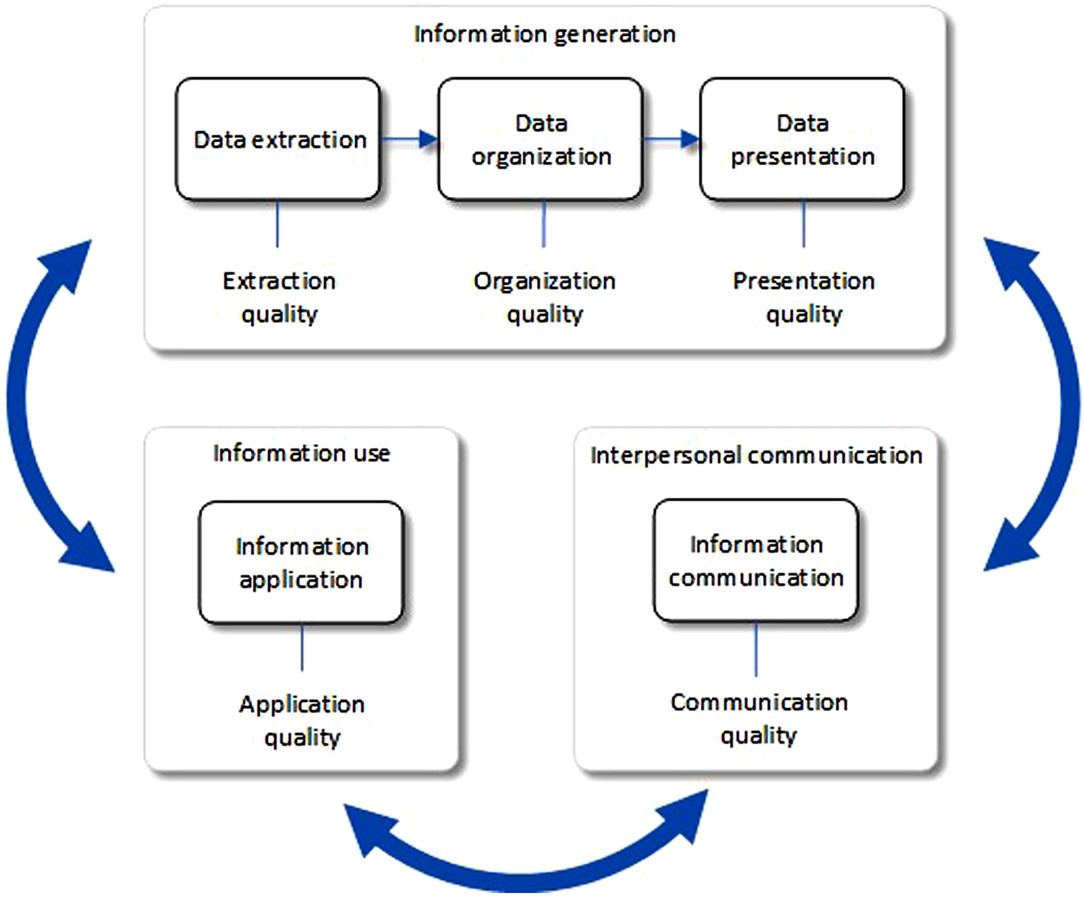

Fig. 2. Conceptual Research Model for IQ Life Cycle.

quality assurance in this division.

The predecessor of the current EHR system was implemented at SHT in 1991 and was the first EHR system implementation formally approved as a full-electronic substitute of paper-based records management by the Norwegian Director General of National Archives in 2007. The EHR system contains electronic patient records for all patients attending the hospital since the system implementation, and also scanned pre 1991 paper records. It consolidates converted data from several hospital mergers and legacy systems, as added functionality of the EHR system makes discontinuance of such systems possible. The EHR system comprises structured data (e.g., hospital contact data, diagnostic codes, and demographics), semi-structured data (e.g., XML-based forms), and unstructured data (e.g., journal documents containing documentation of healthcare services provided to patients). Journal documents consist of free-text clinical narratives, where clinicians choose from different templates based on the task. By March 2017, the EHR system comprised more than 40 million journal documents, relating to 665,000 individual patients.

Quality assurance is an important secondary use of EHR data in SHT. In quality assurance, data are used in two complementary ways: extracting structured data into a balanced scorecard and auditing the unstructured journal documents. Since the EHR system is designed for primary use for patient treatment at the point-of-care, functionality is missing for handling unstructured and structured data for quality assurance purposes. To extract multiple measures and present the development of these over time, the division introduced a balanced scorecard in 2007. The scorecard is a standalone spreadsheet application that is updated manually every month. In this process, administrative personnel extract data using predefined reports (i.e., metadata) from the EHR system and plot the data into the scorecard application (see example in Appendix D). Once updated, the scorecard automatically visualizes the periodical development of selected quality indicators by departments and the degree of achievement of goals set by local, regional, and national government bodies.

Since the structured data alone is unable to provide quality assurance information of the services provided to patients, the division additionally relies on auditing unstructured journal documents by assessing the level of compliance with clinical and administrative guidelines. Clinical audits are performed at both department and unit level but with alternating focus and at irregular intervals, due to the time-consuming and labor-intensive nature of the process. In this process, included patients are randomized, and the auditors, most often medical experts, follow predefined assessment criteria (i.e., metadata) and enter their assessments into an external data processing tool for further analysis and visualization of results. However, there are no standards within the division for extracting audit assessments, resulting in the use of several

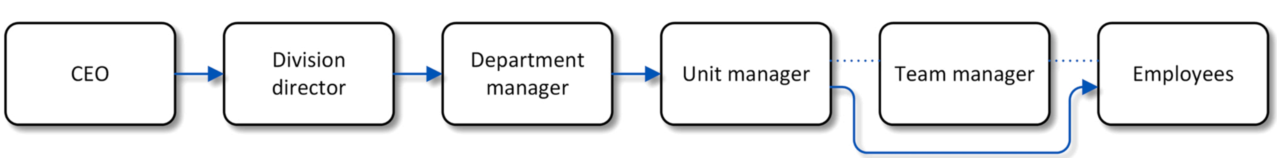

Fig. 3. Line of Management at SHT.

data processing tools. Such tools include a standard surveying tool, spreadsheet applications, word processors, and even paper-based data gathering. In department audits, there is a tendency to prefer a surveying tool, whereas unit auditors prefer a spreadsheet application to structure the findings and support basic analysis and visualization of the results.

