Generative Artificial Intelligence Use in Financial Institutions

Drivers, Barriers & Future Development

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Abstract

This thesis explores the role of Generative Artificial Intelligence (GAI) in financial institutions using Media Discourse Analysis (MDA), identifying drivers and barriers, and envisioning future developments. With the surge of GAI technology, driven largely by advancements in machine learning and data processing capabilities, the financial sector is experiencing a transformative journey. This study uses valence theory to explore the interplay between the perceived benefits and risks associated with GAI adoption in a financial context.

Despite the surge in interest in GAI within financial institutions, there are notable gaps in the existing literature that need urgent attention. Firstly, GAI usage in finance is a new and emerging phenomenon, with a limited number of comprehensive studies. A more thorough examination is needed of the specific drivers and barriers that have emerged during the research. Moreover, the literature lacks a forward-looking perspective on the future development necessary for successful GAI integration. It is crucial to address these gaps to develop a nuanced understanding of GAI's role in finance and to guide policymakers, industry leaders, and researchers in navigating the complexities of this transformative technology.

The MDA revealed that the primary drivers for GAI adoption are value creation, boosting innovation, enhanced customer experience, and security and regulatory compliance enhancements. The barriers are revealed to be risk, negative employee impact, implementation challenges, and ethics and regulatory challenges. Future developments that could potentially moderate the tension between these two dimensions were found to be roadmap, governance initiatives, and technology-based advancements.

This approach provides researchers and practitioners with a comprehensive overview of the dynamics involved in adopting GAI technologies for financial institutions. Additionally, the research offers practical insights for stakeholders, including policymakers, financial executives, and technology developers, by advocating for proactive governance and strategic planning.

The findings suggest that media representation plays an important role in shaping public and organizational perspectives on GAI, which in turn influences policy and corporate strategies. The study advocates for a proactive approach to governance and strategic planning to harness GAI's benefits while effectively mitigating its risks.

Acknowledgment

This thesis is the final chapter of our five-year journey to achieving our master's degree. It has been a long road, but we feel grateful for all the knowledge we have obtained and everyone who has been part of helping us achieve this end and fulfill our master's in management accounting.

First and foremost, we would like to express our gratitude to our supervisor, Amandeep Dhir. His guidance, expertise, and support have been instrumental in shaping this thesis. The feedback and encouragement he has given us have expanded our horizons and allowed us to reach a higher level of academic rigor.

Special acknowledgment goes to our family and friends. Their constant support, understanding, and patience were a much-needed source of strength and encouragement throughout this journey. Their belief in us has kept us motivated and focused, even during the most challenging times.

We are also grateful to the journalists and content creators in the media whose work on the topic of Generative Artificial Intelligence in financial institutions provided a rich source of data for our study. Their contributions have been invaluable in shaping our understanding and analysis.

As we close this chapter, we look forward to the future with excitement and anticipation, confident that the knowledge and skills we have acquired will serve us well in our professional endeavors.

Kristiansand, Norway

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01 June 2024

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AI	–	Artificial Intelligence
GAI	–	Generative Artificial Intelligence
GAN	–	Generative Adversarial Networks
LLMs	–	Large Language Models
MDA	–	Media Discourse Analysis
RQ	–	Research Question

1 Introduction

This section covers the background of the thesis, research questions and objectives, theoretical framework, delimitations, preliminary literature review, research methodology, and the structure of the thesis.

1.1 Background

Generative artificial intelligence (GAI) is a recently developed type of technology that can generate new content, such as text, images, videos, audio, and synthetic data (Lawton, 2024). The technology can act on natural language from an individual and produce content based on the received prompt (Cloudflare, n.d.). GAI has been in the limelight of recent technology trends after the release of ChatGPT in November 2022 (OpenAI, 2024). In April 2023, a survey from McKinsey showed that seventy-nine percent of the respondents have had some kind of exposure to GAI, while twenty-two percent stated that they are regularly using the technology in their own work (Chui, et al., 2023). According to Dimension Market Research, the global market value of GAI will increase from 14.9 billion USD to 266 billion USD from the year 2024 to 2032 (Global Newswire, 2024). A report from Bloomberg Intelligence predicts the GAI market size to be 1.3 trillion USD in the year 2032 (Bloomberg, 2023).

Banking is among the industries that could benefit the most in terms of increased revenue from GAI technology, with an increase of 200-340 billion USD annually, if all anticipated use cases were fully implemented (Chui, et al., 2023). GAI has the potential to be utilized in many different ways in finance, among these use cases, there are, GAI fueled chatbots that can provide assistance day and night, personalization of products and services, provide insights to employees or organizations, analyze and summarize large quantities of data, and more (Chui, et al., 2023). McKinsey’s report identifies sixty-three different GAI use cases (Chui, et al., 2023).

Use cases vary depending on the company utilizing the technology, some create their own models, and some partner with large tech companies. AlphaSense and Morgan Stanley recently released different GAI assistants, which both help researchers in business and finance by tapping into a large library of documents and information, giving users fast and accurate insights (Sergiienko, 2024). Featurespace also recently launched a model called TallierLT, which is a Large Transaction Model (LTM) powered by GAI. This model uses GAI technology to monitor transactions, improving fraud detection (Sergiienko, 2024).

ZestFinance has launched a model called ZAML Platform. This model utilizes GAI to analyze non-traditional data in underwriting, enabling financial inclusiveness by providing an alternative for individuals lacking credit history (Sergiienko, 2024).

Due to the massive surge in popularity, investment, interest, and opportunity associated with GAI, the authors of this paper want to contribute to the emerging literature in the field by providing a comprehensive overview of drivers, barriers, and future developments of GAI. A driver is a factor that influences the activity of another entity (Hayes, 2023). In this study, the authors want to examine what some of the drivers of GAI use in financial institutions are. There are many benefits to implementing GAI, value creation and enhanced customer experience being some of them. This study will create a comprehensive overview of these drivers.

There are many barriers to implementing GAI in financial institutions. GAI can potentially generate content that infringes on intellectual property, there can be bias in existing data, which a model can use to create unfairness, as well as a potential for the content to be inaccurate (Chui, et al., 2023). These are some of the factors that financial institutions must consider when deciding when, how and if they should implement GAI in their infrastructure. This study will explore these barriers further and provide a comprehensive overview of them.

When deciding when, if, and how financial institutions should implement GAI use, there are several factors that moderate the drivers and barriers. The future development of GAI includes a roadmap of changes that need to be addressed beforehand, there should be governance initiatives, and GAI might need to mature more. These factors affect the drivers and barriers of GAI use. Therefore, this study will provide a comprehensive overview of the future development of GAI use. The extended valence framework is utilized to understand the dynamics between the drivers, barriers, and future development of GAI use in financial institutions.

Gaps in existing literature

The first gap in existing literature the authors want to address is that GAI use in financial institutions is a recent phenomenon, and the latest literature is growing at a rapid pace. There are few studies, so we know less than what is desirable about it. Secondly, we are missing literature that has a comprehensive overview of different drivers for implementing GAI use in financial institutions. Thirdly, there is also a lack of a comprehensive overview of barriers which are experienced by financial institutions before implementing GAI. Fourthly, an overview of future developments that may need to be in place before financial institutions want to implement the technology. There is also a need for a framework that investigates both drivers and barriers and gives an overview to financial institutions so that they can foresee how the implementation process goes. Lastly, prior research mentions the need for more specific research into specific financial sectors, such as the application of GAI in accounting, the integration of GAI in existing workflows, and the development of frameworks addressing regulatory challenges (Chen, et al., 2023; Khan & Umer, 2024; Zhao & Wang, 2023).

1.2 Research questions and objectives

The main research objective of this study is twofold. One is to understand drivers and barriers in the implementation process of GAI use in financial institutions. The second is to understand the moderating aspect of future development on shaping the future of GAI in financial institutions. To answer these research objectives, we have used these three research questions (RQs): **RQ1:** What are the drivers of implementing GAI use in Financial Institutions? **RQ2:** What are the different barriers experienced by Financial Institutions while implementing GAI use? **RQ3:** What considerations are relevant to shaping the future development of GAI use in financial institutions?

1.3 Research methodology

The authors have decided to use a media discourse analysis (MDA), which is an inductive qualitative research method used to analyze interactions made through a broadcast platform, such as news articles or publications, videos, and podcasts (O'Keefe, 2011). Prior literature has used various approaches to media discourse analysis, such as socio-cognitive, discourse-history, and critical discourse analysis (Karman, 2023). The MDA lays the foundation for understanding how the research was conducted, detailing specific methods and approaches used to gather and analyze data. The chapter is essential as it offers transparency and rigor to the study, ensuring that the findings are credible and can be replicated or scrutinized by other researchers.

Section 3 delves into the strengths of grounded theory, which was applied to analyze the complex discourse surrounding GAI in financial institutions. The section also addresses ethical considerations and limitations and emphasizes the importance of validity and reliability in the research process. By thoroughly outlining the research methodology, the chapter aims to provide a clear and detailed account of the steps taken to achieve the study objective. This is necessary to ensure that the research process is understood and appreciated for its methodological soundness, ultimately contributing to the overall integrity and reliability of the study findings.

1.4 Theoretical Framework

When investigating the implementation of GAI use in financial institutions, it is important to consider the willingness of financial institutions to engage in GAI technology. A concept that explores this is valence theory (Peter & Tarpey, 1975). The theory integrates insights from both economics and psychology to provide a comprehensive model of human behavior (Kim, et al., 2009). The theory recognizes the fact that consumer's perception of products consists of both the desirable and the undesirable features (Peter & Tarpey, 1975). The desirable features are referred to as positive valence, and the undesirable features are referred to as negative valence (Peter & Tarpey, 1975). The difference between expected positive and expected negative utility is referred to as net valence (Peter & Tarpey, 1975).

The valence theory is relevant to this study because it is one of few behavioral theories that simultaneously views the perception of risk and benefits, resulting in a better evaluation of the adoption dilemma faced by financial institutions (Dhir, et al., 2021; Peter & Tarpey, 1975). The theory can be implemented in this study by viewing drivers as perceived benefits, and barriers as perceived risks. Future development functions as a moderator between the perceived benefits and risks and will add positive valence if the developments are made in due time.

1.5 Delimitations

When writing this thesis, the authors established operating boundaries for the data gathering and analysis. Firstly, it was determined that three data sets would suffice. When collecting the data, the authors would look for news articles, videos and other (blogs and company websites) types of media. These were labeled A, B, and C, where A is news, B is videos, and C is other. All data was gathered using Google search engine filtering for news, and videos, respectively.

The focus of this thesis was looking into the use of Generative AI in financial institutions. The authors are not conducting research on all types of AI technology but generative AI specifically. When it comes to its use in financial institutions, most media were related to banking. The authors used several different search queries as the perimeter when conducting the research and collecting the data from media and prior literature. The queries used for the search were “Generative Artificial Intelligence”, “Generative AI”, “Gen AI”, and “GAI”, along with “Banking”, “Financial Market” and “Financial Sector”.

The authors elected to do a media discourse analysis (MDA) using secondary data. This type of data is not published for the purpose of this research, but rather for other purposes. Therefore, there might be nuances, and opinions that might be lost due to the relevance to this study. The MDA covers popular media, which are primarily news outlets, television and radio, social media, films, music, podcasts, etc. Because of the lack of prior literature, a substantial number of media have been gathered and used to complement the background for the writings. MDA often involves adopting a specific theoretical or ideological viewpoint to frame the analysis. The viewpoint influences what aspects of the media are emphasized and how they are interpreted.

When conducting the research, the authors elected to only use material written in English. The authors of this paper also discovered during the data collection most of the data were published in the year 2023. Out of 571 news media articles, 497 were written in 2023, and 61 were written in the beginning of 2024. When it comes to videos, 371 out of 615 were published during 2023, and 63 were published in early 2024. This is also shown in Table 4.

1.6 Contributions of the thesis

This study contributes to a limited amount of existing literature on the topic. It provides financial institutions with a comprehensive overview of drivers, barriers, and future development of Generative Artificial Intelligence (GAI) use in financial institutions. We offer a framework that financial institutions can use to implement GAI more effectively regarding drivers, barriers, and future developments in the topic. The authors identify gaps in prior literature and provide insight into the media discourse on the topic, giving other researchers a comprehensive overview of drivers, barriers, and future developments that they can use in more specific research or development.

The thesis offers valuable insight into future developments that may need to be addressed before widespread GAI adoption, such as governance initiatives, roadmaps, and technology-based advancements. These insights can guide future research and theoretical explorations in the field of financial technology.

This thesis gives useful insight and uses for business managers, technology executives, and financial institutions. This research underscores the need for a comprehensive regulatory framework to address GAI's ethical and regulatory challenges. Government officials can use these findings to develop policies that promote responsible AI use, protect consumer data, and ensure fair practices in financial institutions.

By understanding how GAI can be used to personalize and enhance customer experience, business managers can develop more effective marketing strategies that cater to individual customer's needs and preferences. Insights into drivers of GAI adoption, such as innovation and value creation, can help business managers position their companies as leaders in technological innovation. This positioning can provide a competitive advantage in the market, attracting tech-savvy customers and investors.

To summarize, this study provides significant theoretical and practical contributions to the field of financial technology. It enhances our understanding of the dynamics of GAI adoption in financial institutions and offers actionable insights for business managers, policymakers, technological executives, and financial institutions. The findings underscore the importance of strategic planning, robust governance, and proactive policy development in harnessing the benefits of GAI while addressing its challenges.

1.7 Structure

This thesis gives a comprehensive overview of GAI use in financial institutions. The *introduction* highlights the significance of GAI in finance, framing the study's objectives and scope. The *literature review* offers a theoretical foundation, linking past findings with the research questions and exploring the guiding theoretical framework. Details about *research methodology* can be found in chapter three, where the authors cover qualitative methods and media discourse analysis, along with ethical considerations, validity, and reliability. The chapter on *findings* presents drivers, barriers, and future development of GAI, transformed into comprehensive figures. Next is the *discussion*, which integrates findings with the theoretical framework and literature discussed earlier. *Study implications*, consider theoretical and practical implications, offering recommendations for policymakers, and industry executives. The *conclusion* summarizes key findings, reflects on the study scope and limitations, and proposes future research directions. Lastly, the *references* and *appendix* provide supporting material and two discussion papers.

2. Literature Review

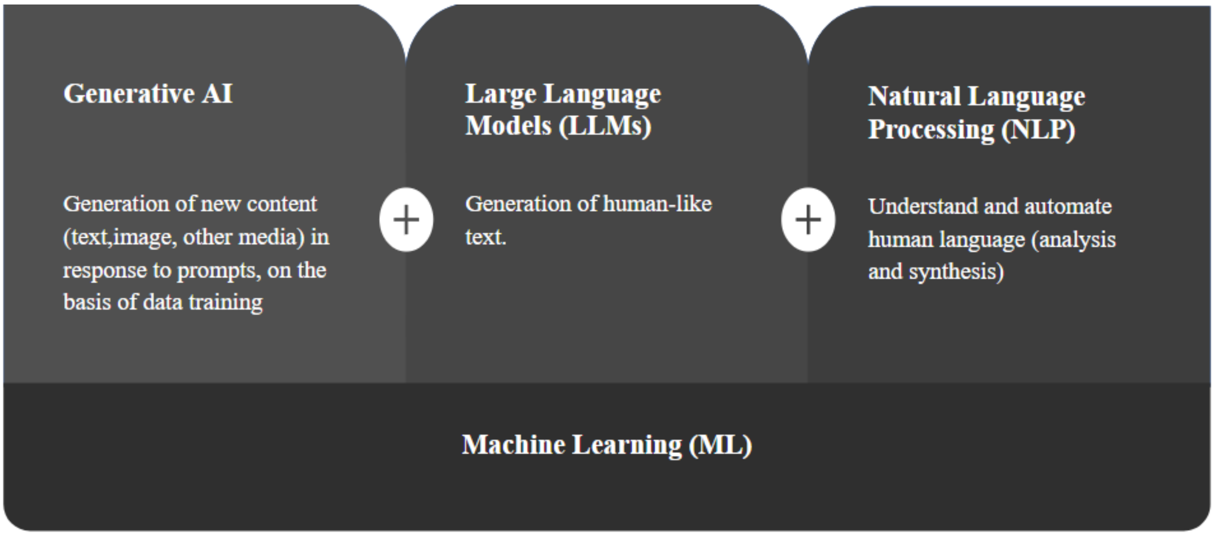
This section will provide a comprehensive overview of existing literature related to the use of Generative Artificial Intelligence (GAI) in financial institutions. First, the authors provide a brief but in-depth introduction to GAI and closely related technologies. Second, they have conducted a literature review, showcasing all findings related to drivers, barriers, and future development in prior literature on GAI use. Third, the authors present the theoretical framework, which is later used to discuss the findings in this thesis.

2.1 Generative Artificial Intelligence

Generative Artificial Intelligence (GAI) is a technology within the realm of Artificial Intelligence (AI) comprised of models that after being trained on data can create new content and outputs as a response to prompts (OECDpublishing, 2023). Large Language Models (LLMs) are one type of GAI involving the generation of language/text. However, GAI is also involved in the generation of visual outputs, audio, images, code, or other types of content generation (OECDpublishing, 2023). In other words, *"GAI describes algorithms that can be used to create new content, including audio, code, images, text, simulations, and videos"* (McKinsey&Company, 2024). A visualization of the relationship between Generative AI and LLMs can be viewed in Figure 1.

GAI models can process massive amounts of unstructured data, including users feedback, to learn and further enhance their capabilities (OECDpublishing, 2023). Based on various algorithms and mathematical models, such as Generative Adversarial Networks (GANs), which uses deep neural networks, GAI models can create brand new content as output (OECDpublishing, 2023).

Figure 1: Generative AI inspired by OECD Publishing, 2023.



2.2 Generative AI and financial institutions

The literature review is based on findings from Web of Science. This database allows users to conduct comprehensive literature reviews by utilizing an advanced search engine that enables efficient searching on literature in relevant disciplines from around the world (Clarivate, n.d.). By entering this query “*"Generative AI" OR "Gen AI" OR "GAI" OR "Generative Artificial Intelligence" OR "ChatGPT" (Topic) and "Banking" OR "Financ*" (Topic)”* the database presented ninety-five results, ranging from 2024 to 2008. Eighty of these results are from 2023 and 2024. After going through all the literature, the authors are left with twenty-one relevant prior studies, of which eight were published in 2024 and thirteen in 2023. In Table 1, a comprehensive overview of prior literature is presented. The table is structured by the categories, research profile, drivers, barriers, future development, limitations, and key findings. Figure 2 shows the different drivers, barriers and future development as identified by prior literature.

2.2.1 Drivers

GAI technologies are rapidly transforming the financial sector, driven by their potential to create value, boost innovation, enhance customer experience, enhance security, and ensure regulatory compliance. The deployment and effectiveness of GAI depend on understanding its drivers comprehensively. This section critically examines the literature focusing on these drivers, evaluating the strengths and weaknesses of current research, and identifying areas for further investigation.

Value creation

The promise of GAI to streamline operations and enhance decision-making is a major driver for financial institutions. Researcher such as Gill et al. (2023) provides a range of potential benefits in optimization that include streamlined workflows and efficient content generation (Gill, et al., 2023). However, the discussion does not provide insights into the long-term social and economic implications of GAI. The different ways to enhance efficiency by GAI use are discussed in several of the reviewed literature. The proceedings paper by Lakkaraju, et al. (2023) mentions the potential for GAI to process vast volumes of unstructured data, which can improve efficiency (Lakkaraju, et al., 2023). Scholars seem to agree that GAI use in financial institutions can provide a boost in productivity and streamline operations. In addition to the literature already mentioned, the studies conducted by Chen, et al. (2023) Dwivedi et al. (2023), Khan & Umer (2024), Kim (2023), Neilson (2023), Ooi, et al., (2023), Zhao & Wang (2023), Zheng, Xianrong et al. (2024), and Zheng, Xiaolong et al. (2024) all discuss in various degrees the potential value creation generated from task automation, efficiency enhancements, productivity boost, and streamlining business operations (Chen, et al., 2023; Chen, et al., 2023; Dwivedi, et al., 2023; Khan & Umer, 2024; Kim J. H., 2023; Neilson, 2023; Ooi, et al., 2023; Zhao & Wang, 2023; Zheng, Xianrong et al., 2024; Zheng, Xiaolong et al., 2024) What should be noted is that many of the literatures discussing these benefits, has not researched this as their main objective, but rather briefly mentioned them while explaining GAI or similar concepts.

The study conducted by Lakkaraju (2023) uses few queries in their analysis of GAI chatbots, which covers many categories, more queries and for more specific categories in finance could be beneficial (Lakkaraju, et al., 2023). The study by Neilson (2023) has a relatively small sample size, which might affect the presented findings (Neilson, 2023). The article written by Kim (2023) finds that GAI can increase portfolio efficiency by recommending asset classes in quantitative asset management (Kim J. H., 2023). However, the research reflects results on a monthly basis, while higher frequency could provide more insights (Kim J. H., 2023). It also does not consider risk or implementation challenges.

GAI can potentially enhance the decision-making process (Chen, et al., 2023); (Ullah, et al., 2024; (Zheng, Xianrong et al., 2024); (Zheng, Xiaolong et al., 2024), aid in financial forecasting (Li, Feng, Yang, & Huang, 2024), and identify opportunities for financial gain (Pelster & Val, 2024), to benefit financial institutions. The study conducted by Ullah et al., (2024) finds that the key usage dimensions for GAI to influence investment decision-making in the stock market are *"data analysis, managing risk, optimizing portfolios, forecasting market trends, and conducting sentiment analysis"* (Ullah, et al., 2024). However, this study used financial literacy as the only moderator between GAI usage and investment decision-making, resulting in a narrow view (Ullah, et al., 2024). These usage dimensions could potentially be relevant for GAI influence on other financial dimensions in different financial institutions, but because of the narrow scope of the literature discussing these, further research is required.