The remainder of the quality assurance process is similar for both structured and unstructured data. When quality assurance data are extracted, assessed, organized, analyzed, and visualized, the results are communicated to the line of management. At each management level, results are discussed, interventions are prioritized, and responsibilities for actions are delegated accordingly. In this communication process, however, it sometimes becomes apparent that the current information is insufficient for enactment. This leads to an iterative execution of data extraction to customize the information according to unit-level requirements. At the final stage of the quality assurance process, responsible individuals act upon prioritized interventions. Since such interventions often invoke changes in work processes, they cannot be realized without operational-level enactment. Thus, communication of quality assurance results between management levels and clinicians at the operating level is crucial in terms of continuous quality assurance at SHT.

4. Research method

This study aimed to understand how IQ transforms within the process of secondary use of EHR data. Therefore, the nature of this study is explorative. To enhance our understanding, we conducted an interpretive case study (Walsham, 2006) of secondary use of EHR data for quality assurance of services provided to patients in a Norwegian hospital (presented in Section 3). For this, we interviewed various stakeholders at different locations of SHT. Being involved in the hospital's quality assurance process, the first author facilitated access to key stakeholders. Riemer (1977) argued that researchers should take full advantage of being insiders by turning familiar situations, timely events, or special expertise into objects of study, rather than neglecting at-hand knowledge. This notion is supported by Creswell (2009), stating that "the more experience that a researcher has with participants in their actual setting, the more accurate or valid will be the findings" (p. 192). To reduce biases and increase the validity of this study, we followed the principles for conducting and evaluating interpretive studies suggested by Klein and Myers (1999).

The sources of data for this study included semi-structured interviews with employees, acquisition of audit reports, templates used in data extraction, meeting minutes, and direct observations of quality assurance activities. Following the management line, we collected data from all organizational levels of three different departments within the division of psychiatry—top management, division staff, department management and staff, unit management, and operational level. Using snowball sampling, we identified and recruited relevant informants, such as administrative personnel, managers, and clinicians (e.g., psychologists, psychiatrists, and nurses). Table 1 presents an overview of the informants from the 31 interviews conducted in the period from September 2016 to June 2017 (more details on the informants are presented in Appendix A). The average length of the interviews was 60 min, and these were all transcribed and imported into NVivo 11 for further analysis.

Methodologically, we applied Braun & Clarke's (2006) thematic analysis in analyzing the collected data, engaging in the following processes: familiarizing ourselves with the data; generating initial codes; searching for, reviewing, and naming themes; and finally building the construct (Braun & Clarke, 2006). Specifically, we began our analysis by identifying all events of human–information interactions in the case, to reveal how information quality transforms from data elements of the EHR system to the operational enactment of the information in secondary use. This open coding process was complex because of the division's layered structure, the involvement of many actors, and the utilization of different technologies in the various phases of quality assurance. Thus, several rounds of hermeneutic processing were needed to code all the actual events of human–information interactions. After the initial round of open coding was completed, the codes were refined and categorized through an iterative process of moving around data, concepts, and categories (Klein & Myers, 1999). The process of open coding and categorization of events is presented in Appendix B.

Next, we mapped the categorized events of the case to the processes in the secondary use of EHR data, as presented in our model in Fig. 2, Section 2.3. Finally, we coded IQ dimensions emphasized or perceived by different stakeholders in the various processes. As the process of coding events, the coding process of IQ dimensions started as open coding and was refined and categorized through several iterations. The categorization was grouped as IQ life-cycle processes, IQ categories, and IQ dimensions. During the interviews, we chose not to provide the informants with descriptions of IQ dimensions from the existing literature but instead encouraged them to describe their perceptions of what constitutes adequate IQ freely. This decision was based on previous experiences where informants had difficulties relating to the concepts of quality dimensions, and where their responses were often influenced by the descriptions provided. Wang and Strong (1996) also favored such an empirical approach to researching IQ dimensions. Through interpreting the informant statements, we were able to corroborate the IQ dimensions relevant to the informants with existing definitions of the dimensions. To illustrate this coding process, consider the following statement from an informant:

> [The information] *needs to be perceived as useful by the clinicians and helpful in their work with the patients*. (Manager, unit level)

We coded this statement as information 'usefulness', an IQ dimension of application quality. After all the dimensions were coded, we searched the literature to find existing definitions of IQ dimensions that covered the meaning of the coded IQ dimensions. In this example, the following definition by Knight and Burn (2005) was found to cover our findings on 'usefulness': "the extent to which information is applicable and helpful for the task at hand" (p. 162). An overview of IQ dimensions identified in the analysis is presented in Appendix C. These IQ

Table 1
Overview of Interviews.

Background	Top management	Division staff	Department management	Unit management	Operational level
Administrative*	0	0	3	3	0
Nurses**	0	1	3	4	4
Psychiatrists	1	0	0	0	1
Psychologists	1	1	0	0	3
Other clinicians***	0	0	2	2	3
Total	2	2	8	9	11

* Includes secretary, sociologist, and IT professional.
** Includes nurse, registered nurse, and psychiatric nurse.
*** Includes child welfare officer, clinical social worker, physiotherapist, and social educator.

dimensions were thereafter interrelated through constant comparison of the IQ dimensions.

Discussions with other researchers and practitioners were conducted throughout the study to ensure the validity of our analysis. The different backgrounds of the authors as outsiders and insiders of the organization under scrutiny facilitated a critical and in-depth analysis of the research context. Additionally, we conducted member validation (Bygstad & Munkvold, 2011) by providing informants with early drafts of this manuscript to verify our analysis's accuracy. In the next section, we present the findings of the case analysis.

5. Findings

Our case analysis documented how IQ in secondary use of EHR data transforms through three distinct processes: information generation, interpersonal communication, and information use. In each of these processes, actors heuristically contribute to generating the information artifact by targeting the IQ dimensions they perceive as valuable. Sometimes, the IQ is unsatisfactory for the application, and the information needs to be modified. In the following subsections, we present our findings of how IQ is transforming through the three processes and how the processes are interconnected when information products need to be modified. An overview of the IQ dimensions identified in each process is presented in Appendix C.

5.1. Information generation

In the subsequent sections, we present key findings related to IQ in the three subprocesses of information generation.

5.1.1. Extraction quality

Since data extraction is a subprocess of information generation, extraction quality represents the information producers' view of IQ. For secondary use of EHR data in quality assurance, data extraction at SHT is two-fold: 1) assessment data of compliance with clinical and administrative guidelines are extracted by medical experts auditing unstructured journal documents; and 2) structured data as a source of balanced scorecard quality indicators are extracted by administrative personnel, by running built-in EHR system reports. After extracting structured and unstructured data from the EHR system, the data are entered into a data processing tool, such as standard surveying tools, spreadsheet applications, word processors, or paper-based templates for further analysis. For example, the tools offer features such as assembling individual assessments in a standardized form (i.e., structuring the unstructured audit data).