Enhanced customer experience

Prior literature discusses that GAI use in banking can facilitate several potential enhancements in customer experience. These include but are not limited to personalization through new consumer insights analyzed by GAI, and offer customized products and services to facilitate individual needs (Khan & Umer, 2024); (Ooi, et al., 2023) ; (Sohail, et al., 2023). The study conducted by Chen et al. (2023) mentions improved accessibility and financial inclusion as important benefits as well as drivers to implement GAI use in financial institutions, especially in populations that are underserved in terms of financial services and products (Chen, et al., 2023). Meanwhile, the study conducted by Ooi et al. (2023) provides a different perspective on how enhancements to customer experience can come from hyper-personalized service and product offerings in many different sectors, including finance and marketing (Ooi, et al., 2023). Even though both reviewed approaches seem to consider customer experience as an important driver of GAI use, they have different approaches when identifying them. This shows that emerging literature is not all inclusive of potential ways to enhance customer experience, resulting in the need for more literature providing a comprehensive overview.

Security and regulatory compliance enhancements

According to the study conducted by Li et al. (2023), GAI has capabilities to enhance financial risk modeling, such as fraud detection, credit scoring, and bankruptcy prediction (Li, et al., 2023). The study refers to McKinsey & Company's deep learning-based solution, which leverages user history data and real-time transactions to detect fraud (Li, et al., 2023). Zhao & Wang (2023) also state that the technology can provide significant benefits in fraud detection by analyzing financial data with historical patterns (Zhao & Wang, 2023). None of the reviewed literature presents any specific impact the technology has had on fraud detection or devised any potential implementation strategies.

Ethical consideration is an important consideration when contemplating GAI use in financial institutions. An article written by Tkachenko (2024) explores how synthetic data can be used to address these considerations (Tkachenko, 2024). The article presents how GAI can construct as well as analyze synthetic data, which can then circumvent issues related to confidential datasets and the privacy of sensitive consumer, client, or company information (Tkachenko, 2024). However, even though the article proposes using synthetic data to alleviate ethical concerns, Tkachenko (2024) also states many emerging ethical concerns regarding the use of synthetic data. This enforces the need for more multidisciplinary research on the topic.

2.2.2 Barriers

With the rapid transformation of the financial sector using GAI technologies, financial institutions might experience various barriers alongside the drivers. Barriers such as risks, negative employee impact, implementation challenges, and ethical and regulatory challenges are some of the issues faced by financial institutions that wish to use GAI. The effective handling and navigation of these barriers are essential for effective use and comprehensive implementation and development of GAI. In his section of the thesis, the authors critically examine the literature, focusing on the mentioned barriers, giving a comprehensive evaluation of current research, and identifying areas that need to be investigated further.

Risk

The literature shows several concerns about risk and potential threats when using GAI, and the one being discussed the most is hallucinations. Khan & Umer, (2024), Li, et al., (2023), Li, et al., (2024), Roychowdhury, (2024), and Samsi, et al., (2023), brings up and warns about GAI hallucinations. Roychowdhury (2024), covers this topic particularly well, both explaining the term and how to minimize it, this article, however, is the only one of the literature reviews that goes into the subject deeper than just briefly mentioning it and explaining the term. It’s clear that there’s a need to study this topic further and develop more solutions, hallucinations are an unwanted outcome of GAIs that need to be further studied (Roychowdhury, 2024).

With the adoption of GAI new potential for fraud also emerge. GAI can create very natural sounding synthetic voice audio, from just a small sample of a person’s voice. (Barrington, et al., 2023). By combining synthetic voice with the potential to create high-quality deep fake videos, the possibility to create highly realistic deep fake videos, which can possibly fool banks, and financial institutions' security systems (Barrington, et al., 2023). It is critical to look further into this and develop more research and counter measures for this security risk. Otherwise, the reliability of the future of the financial institutions might be at high risk. Data security naturally follows. Its critical to align applications of GAI with standards so we can have better data security (Zhao & Wang, 2023). This view is also supported by Chen, et al., (2023), which state *"policymakers should also consider other ways to prepare people for future AI developments"* (Chen, et al., 2023).

Negative employee impact

The literature shows a clear warning and concern when it comes to a negative impact on the employees and some of the steps that will need to be taken to address this concern. As presented in Table 1, several researchers like Dwivedi, et al., (2023), Gill et al., (2023), Khan & Umer, (2024), Li et al., (2024), Sohail, et al., (2023), and all speak about the need for and importance of «Human Oversight». Financial Technology is gaining prominence, and its adoption may redefine jobs (Gill, et al., 2023). Some tasks could be automated, human-AI collaboration will become crucial (Gill, et al., 2023). To verify the trustworthiness of insights and offers, human involvement is necessary (Sohail, et al., 2023). However, the literature does not go into specific suggestions on how this involvement or oversight should be implemented or look like. This is highly relevant and important for using GAI in financial institutions, as people in the industry will be concerned about their jobs and what is to come. Employees must then upskill to complement the GAI abilities, especially in the fields of strategic decision-making, relationship management, and ethical oversight (Gill, et al., 2023).

Implementation challenges

Samsi, et al., (2023) and Neilson, (2023) describe the barrier of computing cost and dedicated hardware. "*GAI models carry significant computational challenges, especially the required computational costs and energy costs"* (Samsi, et al., 2023). Also, *"limitations concerning the unknown cost of continued use of GAI technologies in the future"* (Neilson, 2023). This literature shows the concern for how much GAI might cost businesses in the future. Research and investments to address this concern need to be made as soon as possible to ensure the cost of this technology does not exceed its use and value.

A comprehensive understanding of limitations such as integration complexities is crucial (Zhao & Wang, 2023). Alongside the difficulty of cost, it is important to know or find out the time and effort that is needed to implement GAI into financial institutions. As with many of implementation challenges found in the literature do we find the need of future research. The youth of this topic and how recent the boom in technology is quite transparent. *"Having the infrastructure to make generative AI or any form of digital technology in banking services work can also be challenging"* (Ooi, et al., 2023). "*The challenge lies in exploring a working relationship between various banks for the possibility of sharing and combining data to develop a banking GAI model"* (Ooi, et al., 2023). "*Financial exclusion could arise from various sources, including the lack of access to digital infrastructure"* (Zheng, Xianrong, et al., 2024). The literature presented in Table 1 suggests a need for a shared infrastructure for banks and financial institutions to share and combine their data so they can create a good working GAI for the industry. The challenge for this, however, is the lack of trust and competition between businesses. It is going to be a long road ahead to create a solid and strong foundation for a GAI infrastructure for financial institutions.

Ethics and regulatory challenges

Finally, the barriers in the literature include ethics and regulatory challenges. There are a lot of different discussions on this topic in the literature, however, the main talking points are biases, privacy, ethical concerns, and regulatory compliance. For example, Zheng, Xianrong, et al. (2024) states that *"AI poses some challenges, including ethical considerations and potential biases"* (Zheng, Xianrong, et al., 2024). Because of the potential bias in algorithms, financial services using FinTech algorithms are not always fair (Zheng, Xianrong, et al., 2024). Though a lot of sources mention and warn about potential biases in GAI, they do not delve further into the subjects. Some suggestions for further research about biases can be to test them and conduct a report of what biases shows in the data and how often they happen.

In addition to the concerns about bias, there are concerns regarding privacy. If malicious third parties are able to access individuals' or organizations' data, their privacy can be compromised (Khan & Umer, 2024). However, ensuring that GAI follows privacy protocols which is transparently shared with all participating entities, such as financial institutions or individuals engaging in financial activity is important (Khan & Umer, 2024). As with almost all the rest of the literature, the research does not go deeper into what more is done to protect privacy, and how much is leaked, the data is still just in its infancy, and it is reflected in the literature. Researchers should in the future look into what financial institutions do to protect its clients and themselves from malicious actors and organize what intuitions has done the most to protect their privacy.

Ethical considerations were naturally something to come across during the review of the literature. All new and fast-developing technologies should be ethically scrutinized to test whether they can hold up to the standards we humans have set, both in a private position and in business settings. Li, et al., (2023), Sohail, et al., (2023), Zhao & Wang, (2023), and Zheng, Xianrong, et al., (2024), all touch on the topic on varying levels. Sohail et al. (2023) states that there is an urgent need for author guidelines regarding AI use in academic publishing because of the increased use of GAI technologies (Sohail, et al., 2023). This is related to the ethical concerns which might present itself when GAI writes academic texts, such as GAI not addressing copyright, the potential for plagiarism and lack of referencing when generating text (Sohail, et al., 2023). These barriers are particularly worrisome and relevant because currently, anti-plagiarism software, or human readers, are having significant trouble with distinguishing between what text is generated by AI and what is written by a human (Sohail, et al., 2023). Additionally, the reviewed literature mentions other ethical concerns, such as potential data breaches, hardware or software which can malfunction, programming errors, and changes in the algorithms (Zheng, Xianrong, et al., 2024). It is clear from the literature that the ethics of this fast-developing technology is at the forefront of the researcher's mind, it is important not to let up on the pressure to ethically handle GAI, especially when it comes to its use in financial institutions.

Ethics follows regulatory questions, and the literature on GAI in financial institutions provides some insight into the mindset for this subject. Dwivedi, et al., (2023), Neilson, (2023), Chen, Wu & Zhao, (2023), and Khan & Umar, (2024), either mention regulatory needs by calling out their necessity or delving a little further into the concept for GAI. *"Laws and regulations should be designed to penalize the unethical usages of GAI"* (Sohail, et al., 2023). "*Unlike humans, chatbots do not have a legal personality under the current legal and regulatory framework"* (Chen, et al., 2023). It is clear that a regulatory framework is wanted with in regards to GAI. However, there is still very little research done on what the framework would look like. Some future studies can be on how regulatory framework should be made and implemented in financial institutions, both for the benefit of the consumer and the institution.

2.2.3 Future development

Prior literature on GAI use in financial institutions proposes many recommendations for future development, including suggestions for a roadmap with on what companies planning to implement the technology might need to do, governance initiatives such as regulatory and ethical frameworks that external organizations need to develop, and how the technology might need to mature before it is regarded as both safe and beneficial to implement.

Governance initiatives

Governance initiatives regarding regulatory and compliance frameworks, policies, and ethical guidelines are a recurring topic when considering which future developments are needed to safely implement GAI use. The research conducted by Li et al. (2023), Chen et al. (2023), Ooi et al. (2023), Ullah et al. (2024), and Khan & Umer (2024), all express a need for some variation of these frameworks or guidelines. Ullah et al. (2023) says in their article that the Securities and Exchange Commission of Pakistan should create regulatory framework and policies to protect against fraudulent activities and misleading information and protect the privacy of data (Ullah, et al., 2024). Ooi et al. (2023) discusses the potential of regulators and banks to create regulatory frameworks for GAI use and development by working together (Ooi, et al., 2023). Meanwhile, Khan & Umer (2024) propose that the issue should be tackled on a global level, with clear standards for navigating the legal implications proposed by GAI in finance (Khan & Umer, 2024). Even though prior literature has different proposals for which organ should create these regulations, they agree that the topic is important for future development of GAI use in financial institutions.

Roadmap

Regarding how to implement the technology, the literature mentions the need to know when and where to use GAI in financial institutions to be of importance. Ooi et al. (2023) state in their article that banks need to reflect on who will use the technology, whether it is a consumer-facing chatbot or used for training and streamlining operations by managers (Ooi, et al., 2023). The paper from Gill et al. (2023) agrees that the GAI needs to be tailored to specific use cases to optimize business processes (Gill, et al., 2023).

To strategically implement the technology, the literature identifies important factors, such as understanding the limitations of GAI use, investment in infrastructure and human resources, and continuous research on the technology and adoption (Dwivedi, et al., 2023; Khan & Umer, 2024; Li, et al., 2023; Sohail, et al., 2023; Zhao & Wang, 2023).

Technology based advancement.

For GAI use in finance to be more efficient, prior literature has mentioned different technology-based advancements that can improve the usability of GAI. As presented in Table

1, the literature by Gill et al. (2023) and Khan & Umer (2024) both consider making the models more dependable as an important future development, and as such, the GAI might present less misinformation, understanding the context better, and handle complex financial jargon (Gill, et al., 2023; Khan & Umer, 2024). The paper by Roychowdhury (2024) presents prompt engineering as a way to handle the misinformation and hallucinations GAI can produce. Dwivedi et al (2023) and Sohail et al. (2023) both addresses the need for a user-friendly technology, improving the conversational capabilities, and understanding the needs user has when considering how far to push these technologies on consumers (Dwivedi, et al., 2023; Sohail, et al., 2023).

Trust is important when dealing with financial institutions, and as such Zheng, Xiaolong (2024), and Ullah et al. (2024) mention in their literature that the GAI models financial institutions potentially use need to be transparent and explainable (Ullah, et al., 2024; Zheng, Xiaolong, et al., 2024).

Figure 2: *Drivers, barriers, and future development as suggested by prior literature.*

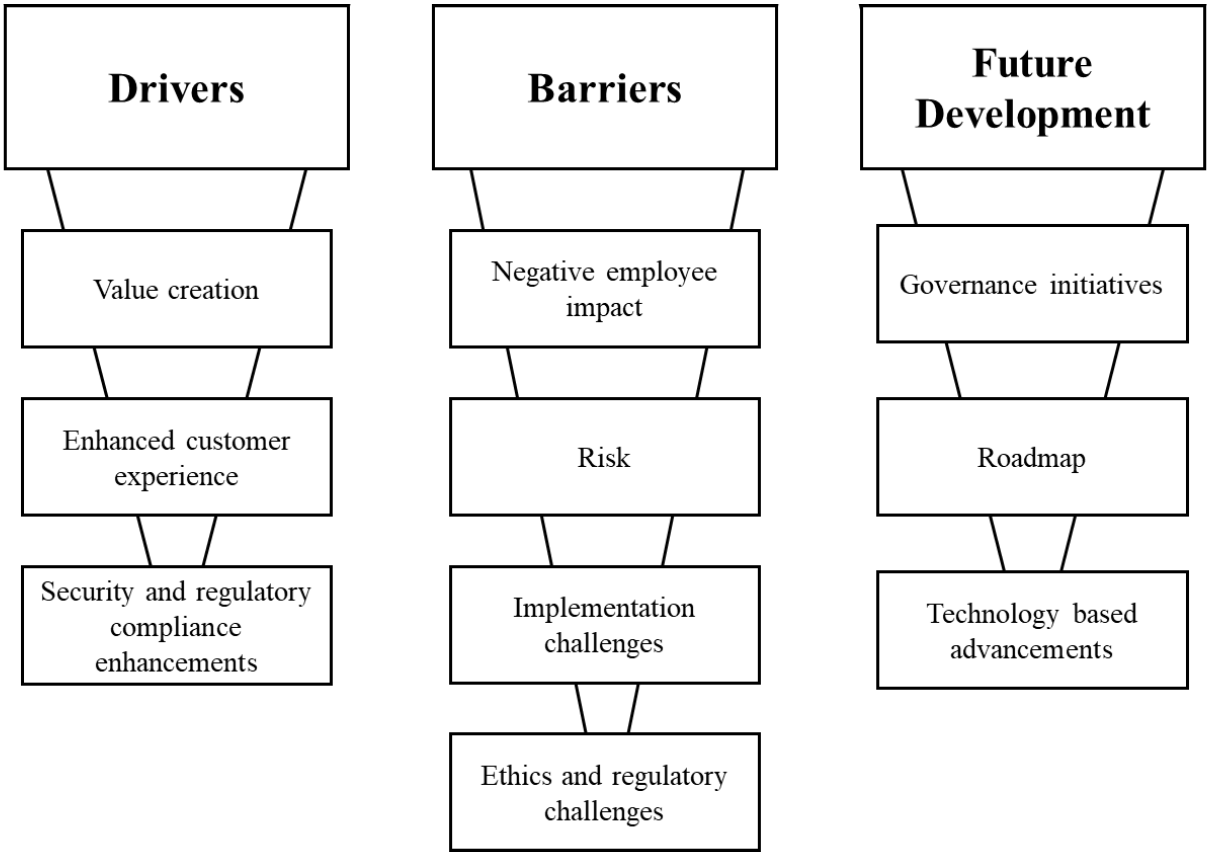


Table 1: *Overview of prior literature*

Research Profile	Drivers	Barriers	Future Development	Limitations	Key Findings
Author(s): Samsi et al., 2023 **Document Type:** Proceedings Paper **Country:** United States	Increased interest in leveraging GAI.	Computing cost. Dedicated hardware. Privacy. Hallucinations.		Does not include energy needed to train or finetune the models.	GAI requires a significant amount of hardware and energy.
Author(s): Zhang & Yang, 2023 **Document Type:** Proceedings Paper **Country:** England	Chinese GAI model generates accurate outputs in the region's financial domain.	Less progress on GAI in the Chinese market.	Chinese GAI model development for increased Chinese demand.	The study researches their own Chinese model compared against other models, without declaring competing interest.	The financial chat model XuanYuan 2.0 can generate accurate responses in Chinese finance
Author(s): Barrington et al., 2023 **Document Type:** Proceeding Paper **Country:** Germany		Financial institutions can be compromised by voice cloning. Potential fraud.		Does not discuss GAI use as a potential measure to detect voice cloning fraud.	By only analyzing few minutes from a person's voice, GAI can create hyper-realistic synthetic audio. Combined with high-quality visual generation,

					it can create very realistic deep fake videos.
Author(s): Gill, et al., 2023 **Document Type:** Proceedings Paper **Country:** Italy	Optimization and customization.	Trustworthiness. Human oversight. Upskilling employees.	Tailoring for specific use cases. Increase dependability.	The study does not investigate the future economic and social implications caused by GAI in FinTech	Potential benefits of integrating GAI in FinTech. Potential challenges of implementing GAI in fintech.
Author(s): Lakkaraju, et al., 2023 **Document Type:** Proceedings Paper **Country:** United States	Increased interest. Improve efficiency.	Potential biases inherent in GAI Biased advice could have significant impact on users' finances.		This study used few queries to cover many categories of finance, more queries for specific categories can be used.	The answers from GAI change for the same questions. Chatbots cannot do numeric reasoning. Process vast volumes of unstructured data.
Author(s): Li, et al., 2023 **Document Type:** Proceedings Paper **Country:** United States	New possibilities for GAI applications in finance. Trading and portfolio management. Financial fraud detection.	Hallucinations and explainability. Ethical concerns and bias. Governance.	Continuous research. Robust evaluation frameworks. Appropriate safeguards.		Practical roadmap for adoption.

	Using AI in services related to advice and customer service.				
Author(s): Dwivedi, et al., 2023 **Document Type:** Article Country: UK	Streamline operations. Boost productivity. Customer insights.	Regulatory compliance. Human oversight. Employee layoff.	Support transitioning workforce. User-friendliness.		Major boost in productivity. Practical, ethical moral, and policy challenges. Need for new laws to govern GAI.
Author(s): Neilson, 2023 **Document Type:** Article **Country:** Australia	Improve efficiency. Reduce cost.	Regulatory adherence. Accountability and responsibility. Ethical considerations and bias. Software cost.		Small sample size.	GAI plays an important part in task and workforce developments, and compliance, which offers significant benefit in content creation.
Author(s): Sohail, et al., 2023 **Document Type:** Article **Country:** Saudi Arabia	Improve efficiency. Customer personalization.	Regulations in the financial sector. Human oversight. Ethical concerns.	Investment in infrastructure and human resources. Improving conversational capabilities. Increase the amount and diversity of data used in training models.		Showcase of different applications in different domains. Uncovered potential future direction. Identified and discussed ethical concerns.

			Integrate feedback from humans.		
Author(s): Chen, et al., 2023 **Document Type:** Article **Country:** England	Improved accessibility, efficiency, and cost reduction. Aid investors make informed decisions. Improve the efficiency of financial markets. Financial inclusion.	Data security. Lack of regulations.	Develop relevant regulatory frameworks. Ensure compliant output from chatbots. Inclusion of governments in overseeing challenges regarding equality and employment.		Value creation. Regulatory barriers. Need for regulatory and compliance framework for future development.
Author(s): Zhao & Wang, 2023 **Document Type:** Article **Country:** United States	GAI can be used for optimizing accounting tasks. Support auditors in fraud detection. Guidance to clients and empower employees.	Data integrity. Integration complexities. Ethical considerations, privacy, bias.	Comprehensive understanding of limitations.	The study does not research the process of integrating GAI for use in already existing workflows specific to accounting	This study examines GAI in accounting and explores potential applications and challenges. Practical insights for accounting stakeholders and professionals.
Author(s): Ooi, et al., 2023 **Document Type:** Article	Develop marketing campaigns.	Access to data. Having the right infrastructure.	Regulatory framework for developing and using GAI.	Research is needed in evaluating policymakers' attitude towards implementing	GAI value creation and customer experience in banking.