Whereas actors extracting structured data most often stated that accuracy was the most critical dimension of extraction quality, extractors of unstructured data additionally emphasized the importance of accuracy, completeness, objectivity, and credibility. Accuracy refers to the level of measurement errors during the data extraction (Liu & Chi, 2002), as described by an administrative consultant in extracting structured data by using built-in EHR system reports and entering the data into the balanced scorecard:

> *When I work with the balanced scorecard, my goal is that the data I extract must be as correct as possible…. They must represent reality. It has happened that I have punched the wrong numbers* [into the balanced scorecard]*…, but I can easily see if I have missed terribly.* (Administrative consultant, department level)

Unlike the extraction of structured data, where built-in reports in the EHR system summarize data from all patients in a predefined period, actors extracting and assessing unstructured data often emphasized the importance of completeness of data. Completeness of data refers to how the sample size (Liu & Chi, 2002) of audited patient journals affected the quality of the extracted data. This is illustrated by a unit manager's description of the sampling method used in a unit audit:

> *I think some of the other* [departments] *just performed spot sampling. I was the only one sampling* [all patients admitted during] *the first quarter. It gives a more correct picture than just doing one-day sampling…. For me to find it interesting and thus use it, I found out that I needed to have more data.* (Manager, unit level)

However, since audits are time-consuming and labor-intensive, aiming for data completeness is often not feasible for unstructured data. Thus, actors performed a randomized sampling of patient journals in to secure objectivity and avoid biases of the data (Wang & Strong, 1996), as described by one of the informants:

> *It was a randomized sampling* [of patients]*…where we evaluated how* [clinicians] *documented…. You need to read through many journals…, and if you select* [patients] *that you are familiar with, it might get really biased. So, you need the competence of performing randomized sampling.* (Medical advisor, division level)

Since auditing is a process that assesses compliance with guidelines, clinical expertise is needed when interpreting clinical documentation. Informants believed credibility to be necessary, i.e., "the extent to which the collector has integrity" (Liu & Chi, 2002, p. 302) since medical experts performed such assessments:

> *Evaluated by peers…. Yes, you'll probably achieve increased credibility because of that.* (Medical advisor, division level)

5.1.2. Organization quality

Organization quality represents the perceptions of actors involved in organizing data. The process of organizing data for quality assurance at SHT consists of activities before and after the data extraction process. Before data can be extracted, the scope of the quality assurance is set, and criteria for how data must be extracted and assessed are determined. After extraction, data are systematized and maintained in a data processing tool. While the use of spreadsheet applications in extracting data for the balanced scorecard is internalized in SHT, the use of data processing tools varies when extracting unstructured data.

Actors involved in data organization highlighted adequacy of scope, granularity, and consistency as critical IQ dimensions of organization quality. These actors play an essential role in providing clarity of data extraction criteria and ensuring the adequacy of scope (Eppler, 2006)—that the extracted data conforms to intended specifications. The process of ensuring the adequacy of scope when extracting unstructured audit data is illustrated by one of the informants:

> *We are also involved in figuring out what* [the auditors] *are looking for—the indicators which could provide evidence of discrepancies within journals…. At this point in time, we are particularly concerned with patient safety and transferring of knowledge…. We would use clinical guidelines, or best practices, and the standards we are obliged to follow…, and make a guideline or checklist or questionnaire for* [auditors] *to compare against* [journal documents in] *the EHR system.* (Quality advisor, division level)

Granularity is related to the level at which data is extracted and organized according to user requirements (Michelberger, Mutschler, & Reichert, 2011). It ranges from division level to individual-level data for clinicians. For information targeting clinicians, the actors emphasized an individual level of granularity, as stated by one informant:

> *I made a summary of consultation productivity for the first half of the year, because we were told that we were performing low. Then I designed it on an individual level for them* [the clinicians] *to get feedback whether they were top-third performers, and thus delivering as expected, if they were in the middle, which is tolerable, or if they were among the bottom-third performers.* (Manager, unit level)

Consistency was found to be an important quality dimension for data organizers and was related to adequacy of scope. Whereas adequacy of scope relates to how criteria for data extraction are operationalized and correspond to intended specifications, consistency relates to how the same criteria for data extraction are logically compatible between data sets (Liu & Chi, 2002). One informant responsible for extracting balanced scorecard data reflected on the importance of consistency and how this was achieved using a data extraction manual provided by the data organizer:

> *We often achieve* [consistent] *data because we have an excellent* [data extraction] *recipe. It's as simple as that. Then all the data from all the departments are being extracted in the same way, and we avoid people saying, "I used this report because I thought it was the best for the purpose and gave the best results". You'll avoid that. We'll all have the same basis if everyone follows the recipe. And I think they do.* (Administrative consultant, department level)

5.1.3. Presentation quality

Presentation quality represents the perspective on IQ of actors compiling data into information products. The information users' view on the quality is presented later as application quality (Section 5.3.1). Once data are extracted and organized in a data processing tool, the presentation process consists of 1) analyzing data to find patterns and discrepancies; and 2) visualizing the findings from the analysis. Because of differences in the use of data processing tools, where there was a tendency to use more sophisticated tools at higher organizational levels, data presentation varied accordingly. In general, more sophisticated tools provided a more systematic analysis and more advanced graphical visualization of the results.

The analysis showed that actors designing information products emphasized ambiguity, understandability, conciseness, comparability, and amount as important IQ dimensions. Ambiguity refers to designing the information product to reduce the possibility of contradicting values of the same element (Stvilia, Gasser, Twidale, & Smith, 2007). This is illustrated by the following statement from an administrative consultant about delivering the information product to a unit manager:

> *When I deliver the document* [of quality assurance information]*…, I often write comments…so there will be no doubts or misunderstandings about what I have written.* (Administrative consultant, department level)

Regarding understandability, actors designed the information product in a manner that they believed was easily comprehendible (Kahn et al., 2002). Closely related to understandability, actors also emphasized conciseness, stating that information needs to be represented clearly, to-the-point, and compactly (Kahn et al., 2002). Comparability refers to a quality dimension where results are compared over time or between different organizational entities (Canadian Institute for Health Information, 2017). A quality advisor described how this dimension was integrated during analysis and presentation of data:

> *I made a pivot table* [in the spreadsheet application] *to compare the results* [between the units]. *Because there is a learning* [opportunity] *in doing that, and it's interesting to compare…. Then, we performed an analysis and compiled it* [into an information product]. (Quality advisor, department level)

In the presentation of data, the amount of data considered appropriate (Liu & Chi, 2002) was perceived differently by managers and clinicians. Whereas actors designing information emphasized presentation of all data so that managers could see the bigger picture, it was important when designing for clinicians to keep the amount of data to a minimum, to reduce information overload.