Country: United States	Personalized and efficient services to customers. Reduce risk and detect fraud. Streamline business operations and reduce cost.	Accuracy of GAI results. Accountability.	Collaboration to merge data and train GAI models. Where to use GAI - in training and streamlining, or a consumer facing chat-bot.	GAI, are they trying to stop it or integrate it?	Challenges banks face in integrating GAI. Recommendations for better implementation of GAI in banking.
Author(s): Kim, 2023 **Document Type:** Article **Country:** United States	Improve efficiency. Utilizing LLM in quantitative investment can be beneficial.			This research shows result on monthly basis, however, using a higher frequency could be more insightful. Findings only showcase potential value and efficiency, and not risks or implementation challenges.	Increased portfolio efficiency by GAI asset class recommendations. GAI can be used as a quantitative asset manager, generating recommendations based on economic conditions
Author(s): Li, et al., 2024 **Document Type:** Article **Country:** Switzerland	GAI can assist and improve human financial forecasting.	GAI might be inaccurate. Human oversight. Black box.		Due to the black box, little is known about the internal process of which GAI makes financial forecasts. The research is limited to a two-year forecast,	Chat GPT can provide financial forecast with less optimistic bias, and higher accuracy.

				so it is inefficient in a dynamic market.	
Author(s): Pelster & Val, 2024 **Document Type:** Article **Country:** United States	GAI can successfully identify stocks that yield superior performance.	Factual accuracy from GAI varies over time.			In analyzing information and selecting stocks, GAI can be useful. GAI is not always factually correct, caution is advised.
Author(s): Roychowdhury, 2024 **Document Type:** Proceedings Paper **Country:** United States		Hallucinations are bad for decision makers.	Prompt engineering techniques can be used to minimize risk of hallucinations.		Hallucinations can have extreme impact for decision making tasks.
Author(s): Zheng, Xiaolong et al., 2024 **Document Type:** Article **Country:** United States	Improve efficiency and accuracy. GAI can identify and correct bias in economic decision making. GAI can analyze without inherent	Existing biases might increase if GAI models use biased data to train. Large capacity for information and data is needed.	Increase transparency and trust.		Financial and economic activities might change because of GAI application.

	bias or preconceptions. Enhance human decision makers.	Increased automation can lead to partial unemployment. Privacy and ethical concerns.			
Author(s): Ullah, et al., 2024 **Document Type:** Article **Country:** England	GAI in investment decision making.	Need for large amount of quality data. Bias.	GAI efficiency evaluation. Regulatory and ethical initiatives to promote education on GAI use, data availability, privacy concerns. Transparent and explainable algorithms.	Narrow view, using financial literacy as the only mediator between GAI usage and investment decision making. Lack of public data. Future research could benefit from longitudinal studies. A Pakistani sample might not be generalizable to other countries.	The study discovers important GAI use cases which influence decision making in investments. Financial literacy is also important in influencing decision-making. Combining financial literacy and GAI is important to get the best results.
Author(s): Tkachenko, 2024 **Document Type:** Article **Country:** Switzerland	Using synthetic data to address ethical considerations.	Representativeness of synthetic datasets.	Synthetic data need to retain intricate correlations present in genuine data.		Potential use of synthetic data to address ethical considerations.

Author(s): Khan & Umer, 2024 **Document Type:** Article **Country:** England	Improved efficiency. Improved accuracy. Personalization.	Biased outcomes. Hallucinations. Privacy concerns. Transparency and accountability. Human replacement Legal issues.	Regulatory and ethical initiatives. Combine and leverage both AI and financial professionals in a hybrid approach. Increase dependability.	Identifying and mitigating bias with specific focus. Operationalizing and quantifying biases. Research into development on security and privacy protocols for GAI in financial context.	Functions of GAI in finance. Ethical challenges of using GAI in finance. Possible solutions to challenges.
Author(s): Zheng, Xianrong et al., 2024 **Document Type:** Review **Country:** Switzerland	Enhance processes in decision-making. Task automation and improved efficiency.	Ethical considerations. Potential bias.	Responsible GAI. How to apply GAI in finance, fraud detection and trading.	The study only briefly mentions GAI potential uses and challenges.	GAI can enhance efficiency. GAI can power chatbots.

2.4 Valence theory in technology acceptance and adoption

Valence theory is a behavioral theory used to explore the decision-making process, taking both perceived risks (negative valence) and perceived benefits (positive valence) into account simultaneously (Peter & Tarpey, 1975). The net valence is the arithmetic difference between these two concepts (Peter & Tarpey, 1975). If the net valence is positive after calculating the difference, in this case, GAI will be adopted by the decision-making financial institution (Peter & Tarpey, 1975).

Using valence theory to analyze decision-making in technology adoption is not unusual among scholars. Using the search query “"valence theory" (Topic) AND "technology" OR "artificial intelligence" OR "AI" OR "GAI" OR "generative artificial intelligence" OR "generative AI" (Topic) and English (Languages)” on web of science resulted in fifteen articles, where eight of them discuss valence theory in Generative Artificial Intelligence (GAI) or other technological implementations. These articles are showcased in Table 2.

As presented in Table 2, Bedué & Fritzsche (2022) used an extended valence framework to investigate the dynamic relationship between not only risks and benefits, but also trust, as a single construct of acceptance. (Bedué & Fritzsche, 2022). Leong et al. (2024) used it similarly and extended the framework to incorporate trust to develop new associations in mobile usefulness and ease of use (Leong, et al., 2024). Chin et al. (2020) used a variation of the extended framework to assess the impact of trust on the intent of adopting mobile payment systems (Chin, et al., 2020).

Furthermore, Table 2 provides comprehensive insights into the different ways positive and negative valence has been conceptualized for use in specific contexts, as well as showing what extension to valence theory has been used in the different studies. Perceived benefits is the entity that increases positive valence as proposed by Pelter and Tarpey (1975), prior use cases has explained or expanded this dimension by including concepts such as convenience, utilitarian value, cost and time savings, and lifestyle compatibility (Chin, et al., 2020; Leong, et al., 2024; Mombeuil, 2023; Mou, et al., 2020; Ozturk, et al., 2017; Tang, et al., 2020). To contrast the perceived benefits and positive valence, there are perceived risks and negative valence. As shown in Table 2, prior use cases have conceptualized the causes of negative valence as perceived risks, uncertainty, privacy and security, negative utility, and perceived costs, to mention some (Chin, et al., 2020; Leong, et al., 2024; Mombeuil, 2023; Mou, et al., 2020; Ozturk, et al., 2017; Tang, et al., 2020).

In this study, we extend the valence theory proposed by Pelter & Tarpey (1975) by incorporating future developments as a moderator. This study conceptualizes perceived risks as barriers, perceived benefits as drivers, and future development as a moderator affecting the relationship the drivers and barriers have on potential intention to implement GAI use in financial institutions. The barriers identified by prior literature on GAI in financial institutions are risks, negative employee impact, implementation challenges, and ethics and regulatory challenges. These barriers add negative valence and are equivalent to perceived risks in this context. The drivers are value creation, boosting innovation, enhanced customer experience, and security and regulatory compliance enhancements. These concepts add positive valence to the net valence equation, because of this, the study conceptualizes the drivers as perceived benefits.

When financial institutions consider their intention to implement GAI use, the weight of positive valence must be higher than the weight of perceived risks if the technology is to be implemented. Future development adds a moderating factor to the equation. If these future developments are in place, it will significantly add positive valence. However, as described by prior literature, these future developments are still in progress or are still just desired by financial institutions. So, until these future developments are in place, the intention to implement GAI use relies on the complex relationship between the drivers and barriers. Figure 3 shows the potential weight distribution of drivers (positive valence) and barriers (negative valence) on the intention to implement GAI use in financial institutions, with future development as a moderator.

Table 2: *Prior literature on technology acceptance and adoption using valence theory*

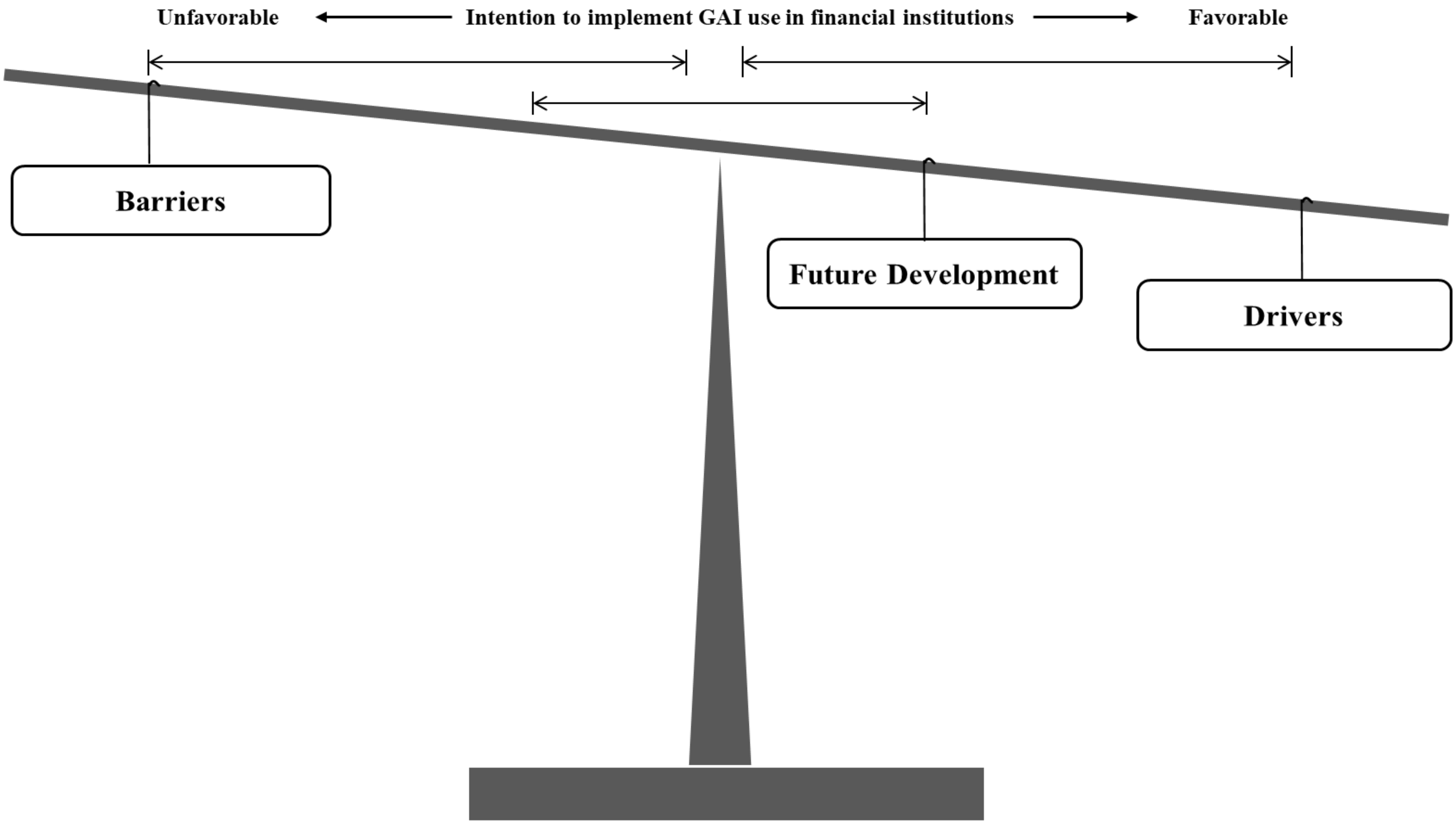
Research Profile	Positive Valence	Negative Valence	Extended dimension	How valence theory is used	Why it's used
Author(s): Ozturk, et al., 2017 **Document Type:** Article **Country:** England	Perceived benefits Convenience Utilitarian value	Perceived risks Uncertainty Consequences of transaction Privacy concerns		The study used valence theory to examine factors affecting restaurant goers' intention to use mobile payment technology.	The theory has previously been used to examine behavior of consumers in other contexts.
Author(s): Chin, et al., 2020**,** **Document Type:** Article **Country:** United State	Perceived benefits: Cost savings, time savings, convenience	Perceived risks Privacy Security	Trust: Privacy, security, familiarity	Use the extended valence framework to assess the impact of trust on the intent of adopting mobile payment systems	Other studies used other theories, models, or antecedents to study the valence on mobile payment system adoption
Author(s): Ghasemaghaei, 2020 **Document Type:** Article **Country:** England	Cognitive Absorption	Disorientation	Product Knowledge Gender	Investigate and explain the impact of disorientation, cognitive absorption, and effectiveness of recommendation agents on user's intention to use the technology when shopping online.	Valence theory examines two important parts of decision-making regarding online shopping experiences.

Author(s): Mou, et al., 2020 **Document Type:** Article **Country:** England	Monetary savings Product offerings Convenience	Uncertainty regarding product description and performance. Financial, privacy, confiscation, and delivery risks.	Website quality Age Gender Frequency Familiarity with the site Repeat purchase behavior	Consumers repurchase intention, will the consumer continue to purchase from the same online provider.	The study is an early adopter of using valence theory on the repurchase intention of international buyers in CBEC.
Author(s): Tang, et al., 2020 **Document Type:** Article **Country:** England	Positive utility Perceived enjoyment Perceived compatibility Perceived usefulness	Negative utility Perceived cost Perceived complexity Perceived risk	Social influence Downloading intention Facilitating Conditions	The study uses valence theory to better understand adoption of mobile apps.	Valence theory is good for exploring factors affecting intention to download paid apps.
Author(s): Bedué & Fritzsche, 2022 **Document Type:** Article **Country:** Germany	Perceived benefits from trust	Perceived risk of trust	Trust: Ability, Integrity, Benevolence	The study uses valence theory to consider socioeconomic factors to comprehensively view trust in AI. Trust is used as a moderator between perceived benefits and perceived risks.	Good use for unfamiliar technologies. Very suitable for the consideration of AI technology. Important for trust building with new technologies.

Author(s): Mombeuil, 2023 **Document Type:** Article **Country:** Netherlands	Lifestyle compatibility Relative advantages	Perceived risks Perceived costs	Trust: M Payment Ecosystem	Extended Valence Framework is used here to investigate what affects the willingness to use mobile payment systems for specific transactions.	Valence theory views both positive and negative factors on adoption of mobile payments simultaneously.
Author(s): Leong, et al., 2024 **Document Type:** Article **Country:** China	Perceived benefits Epistemic benefit Convenience	Perceived risk Psychological risk Physical risk	Trust in mobile sharing economy	develop new associations between trust, perceived benefit, and perceived risk in behavioral intention of mobile sharing economy using extended valence framework.	The theory is accepted to be used in e-commerce.

Figure 3: *Potential net valence of implementing GAI use in financial institutions with future development as the moderator.*

Figure inspired by Dhir et al. (2021)



3. Research Methodology

In the following chapter will the authors present a comprehensive description of how the research has been conducted. The authors will explain the reasons for utilizing a qualitative research design and applying a methodology that harnesses the strengths of grounded theory to media discourse analysis. This chapter will also address ethical considerations and limitations and emphasize the validity and reliability of the research.

3.1 Media Discourse Analysis

The study is inductive in nature (Streefkerk, 2019), this means that the authors have developed the research without relying on existing literature, because there is little already existing, and as such, the theories will be a product of the research process (Bryman, 2016). Because this research is meant to dissect and understand the complex discourse of generative AI in financial institutions, the authors decided to go for a qualitative analysis approach (Creswell, 2013; Hammarberg, et al., 2016). Qualitative research is usually conducted when the subject or problem needs to be explored and when the available research is partial or inadequately captures the issue at hand (Creswell, 2013).

There are many options when choosing the qualitative approach for our research, and choosing the right approach is important for understanding and navigating the data and research at hand. Using a recognized approach will also benefit the research in terms of rigor and sophistication (Creswell, 2013).

Deciding which approach was right for us had variable deciding factors. The decision to go for an exploratory approach, such as the media discourse analysis (O'Keefe, 2011) came from limitations in data availability, as well as challenges in the feasibility of conducting other forms of research. Furthermore, specific techniques from grounded theory have been deployed to enrich the interpretation of the research.

When communications occur on a broadcast platform, such as written in news articles, spoken in videos or podcasts, etc., where the recipient or the consumer of the discourse is non-present, it is referred to as a media discourse (O'Keefe, 2011). Even though the discourse is meant for the readers or listeners, traditionally, the audience could not instantaneously interfere or communicate with the producers of the discourse (O'Keefe, 2011). This phenomenon is not necessarily completely accurate anymore. The audience can, for example, send a question to the producers of the discourse and have it answered in real-time, transforming the audience from a passive recipient to an active participant (O'Keefe, 2011).

Often, the producers of the discourse and the analysts do not have the same expectations of the desired outcome and topics discussed in the produced media (Alvarez, 2002, p. 101).

Grounded theory is the process of systematically obtaining data from research and creating new theories from it (Glaser & Strauss, 1967). In this method, the analysis phase and data collection somewhat overlap in the sense that while the researcher is collecting data, they will simultaneously analyze the data, and that will impact the rest of the data collection process (Charmaz, 2006). A significant part of grounded theory is the systematic approach to collecting data and defining this data through a coding process before analyzing it (Charmaz, 2006). Unlike other qualitative approaches, the codes used to define the data in grounded theory are not predefined but emerge as a part of studying the data (Charmaz, 2006).

In this research the authors have incorporated techniques from grounded theory to efficiently organize the data collected through media discourse. These techniques are often referred to as open coding, axial coding, and selective coding (Gleasure, et al., 2019). Open coding, or initial coding, is the first set of codes, and it is an initial step that moves the researcher toward decisions regarding the overarching categories (Charmaz, 2006; Qureshi & Ünlu, 2020). Axial coding is the second step in transforming data into a more comprehensive dataset. It’s a way to sort and filter the data, remove duplicates, create categories and subcategories, and add coherence to the previous open codes (Charmaz, 2006; Qureshi & Ünlu, 2020). The last step of coding used in this research design is selective coding, in which the authors define relationships between categories and themes emerge from these (Charmaz, 2006; Qureshi & Ünlu, 2020).

3.2 Data Collection

The authors employed a systematic data collection strategy aimed at capturing a wide range of media discourse on the topic of generative AI in financial institutions. The data collection had an objective of gathering diverse perspectives and narratives to ensure a thorough understanding of how generative AI is perceived, portrayed, and discussed across various media platforms.

The data used in this research is all collected through websites reached with specific search words on google news and google videos. This type of data is defined as secondary data (Boslaugh, 2007; Hox & Boeije, 2005; Johnston, 2014). The data has already been collected for another primary purpose, which in this case varies throughout the different media articles and videos (Johnston, 2014). Using already existing data is an asset in terms of feasibility for this research project, reducing time spent and limits the necessary resources collecting primary data would require (Johnston, 2014). Another advantage to using this type of data, is the availability and how researchers can review articles and videos from different times (University College London).

For this purpose, using secondary data as the exclusive form of data provides many benefits, but there are also limitations caused by it. One of the major disadvantages regarding the use of secondary data is that the collected data does not necessarily answer the questions and discourse the researchers have in mind (University College London). When collecting the data the authors used search words such as "“generative ai” “banking”" on google news and google videos, as presented in Table 3. Many of the collected discourse media did not differentiate between AI, Generative AI, and Machine Learning, and that is a direct drawback of using secondary data.

The data collection process started with identifying keywords relevant to generative AI in banking and applying them to Google's search engine with the "news" filter and "videos" filter. As presented in Table 3, using the phrase "“generative ai” “banking”" resulted in 244 articles from Google News, which the authors could rename and start creating open codes from. The same search on Google videos presented 211 results that the authors downloaded and generated transcripts from. The searches also provided some results that were neither news articles nor videos, which were included as *other* data in our coding and analysis.

Table 3 presents every combination of keywords used and the number of results they provided in each category, respectively. Most videos are from YouTube, but other streaming services have been included if the video was downloadable and transcribable. These results include every single article or video found doing the searches.

Table 3: *Search results based on keyword combinations used on different google search services for data collection.*

Google News	Google Videos	Other	Keywords
82	173	4	Gen AI + Banking
40	x	x	Gen AI + Financial Sector
23	69	2	Gen AI + Financial Market
245	212	6	Generative AI + Banking
81	x	x	Generative AI + Financial Sector
x	158	x	Generative AI + Financial Market
30	x	2	Generative Artificial Intelligence + Banking
3	x	x	Generative Artificial Intelligence + Financial Sector
41	3	x	Generative Artificial Intelligence + Financial Market
22	x	x	GAI + Banking
2	x	x	GAI + Financial Sector
2	x	x	GAI + Financial Market
571	**615**	**14**	

After applying the keyword to Google search, the process of collecting included creating a code to name the different types of media. News articles are labeled A, with a unique number after, such as A1, A2, A3, etc., until A571. Videos are labeled similarly but with a B, and the last type of media is labeled with a C.

The authors structured the data in a spreadsheet with the article code/label, article or video name, the link to the website it was retrieved, the author(s), the publication date in a specific format, the publisher, and the video duration where it was relevant. The authors tried adding the spoken language for some of the videos where they did not speak English or Norwegian. However, the transcription program did not process the ones in foreign languages. Lastly, the authors included the combination of keywords used to find every article and video.

The two authors split the data collection task between them. One person collected the data for news media articles, and the other collected the data for videos. After collecting this data, they swapped roles and made sure no relevant articles were left out.

In some cases, the last few pages of the Google video search had highly irrelevant links, which were not included. These were usually from the same few websites that used the same tags for each of their videos, resulting in a variety of children's animation and adult content that were filtered out before downloading and transcribing.

When filtering the search data, the authors wanted to have an inclusive publication date range parameter, regardless of that, most of the collected media were published after 2022. The data collection took place in January 2024. As shown in Table 4, almost every article and a significant majority of videos were published in 2023 and were starting to emerge in 2024.

Table 4: *Publication year of all collected articles, videos, and other.*

Articles	Video	Other	Date Range
1	7	8	**No date**
0	1	0	**2008**
0	1	0	**2009**
1	0	0	**2011**
0	1	0	**2012**
1	1	0	**2013**
0	2	0	**2014**
0	3	0	**2015**
1	3	0	**2016**
0	3	0	**2017**
2	5	0	**2018**
2	15	1	**2019**
1	35	0	**2020**
4	38	0	**2021**
0	66	0	**2022**
497	371	0	**2023**
61	63	5	**January 2024**
571	**615**	**14**	

3.3 Data Analysis

When conducting the data analysis, the authors applied techniques from grounded theory with an inductive approach. The authors started by reviewing the collected data without presumptions and with an open mindset. After completing the data collection, transcripts were sorted in a folder, and all news article links sorted in a spreadsheet.