5.2. Interpersonal communication

After generation, information products are communicated between individuals or groups within the organization. This communication can be oral, written, or a combination of the two. At SHT, the written communication of quality assurance information is mediated through different technologies, including email, presentation applications, and paper-based reports.

5.2.1. Communication quality

Communication quality represents the perspective of the secondary EHR data users and their emphasis on essential aspects when communicating information products within SHT. The critical communication quality dimensions identified in the analysis were priority, reciprocity, frequency, trust, and efficiency, along with being targeted and demanding. Targeted communication was the most frequently mentioned quality dimension and referred to how actors attempt to target the audience accountable for enacting upon the information (Eppler, 2006). A department manager illustrates this in a situation where a quality indicator revealed variations of performance between clinicians:

> [About the clinicians], *we can tell that they've been doing…good work, and that the quality, for the most part, is very good. If someone is struggling, then we confront that individual. You cannot tell everyone to* [improve] *when it's just one individual that is not performing. Then, you need to talk to that one person.* (Manager, department level)

In communication, actors sometimes emphasize various parts of the information product and, as such, prioritize certain aspects they believed to be more relevant to communicate (Hargie, Saunders, & Dickson, 1994). A department manager illustrates this in a situation where a quality indicator revealed some variations of performance between clinicians:

> *I present* [the report] *in our management meetings…. And we all know each other so well that we don't boast about how good we are…. We stopped doing that years ago. Now, we discuss where the shoe pinches. It does get a bit negative sometimes because we only discuss the things that don't work. You know, out of 77 slides, we might just have one* [slide presenting a challenge]. *But it's that challenge we talk about, and in this meeting, everyone understands that we just talk about that one.* (Manager, department level)

Reciprocity refers to the possibilities for feedback and dialogue when information products are communicated (Mohr & Sohi, 1995). Informants emphasized that reciprocity increased the accountable actors' engagement and commitment. This is illustrated by one of the informant's recollections of how he communicated quality assurance information to his subordinates:

> *It's a balancing act between making* [the communication] *too pompous and serious* [and informal and inclusive]*, because you need to understand how they work. It's an act of balance, you know. I cannot tell them to do this and that—it has something to do with presenting it in a way that makes them feel like a part of the team and inviting them to bring solutions, rather than making them feel* [overwhelmed]. (Manager, unit level)

The demanding dimension is in contrast to reciprocity and denotes a more explicit input (Johlke & Duhan, 2000), particularly in communication with clinicians, as illustrated by one informant:

> *We try to sort out and highlight what's up for discussion* [with the clinicians] *and what's not up for discussion. We try to get an attitude that there are some things that are not up for discussion because it's just the way it is. It's part of the job—a part of our mission—and it simply must be done.* (Manager, unit level)

Frequency refers to the amount of communication between managers and clinicians (Mohr & Sohi, 1995). Trust refers to the actors' perceptions that "a message received is true and reliable" (Renn & Levine, 1991, p. 179). Trust was found to be necessary for communication success, as described by a unit manager who experienced communication challenges because of educational asymmetry between managers and clinicians:

> *It's challenging to be heard when we don't have the specialist competence. It's challenging when information is provided by someone that, according to the clinical specialists, has nothing to do with this…. I believe that if* [clinical experts] *presented* [the audit results]*, it would have been received differently than when* [the department manager] *and I presented it.* (Manager, unit level)

Finally, managers reported that problems with the communication efficiency, the extent to which the message is delivered and understood as intended (Kyeyune, 2018), can sometimes impede the communication, as illustrated by the following quote:

> [The department manager] *always presents the* [quality] *results in our meetings…. He runs through the results very quickly, and I'm always wondering whether I managed to catch everything.* (Manager, team level)

5.3. Information use

Different organizational actors use information products for various purposes in the quality assurance process after information generation and communication. The quality dimensions suggested by actors using the information at SHT are described next.

5.3.1. Application quality

Application quality represents the actors' perspective and their emphasis on essential aspects when applying information products. The key actors involved in the application are managers and clinicians. The analysis revealed granularity, urgency, relevancy, comparability, completeness, usefulness, and conciseness as the most frequently mentioned application quality dimensions. A complete list of dimensions is presented in Appendix C. As emphasized by actors designing information products, actors applying information confirmed the importance of granularity. The informants stated that it was critical to match the level of granularity with the organizational level of application. This is illustrated by a statement describing why information at a too high level of aggregation is insufficient for clinicians at the operational level:

> *There is no use in communicating* [quality assurance information] *that nobody understands…. When* [the information] *is available at the lowest level* [i.e., the operational level]*, however*, [the clinicians] *know what it means, and what they need to do.* (Administrative consultant, department level)

Urgency, usefulness, and relevancy were found to be important quality dimensions, particularly for clinicians. Here, urgency refers to "the characteristic of the state of the information needed to pursue actions" (Valecha, Oh, & Rao, 2013, p. 8); usefulness refers to the "extent to which information is applicable and helpful for the task at hand" (Knight & Burn, 2005, p. 162); and relevancy refers to the extent of "pertinence to users' interests of the information" (Kim, Kishore, & Sanders, 2005, p. 78). If clinicians failed to see the urgency, usefulness, and relevancy of the information, managers acknowledged that it was not easy to enact. Several informants emphasized the tension between information relevancy and clinical autonomy:

> *We are struggling to get the clinicians to open their ears to what we are trying to communicate. There is a high degree of autonomy, where people decide on their own what's relevant or not…. There's no escaping from the fact that some people put on their teflon suit and just let things go and continue doing things the way they think is right—the same way they've always done.* (Manager, unit level)

Since the quality of healthcare services is a relative concept, informants stated that comparability is an important quality dimension for managerial application of information:

> *When you compare your* [audit] *results to other departments, or to comparable units, you may observe discrepancies. And you wonder—why are there discrepancies and what's the reason? That's when the discussion becomes interesting.* (Manager, department level)

Although completeness was emphasized as an essential dimension from the data extractors' view of extraction quality, both managers and clinicians stated that this dimension challenged the application, particularly for information products based on unstructured audit data. This is illustrated by one of the informants describing differences of completeness in information based on structured data (balanced scorecard) and information based on unstructured data (audit):

> *I think that the most significant difference is that you'll extract the entire data set for the balanced scorecard. So, if you could do the same for subjects closer to their clinical work* [as in auditing]*, then I think it would weigh heavier* [for the clinicians]. *But because of the small sample size, no one feels accountable at all, and they would say, "It doesn't apply to me, it applies to someone else". So, it doesn't get the weight that it should.* (Manager, unit level)

As emphasized by the information producers' view of presentation quality, conciseness was particularly perceived as an important dimension for operational enactment. The following description of an audit report's quality illustrates the differences in perceptions of conciseness between managerial and operational perspectives:

> [The clinicians] *are allergic to this. It's the amount. It's the graphs and tables. This is really something special—there are colors and all that stuff.* [The clinicians] *want it to be concise. This is too much and is meant for people like me…. Some might find it entertaining but most people don't.* (Manager, department level)

5.4. The transformation processes in the IQ life cycle

In the previous sections, we presented our findings on the different IQ dimensions emphasized by the actors involved in the three processes in the IQ life cycle: information generation, interpersonal communication, and information use. In this section, we will discuss their interrelations and the transformative nature of IQ.

5.4.1. IQ transformation in the information generation process

In the transformation of data into information, the analysis revealed that information quality transforms through the three subprocesses of information generation, as illustrated in Fig. 4. In these subprocesses, and from their perspectives, different actors added specific quality dimensions toward a final information product:

(1) Extraction quality included intrinsic quality dimensions, i.e., accuracy, completeness, credibility, and objectivity; (2) Organizational quality included adequacy of the scope, consistency between data sets, and granularity; (3) Presentation quality included representational dimensions, i.e., ambiguity, amount, comparability, conciseness, and understandability.

5.4.2. IQ transformation in the information use process

When information products were transferred to the application context, the analysis identified that some IQ dimensions in the information generation process could affect information users' perceptions of

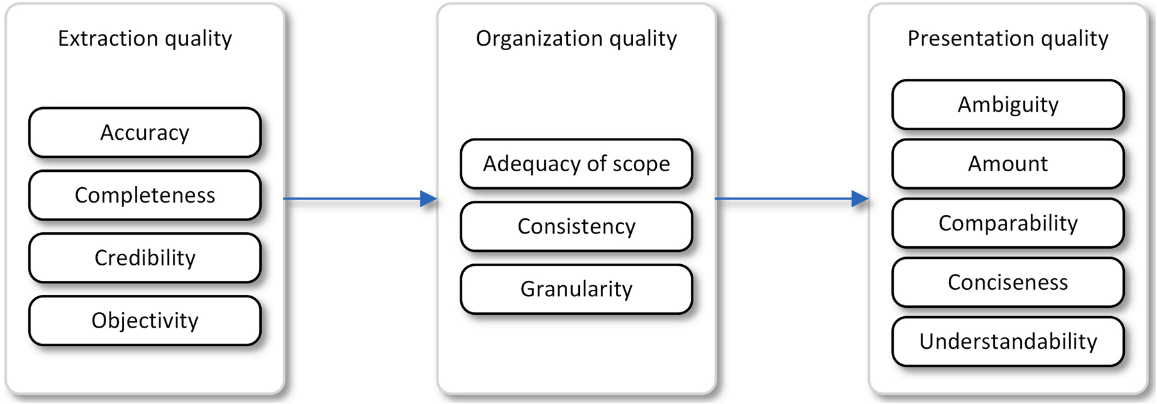

Fig. 4. IQ Transformation in the Information Generation Process.

several application quality dimensions in the information use process, as exemplified by granularity in Fig. 5. Consider the following statement:

> [The unit managers] *won't relate to this unless* [the information] *is split into their unit levels. They don't need it and don't know how to use it.... So, for them to take it seriously, we need to get it broken down to their units.* (Assistant Manager, department level)

Here, the assistant department manager describes how the lack of granularity, an IQ dimension from the information generation process, leads to unsatisfactory application quality in the information use process (i.e., comprising the dimensions of relevancy, urgency, and usefulness).

An example of how quality dimensions did not transform between the information generation and information use processes is given by one informant who was responsible for organizing audits from several units within a department:

> *I made a somewhat standardized form containing the elements* [the auditors were] *supposed to evaluate, but it became obvious that they evaluated far too much.... Some things* [were audited] *consistently across all units, but additionally, some* [units] *included subjects that others didn't. It cannot be compared.... What I learned was that I'll provide a template next time. I assumed they'd all be evaluating the same.... Next, I visualized* [the results] *and tried to keep things simple.* [When communicating the results], *I emphasized the poor basis of data. It was only based on three journals. I told* [the unit managers] *that this is really coarse-grained and only meant to be an indication of what they needed to bring their attention to.* (Quality advisor, department level)

As the example illustrates, the data's scope was not apparent to the actors extracting the data, leading to inconsistencies between the data sets from the units. Furthermore, the informant emphasized the incompleteness of data that he integrated into the final information product. This information product was communicated to unit managers by email, where a unit manager reflected on the quality of this information product:

> *I received* [the audit results] *from* [quality advisor] *with bar charts and stuff. But it has limited value because it was so subjective in many ways. There were no commonalities. We didn't extract the data consistently... and it didn't make much sense to me.... I don't think I'll pass it on* [to his subordinates]*...because it was too few numbers and too few journals.* (Manager, unit level)

The unit manager illustrates how his perceptions of quality dimensions originated from various information generation subprocesses and prevented him from using the information. The perceived challenges of IQ dimensions were lack of completeness of data (data extraction), lack of data consistency (data organization), and lack of understandability (data presentation). This resulted in a lack of usefulness and understandability.

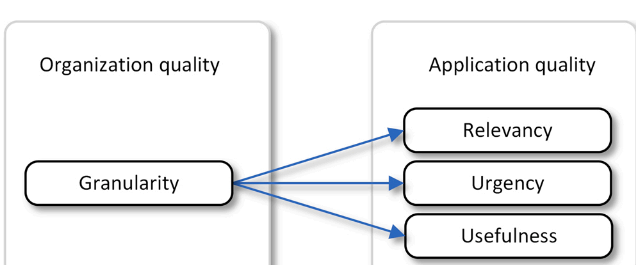

Fig. 5. Instance of Relations between IQ Dimensions in the Generation and Use Processes.