3.3.1 Open Coding

When generating open codes in a media discourse setting, the objective is not necessarily the same as a traditional grounded theory objective, which would be to create a new theory. The objective of this research was to see how Generative Artificial Intelligence (GAI) use in financial institutions is discussed, and represented in media, including narratives, themes, and discourse patterns. Understanding how media representation affects public perceptions is also important in this research. When starting phase 3, as shown in Figure 5, the authors made an additional spreadsheet for the open codes with the coded abbreviations of article names in one column and open codes in the other column. To ensure the findings didn't miss anything, the authors read the articles and transcripts twice before generating the codes.

After reading the articles, the authors started removing everything related to GAI use in financial institutions from the data. Using sentences and paragraphs taken directly from the data, the authors ensured that the purpose of the statements wasn't lost. The authors also made a conscious decision to not rewrite any of them at this stage to ensure that the open codes were as truthful to the source as possible.

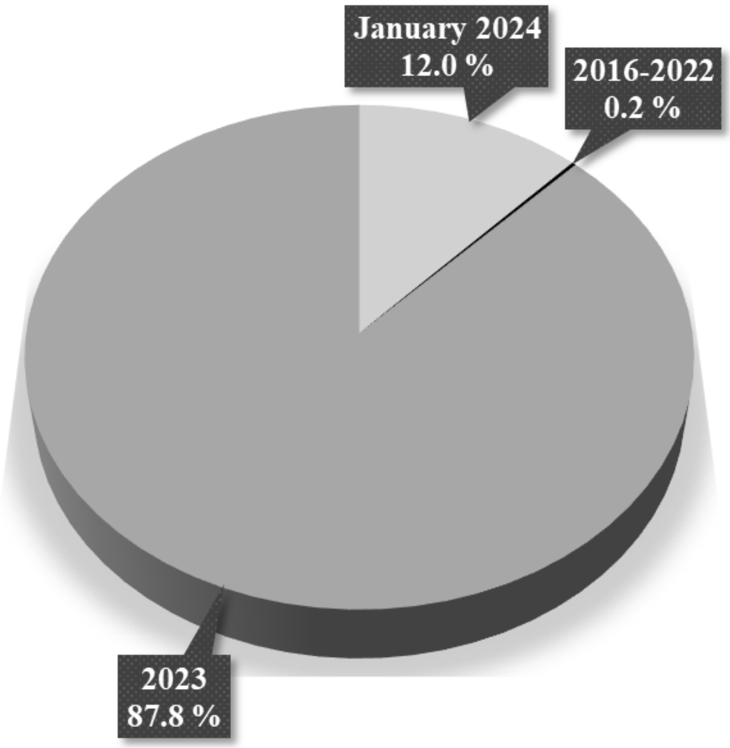
After each author constructed open codes for their respective half of the data set, the authors swapped halves and analyzed the data again from a different perspective. This was to make sure the authors didn't miss any important information or codes. This significantly reduced the chance for unintentional researcher bias, where the authors might accidentally leave out important information because their subconsciousness believed that it was irrelevant to the anticipated result of the analysis (Mehra, 2002).

When open coding had been conducted, the authors were left with only relevant media. This is depicted in Table 5. This further emphasizes the emergent nature of the data, with only 19 out of 651 relevant articles being published before 2023. The table also shows that most videos the authors transcribed were irrelevant to the research objective of this study, and about 20 percent of news articles were also filtered out during the open coding process. As presented in Figure 4, zero point two percent of the media were published before 2023.

Table 5: *Publication year of collected media after open coding.*

News	Videos	Other	Date range
0	7	2	**No date**
0	1	0	**2016**
0	1	0	**2018**
0	1	0	**2019**
0	5	0	**2020**
1	6	0	**2021**
0	4	0	**2022**
395	157	3	**2023**
54	14	0	**January 2024**
450	**196**	**5**	

Figure 4: *Publication year of collected media after open coding as a percentage of the total.*



3.3.2 Axial Coding

When constructing axial codes, the authors copied all the open codes with name labels into a new spreadsheet. This was done to provide a sort of audit trail, prevent obstructing the original codes, and maintain the research's dependability. In the axial coding step of phase three, as shown in Figure 5, the authors removed duplicate codes and identified larger themes (Sybing, n.d.). This process was repeated for the entire data set and all open codes. Which provided the authors with 41 different axes capturing all themes relevant to the research. This process helped us understand the interconnectedness of the themes and link them within the context of the research. This stage was later revisited as part of phase five, as shown in Figure 5.

3.3.3 Selective coding

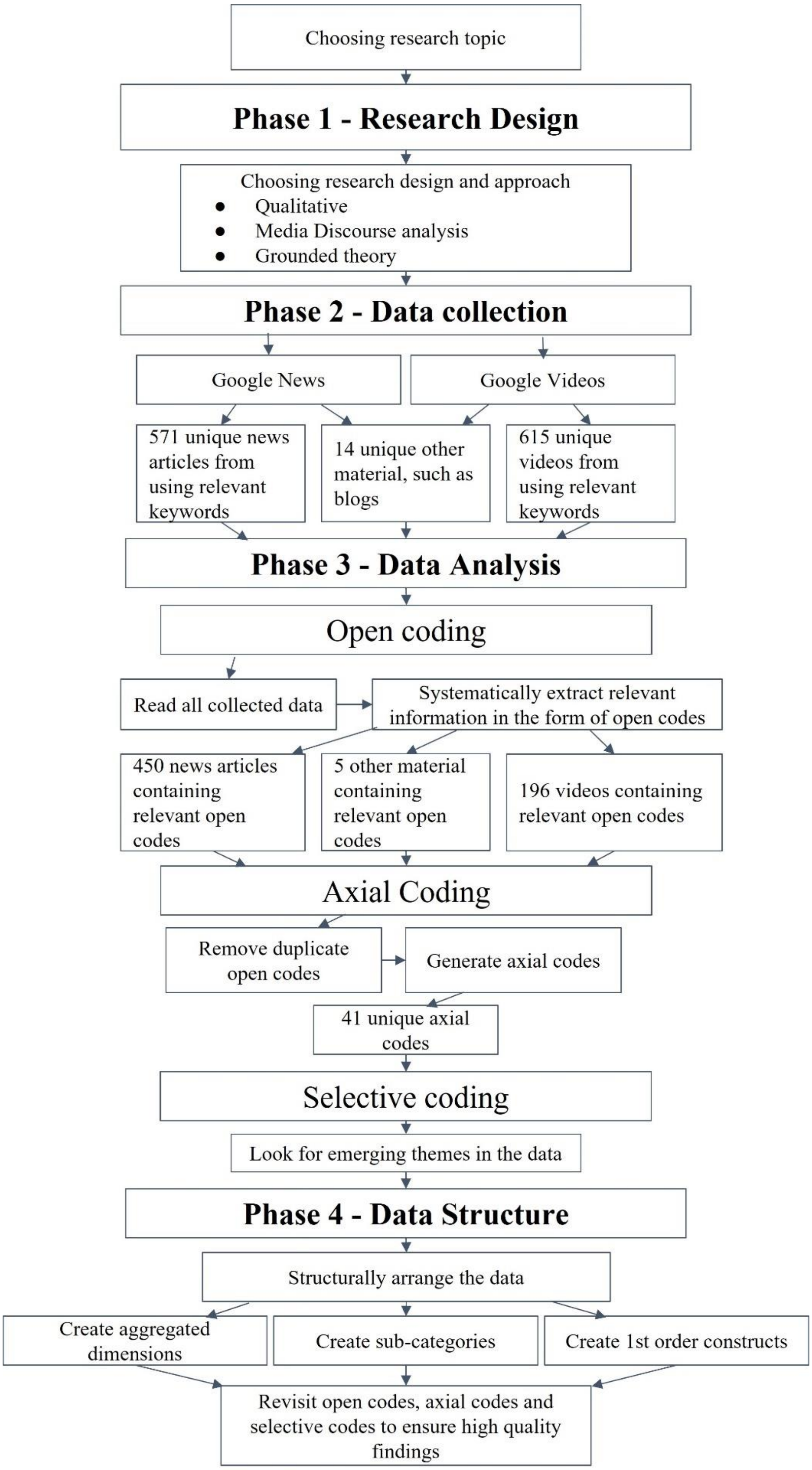
Completing axial code generation enabled the authors to organize the data set and start the process of selective coding, generating overarching themes. This step involves synthesizing the axial codes into central narratives that encapsulate the essence of the discourse on generative AI within the banking and finance industry. Themes such as “Value creation” and “Customer experience” were developed through this process. This process was continued until theoretical saturation was achieved (Faulkner & Trotter, 2017).

3.3.4 Gioia data structure

After completing the open, axial, and selective coding steps, the researchers engaged in phase four, which was to structurally arrange the data (Gioia, et al., 2012). Using a combination of the axial codes and associated open codes, the authors created first-order concepts (Gioia, et al., 2012). These were based on the axial codes made earlier but made clearer through the associated open codes to enhance the explainability of the emergent themes and add more depth to the findings.

The same process was conducted for the previously constructed themes to enhance them. These became the 2nd order themes in the data structure (Gioia, et al., 2012). After having analyzed all the data, the authors could construct the second-order themes to categorize the different first-order concepts, which we then could put into aggregate dimensions that formed the basis of the findings in relation to the research questions (Gioia, et al., 2012). The data structure clearly explained the emerging trends in the data. It also provides a clean and appropriate tool for visualizing the findings.

Figure 5: *Overview of methodology*



3.4 Ethical Considerations

A lot of attention has been given to ethical considerations when conducting this research. The research strictly adheres to principles of respect, responsibility, integrity, and accountability (Gorup, 2020). All data was accessed through publicly available sources, ensuring that we do not infringe on copyrighted material. The publishers and creators of all media we have used as data have been thoroughly systemized and referenced in our coding process. None of the generated codes includes material that can identify a person or contains personal information about any individual. Furthermore, the scope and intentions of the research have been transparently communicated in all aspects of the research, ensuring that the research maintains ethical rigor in data handling, analysis, and reporting.

3.5 Validity and reliability

Validity and reliability are important in ensuring the quality of a study is good (Chetty & Thakur, 2020). Validity refers to the accuracy with which the results reflect what they are intended to measure, while reliability pertains to the consistency of the measurement, ensuring that the results can be replicated under identical conditions (Scribbr, n.d.). To ensure the validity and reliability of the research, the concepts of credibility, transferability, dependability, and confirmability have been utilized, as depicted in Figure 6 (Thomas & Magilvy, 2011). These concepts are used to ensure trustworthiness in qualitative research (Thomas & Magilvy, 2011). The authors decided to use this terminology to further capture the nuances of qualitative research, which might be lost when using terms traditionally associated with quantitative research.

3.5.1 Validity

Validity in qualitative research refers to the appropriateness of the method, tools, and techniques used to measure what is intended to be measured (Chetty & Thakur, 2020). If a study has high validity, the study measures what it is supposed to measure, while the results correspond to existing theories of the same content (Middleton, 2023). A valid measurement is generally reliable and reproducible (Middleton, 2023). Internal validity and external validity are two concepts of validity. Internal validity refers to whether the study examines what it claims to be based on the data collected and analyzed, while external validity refers to how generalizable the findings are for other groups or settings (Cuncic, 2022).