5.4.3. IQ transformation in the interpersonal communication process

The analysis identified that the way information was communicated impacted on how users perceived the application quality. Specifically, communication quality dimensions could either decrease or reinforce users' perceptions of specific application quality dimensions. One example illustrating this is how targeted, and reciprocal communication can affect several quality dimensions perceived by information users, as expressed by a clinician:

> *To me, I don't understand it* [the audit report]. *It would've been better if the unit manager said to me, "We've now assessed some of your documentation, and we see that you need to improve on this or that". That would really be useful. When I see something like this* [the audit report], *I just think it's difficult to understand and relate. That's why I don't read it.... I just think that the* [audit report] *is boring and hard to understand. I don't understand everything. It's much easier when you have a person in front of you who you can talk to and ask if you wonder about anything.... I think* [dialogue] *is more useful, as when* [the unit manager] *informed us about a journal audit of treatment plans. She briefed us about it, and—since people have different opinions on treatment plans—it became a subject of discussion. To me, that's much more useful.* (Clinician, operational level)

This statement illustrates that the clinician was unable to realize the relevance or understand the content of the audit report and emphasized that targeted communication could amend this and improve the perception of its usefulness. Furthermore, the clinician expressed that engaging in dialogue (reciprocity) would improve the perception of its usefulness and increase the information's understandability. This is illustrated by the lines between communication (i.e., reciprocity and being targeted) and application quality dimensions (i.e., relevancy, understandability, and usefulness) in Fig. 6.

For the communication to be targeted, the information product

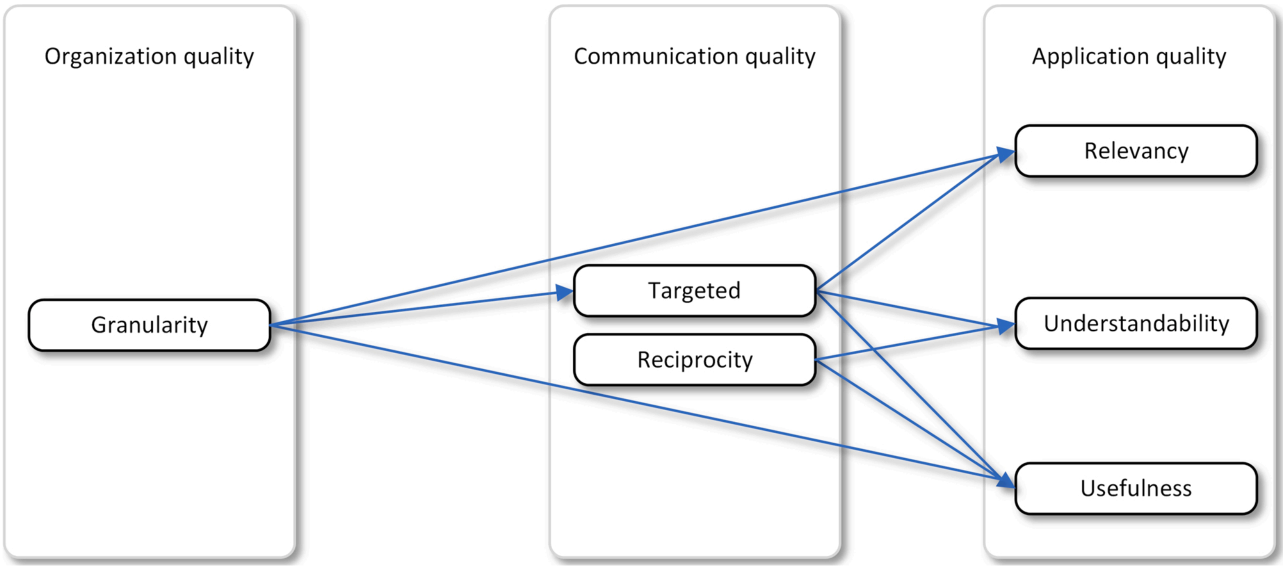

Fig. 6. Instance of Relations between IQ Dimensions in the Generation, Communication, and Application Processes.

needs to have adequate granularity, as depicted in Fig. 6. The figure illustrates the interrelations between IQ dimensions in the information generation, communication, and use processes. Furthermore, information users' perceptions of application quality are directly related to the information product, as presented in Section 5.4.2. These relations are illustrated in Fig. 6 as lines between IQ dimensions from the generation process (i.e., granularity) and IQ dimensions from the use process (i.e., relevancy and usefulness).

5.4.4. *Transformation mechanisms in the IQ life cycle*

In trying to address IQ issues that prevent actors from applying or enacting information, the analysis revealed how information products were transformed throughout the organization. After the information product was generated and communicated, actors actively modified it to address perceived shortcomings in specific quality dimensions. The analysis identified three distinct mechanisms triggering the transformation of the information product: filtering, integration, and regeneration of information. The mechanisms were useful in amending the use quality dimensions in order to increase the possibility of enactment.

The *filtering* mechanism refers to a reduction of the information product. Likewise, *integration* refers to combining/merging additional information to the information product. Common for filtering and integration is that the original information product is modified by altering IQ dimensions in the life cycle's data presentation stage. This is illustrated by a department manager's response to the monthly quality report from the balanced scorecard received from the division staff:

> *I think it's okay for us at a department management level to receive* [the full quality report]. *And then it's up to the management at the various locations to modify it by selecting the parts important to them and, if necessary, add more background data.* (Manager, department level)

This statement illustrates how modifications were needed before communicating the information product in the line of management, including both filtering and integration. For example, the filtering sought to integrate urgency and conciseness by removing excess information. Furthermore, more details needed to be integrated in order to reach the completeness of the information product.

Sometimes, filtering and integration of the information product is not possible because the shortcomings in quality dimensions are rooted in the processes of data extraction or organization. In such cases, information products need to be *regenerated* to incorporate the required quality dimensions. This is illustrated by a team manager's reflection on how the quality of a department-level information product was insufficient for team-level application:

> [The unit manager] *communicates* [the monthly quality report] *that she receives from the division management, and we're really happy that* [the quality advisor] *breaks this down for us*…*because I think it's much more interesting to compare ourselves with the other units. And, in managing our daily work, I think it's most important to know what this means to us—where we are performing satisfactorily and what we need to improve. So, it is definitely more convenient for me when the information reflects our* [organizational] *level.* (Manager, team level)

This statement illustrates how the granularity dimension (i.e., too high level of aggregation) of the balanced scorecard inhibited use of the information at the unit level. Since granularity was integrated with the data organization subprocess, the information product needed to be regenerated through an iteration of the information generation process. Through regeneration (referred to in the statement as "breaking down"), the quality advisor integrated granularity at the unit level, resulting in increased comparability, usefulness, and relevancy. Such regenerated information products are also subject to filtering and integration when communicated in the management line, demonstrating the IQ life cycle and its transformative nature.

6. Discussion

In this study, we examined how IQ transforms in the secondary use of EHR data for quality assurance in a Norwegian hospital. In the analysis, we described IQ's transformative processes as comprising information generation, communication, and use. Based on our findings, we address the knowledge gaps that we discussed in the introduction section.

Existing literature often treats IQ as a fixed product of a well-defined production process by an information system (Lee et al., 2006; Wang, 1998) and mainly from a technological viewpoint (Mettler et al., 2008; Mohammed & Yusof, 2013) in the context of the primary use of data (Cabitza & Batini, 2016). The static view on IQ was found to be challenging because of the actors' active involvement in transforming IQ in secondary use of EHR data. Our findings corroborate existing research that generating and communicating information products in secondary use of EHR data is ad hoc, without clear standards, and without understanding the information needs for the quality assurance process (Foshay & Kuziemsky, 2014). From the traditional perspective, the transformation of data into information products is performed by the

EHR system, where the presentation of data as final information products is predetermined. Such a presentation can be tailored by technical personnel that maintains the EHR system (Lee et al., 2006). As evident in our study, the EHR system lacks functionality for transforming primary EHR data into quality assurance data for secondary use. Thus, external data processing tools for the three subprocesses of information generation (i.e., extracting, organizing, and presenting) are required. In this process of information generation, the analysis documented how actors targeted specific quality dimensions in the three subprocesses toward a final information product. Thus, quality dimensions acquired in a previous subprocess affect the possibilities of adding quality dimensions in subsequent processes.

Our analysis further focused on actors' perceptions of IQ throughout the secondary use of EHR data in a life-cycle perspective. By analyzing the actual events of user-information interactions, we provided an enhanced IQ life-cycle model consisting of information generation, communication, and use processes (see Fig. 7). The generation process of information products was found to comprise three subprocesses: data extraction, where actors extracting the data emphasized intrinsic qualities (e.g., accuracy and objectivity); data organization, where actors responsible for organizing data perceived adequacy of scope and consistency as critical IQ dimensions; and data presentation, where actors responsible for compiling the data elements to the final information product found contextual qualities (e.g., relevancy and comparability) to be necessary. Furthermore, communication quality encompassed quality dimensions perceived as necessary in the communication of information products (e.g., reciprocity, and being targeted and demanding) and use quality comprised quality dimensions emphasized by actors applying the information product (e.g., granularity, relevancy, comparability, and completeness). Fig. 7 illustrates the relations between the quality dimensions:

(1) in the information generation process, actors heuristically contribute to generating the information artifact by targeting the IQ dimensions they perceive as important, as indicated in Fig. 7 by the arrows between extraction, organization, and presentation quality, and (2) information users assess the quality dimensions directly rooted in information generation, as indicated in Fig. 7 by the arrows from information generation to information use.

Another distinctive and transformative characteristic of IQ discovered in the analysis is the continuous modifications of information products evident in communication between organizational levels. Previous organizational research emphasizes that transformation and filtering are responses in coping with excessive amounts of information and thus always occur when information is communicated within organizations (Rogers & Agarwala-Rogers, 1976). As a typical information-intensive organization, it is not surprising to find extensive modifications of information products in this hospital context. Modifications were made heuristically by actors to adapt the information to specific users or groups of users by filtering, integrating, and regenerating the information product. The analysis revealed how information products are transforming from the original information product, as indicated by the arrow between information use and information generation in the bottom part of Fig. 7. Such transformed information products are distinctive from the original information product with their own unique set of IQ dimensions. The need for full or partial regeneration depends on the specific IQ dimension(s) that actors seek to improve before communicating the information product further in the management line. Since it is typically the transformed information product that is presented and applied in the line of management, we argue for the importance of understanding how the transformation of IQ affects managerial application and operational enactment. This suggests that the conventional view of information production (e.g., Wang, 1998) is ill-suited in secondary use of EHR data, by treating the information product as a static outcome of the information system. By only evaluating IQ of the original information product, we cannot fully understand how it is applied and how IQ influences such an application. The

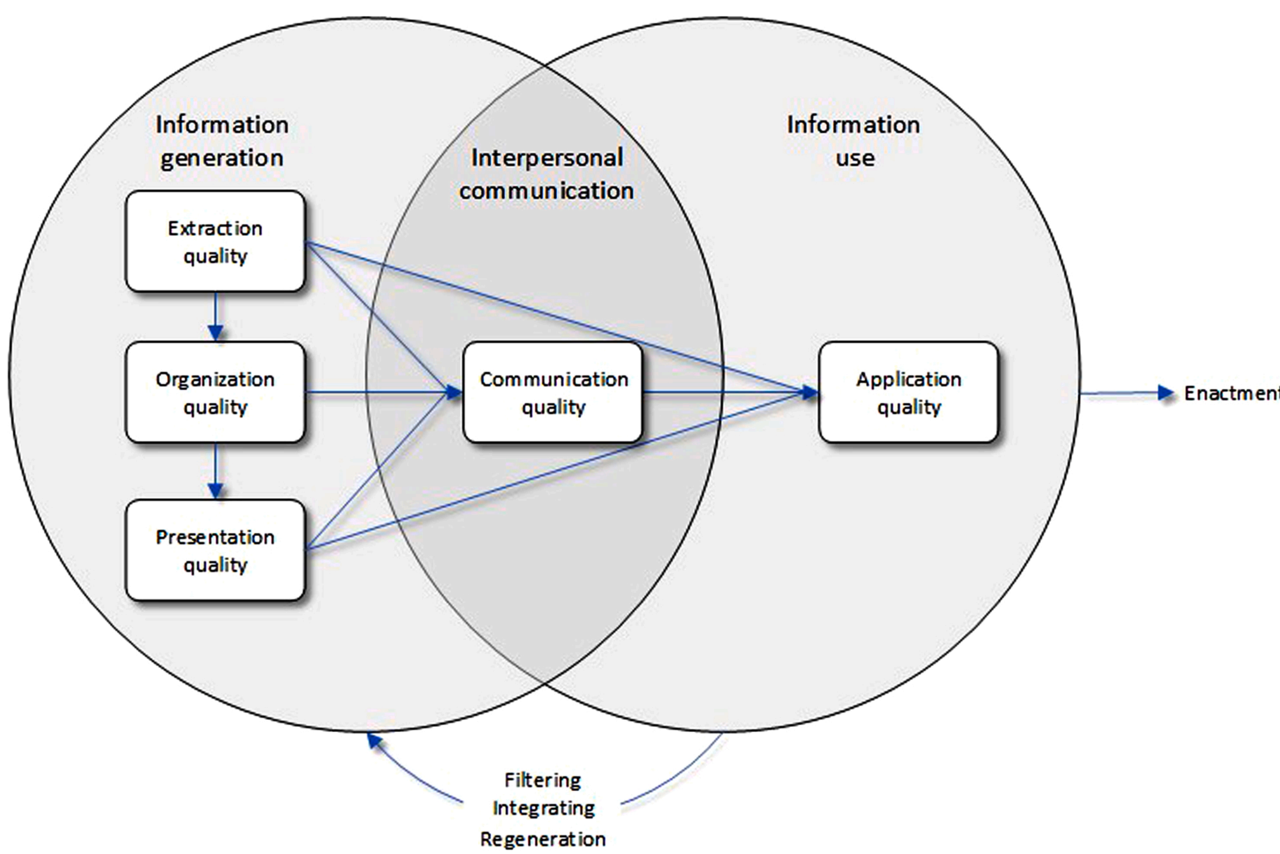

Fig. 7. IQ Life Cycle Model in Secondary Use of EHR Data.

assumption that the use of information products is outside the producer's control (Mettler et al., 2008) could be one reason for treating information products as a static entity.

Moreover, we address the research gap of interpersonal communication by integrating communication quality in our IQ life cycle model. Eppler (2006) introduced communication quality as the quality of interactions among humans, but he did not integrate the concept into his proposed IQ framework. As argued by Avison and Young (2007), our analysis also documented the importance of interpersonal communication in an EHR system use context. Perhaps even more prominent in secondary use of EHR data, communication quality was found to influence users' perceptions of application quality and, therefore, the actionability of the information for application and enactment. Lillrank (2003) defined actionable information as "meaning derived from data and context with a knowledge function" (p. 691), where "only meaningful information can enable purposeful action" (p. 694). By treating the information product of the information generation process as an artifact, as suggested by Lillrank (2003), we argue that information artifacts can enable action possibilities by human actors. For example, Jeffs, Nincic, White, Hayes, and Lo (2015) discussed how the process of translating EHR data to actionable information enables health care organizations to "make appropriate changes in those processes resulting in improved outcome" (p. 269).

This is illustrated in Fig. 7 by the arrow between communication and application quality and the information use process and enactment. As the analysis revealed, communication quality comprises both the sender's and the receiver's views of quality, where the two views apply in communication to both managers and clinicians. Communication quality has some resemblance to service quality, where both are related to the delivery process of the information product (Kahn et al., 2002). The main difference, however, is the role of technology in the secondary use of EHR data. Because of the prominent human involvement in generating and communicating the information product in this context, we suggest communication quality is more suitable than service quality for covering quality aspects of the delivery process of information products. Service quality may also be applicable in this context, but only in cases related to the subprocess of data extraction. However, we found no evidence of actors' emphasis on service quality dimensions of the EHR data for quality assurance purposes.

This study also has some practical implications. First, the identified IQ dimensions influencing secondary use of EHR data can be used to increase the understanding of how information, including its quality attributes, transforms in various stages of the quality improvement process (see Appendix C). Specifically, it can help actors in identifying IQ challenges hampering the use of information. Second, the information product designers should be more concerned about defining and prioritizing information users' requirements. For example, we found discrepancies between producer and user views of the quality of the same information. Since producers often reside close to actors applying the information, it should be feasible to obtain user requirements and preferences and implement such requirements in information products. This study can help to raise awareness of the different perspectives and the need to obtain user preferences. Third, the findings in this research can also guide actors in streamlining the process of secondary use of EHR data. For example, the use of different technologies led to IQ challenges, particularly in the subprocesses of data organization and data presentation. Increased standardization of the information generation process, including the facilitating technologies, could make the overall process of targeting specific IQ dimensions more manageable. Finally, this study shows how IQ can facilitate the application of information by distinguishing between managerial application and operational enactment. We argue that the improvement of healthcare services is impossible without clinical enactment, which is the final aim for the quality assurance process. Thus, unit managers are crucial for securing the quality of the information products and the quality of communication in delivering information to the clinicians.

7. Conclusion

This paper aims to contribute to the debate on how IQ is transforming in the secondary use of EHR data. We began by pointing out limitations of the conventional view of IQ in the healthcare context, which states that once EHR systems generate an information product, it may fulfill user expectations. We identified in our analysis that this view ignores the complexities of secondary use of EHR data, in which users are actively involved in (re)producing and communicating the information product. In our qualitative case study in a Norwegian healthcare context, we found that IQ is transforming through active engagement and interpersonal communication among actors. We also suggested that predominant IQ models have limitations, such as overlooking interpersonal communication. Thus, we employed an IQ life cycle model to analyze the case. Based on the analysis, we enhanced the IQ life cycle model as one of the significant contributions of this study (as depicted in Fig. 7). We integrated communication quality and extraction, organization, presentation, and application quality in the enhanced model. The model also added three mechanisms: filtering, integration, and regeneration. The mechanisms play an important role in the transformation process of the information product in the secondary use of EHR data. Since the existing IQ perspective does not consider interpersonal communication, we argue that the enhanced IQ life cycle model can be applied to understand better such IQ related phenomena in other contexts where information products are the subject of interpersonal communication.

The study also identified potential future research avenues. For example, in communicating information in an organization, our study briefly shows how actors can influence information quality, which affects the secondary use of EHR data. However, some questions arise: What are the actors' rationale behind their actions? How do they interact with other actors? To answer these questions, the actor-network theory (Latour, 2005) or stakeholder theory (Friedman & Miles, 2002) can be possible analytical lenses for future research. Likewise, our research did not investigate how such mediators identify and actualize the action potentials (i.e., affordances) of EHR systems in secondary use of data and how IQ influences the actualization process. As a potential avenue for further research, we suggest studying this aspect using affordances theory (Thapa & Sein, 2018). Finally, to provide a holistic understanding of the phenomena, we suggest using critical realism in understanding how IQ, action potentials of the EHR system, and organizational actors are orchestrated as underlying generative mechanisms.

Declaration of Competing Interest

The authors report no declarations of interest.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ijinfomgt.2020.102227.

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