Credibility

Credibility refers to accurately depicting the data that was studied (Johnson, et al., 2020). The concept relates closely to that of internal validity and concerns whether the study measures what it is intended to measure or not (Shenton, 2004). To ensure the research that has been conducted has high credibility, the authors purposively sampled the data using keywords relevant to the topic of Generative AI and financial institutions without excluding sources and search results. Using a form of triangulation where both written and audiovisual media were included, the authors analyzed a larger scope of media to construct a well-rounded understanding of the discourse on Generative AI use in financial institutions. Furthermore, the authors have reflected on and acknowledged potential researcher biases and cross-checked the data and analysis to ensure that the research findings are trustworthy.

Transferability

Transferability is how well this research findings or methods relate to other cases (Thomas & Magilvy, 2011). Transferability is associated with external validity (Shenton, 2004). This research addresses this by including selection criteria for media sources and by defining and explaining the analytical framework thoroughly. This enables the reader to assess the applicability of the findings to other contexts on their own. Qualitative research is unique in nature, and the analysis of media discourse on Generative AI in financial institutions may severely limit the direct generalizability. However, as the study describes an emerging technology in finance, the findings could be used in a similar context, such as, GAI use in other industries.

3.5.2 Reliability

Reliability in qualitative research refers to how reliable the results are. To be able to consider a measurement reliable, the same results must be able to be produced by using the same method under identical circumstances (Middleton, 2023). Because of the diverse paradigm of qualitative research, the definition of reliability becomes close to impossible to ensure, which is why the authors decided that the more qualitative terminology and concepts of dependability and confirmability fit this study better (Chetty & Thakur, 2020; Shenton, 2004). Dependability corresponds to reliability, while confirmability is a form of objective reliability (Shenton, 2004).

Dependability

To ensure the research is dependable and that other researchers can follow the same steps to find similar results or enhance the original findings, we have thoroughly explained the methods used (Thomas & Magilvy, 2011). The process of data collection and analysis has been documented. Peers, as well as both researchers, have participated in the analysis process (Thomas & Magilvy, 2011). Detailed records of search terms, dates of collection, and analytical decisions have all been included to facilitate external reviewers' verification of the research process and findings.

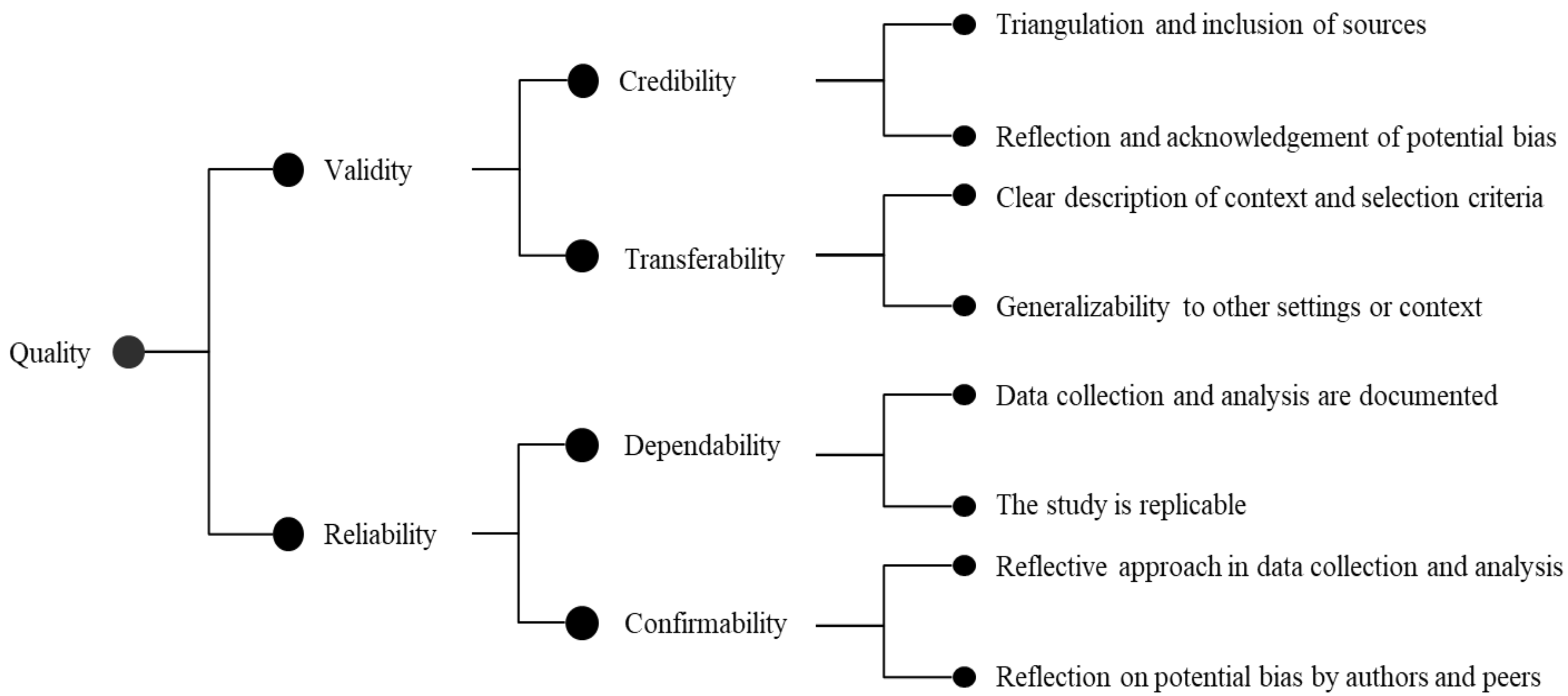
Confirmability

Confirmability is demonstrated here by referring to the reflective approach we used in data collection and analysis (Johnson, et al., 2020; Thomas & Magilvy, 2011). The potential for researcher bias has been thoroughly negated through the inclusion of a wide range of available data. The potential biases have been reflected on by the authors, as well as peers that are undergoing a similar research project on their own.

3.6 Limitations

This paper acknowledges several limitations that may impact the interpretation and application of findings. Firstly, the unintended focus on English media sources, due to using English keywords when searching, as well as problems associated with transcribing foreign audio in videos, might potentially bias the representation of generative AI in banking. Secondly, the analysis covers a dynamic subject, which, as presented in Figure 4, shows that there is a significant increase in media discourse regarding this emerging technology. This means that the findings only represent an early snapshot of time, which is subject to change as new developments in the field or new narratives emerge. Thirdly, many of the discourse producers do not explicitly tell or even know the difference between machine learning, generative AI, and other types of AI. This makes it difficult to interpret whether the topic they write or discuss is right for this research. Lastly, despite efforts to mitigate researcher bias through reflexivity and methodological rigor, the interpretative nature of qualitative analysis inherently reflects the researchers’ perspectives.

Figure 6: *Summary of Validity and Reliability*



4. Results

In this chapter, the authors present the findings obtained through the chosen method of analysis. These results are presented in three different Gioia Data Structures, showcasing three different aggregated dimensions that emerged during this study. These are *Drivers, Barriers,* and *Future development.* Furthermore, eleven different coding sub-categories were developed from the analyzed data.

4.1 Drivers

Everything that enables and promotes the use of Generative Artificial Intelligence (GAI) in financial institutions is defined here as drivers. The four coding sub-categories that create the aggregate dimensions are *value creation, boosting innovation, enhanced customer experience*, and *security and regulatory compliance enhancement*. The first-order constructs were developed by utilizing grounded theory coding strategies based on data that had previously been acquired. Figure 7 provides a comprehensive overview of all drivers that emerged during the media discourse analysis.

4.1.1 Value creation

The first-order constructs used to define and encapsulate the term value creation are *optimization, support, collaboration,* and *edge*. These codes are further detailed by the axial codes the analysis process created.

Optimization

Such as *optimization*, coming from data that discussed *improving efficiency, streamlining operations, boosting productivity, automate tasks,* and *increase revenue.* The data mentions potentials for optimizations several times, such as article A1 saying, "*Could add the equivalent of 2.6-4.4 trillion annually in value"* (A1), or video B46 mentioning "*Gen AI can reduce challenges regarding high volume manual and repetitive tasks, which has high cost, time to complete and manual error*." (B46). These codes specifically mention ways to create value through optimization.

Support

Support consists of *Assist employees, virtual assistant, training and guidance tech,* and *faster decision making*. This first order construct is designed to define every mention the data has in terms of enabling staff to perform better, using a personal virtual assistant which can guide and assist a staff member or decision-maker, or similar ways to enhance employees by the use of GAI, which will in turn create value. "*Assisting your human agents in solving complex issues"* (A299), *"Help developers write code"* (B4), and "*Gen AI becomes a copilot"* (B94) defines the perceived potential of GAI being an asset to employees.

Collaboration

According to the data, GAI bolsters potential for collaboration through partnerships with advanced tech companies. A significant part of the discourse surrounding GAI in banking were mentions of other companies that promote potential partnerships with tech companies such as A16 which says *"SkyHive, a workforce reskilling solution that harnesses gen AI to organize workplace data, automate HR processes and empower a dynamic, skill-based labor economy, and Nuclia, which embeds AI search and generative answers into third-party products,"* (A16). This does not only potentially create value for the banking sector, but also large tech companies might benefit from this, which will be a driver for implementing the technology.

Edge

Edge refers to the potential *competitive advantage* a company that utilizes GAI might achieve. It also encapsulates the potential edge gained from *enhanced products*, and *quality increase*. "*Generative AI excels at turning raw data into actionable insights, offering financial professionals a competitive edge."* (A148), and *"improved product and service offerings"* (A336) discusses the various potential ways technology creates value through edge.

4.1.2 Boosting innovation.

The sub-category named boosting innovation consists of the first order constructs acceleration, and facilitation.

Acceleration

The term acceleration was created by media articles discussing how GAI can be used to make innovative progress faster, and automated. This is backed by the data saying: *"using generative AI to accelerate AI innovation"* (A365), and "*GenAI extends beyond process improvements and cost savings and can help them strengthen their capabilities and foster more and faster innovation"* (A7).

Facilitation

Another way to boost innovation according to media is through *facilitation*, which consists of *assisting research, ideation, testing products and services, and marketing* through

GAI solutions. "*Integrate uses of generative AI to improve customer experience, treasury management, product testing and general business problems"* (A317) mentions using GAI for product testing, *"spark creativity and inspire innovation among employees"* (A314), discusses the use of GAI to assist in ideation among staff members.

4.1.3 Enhanced customer experience.

Customer experience is an important factor when considering implementing generative technologies. Enhancing this experience is a significant driver according to the qualitative data that we have collected.

Customization

The first, first order construct that we developed as a response to the data is *Customization* which considers *customer insights, personalization, personalized pricing, enhanced banking experience*, and *credit qualification*. This statement is backed by data saying: "*Increasing accessibility to banking by generating targeted, responsive marketing content and specific, personalized product offerings."* (A63), *"Gen AI has the potential to play a strong role in connecting more Black consumers with traditional banking services by providing specialized, bespoke, and accessible services to those consumers."* (A63).

Responsiveness

The second first order constructs that relates to enhanced customer experience is *responsiveness*, which derives from *service chatbots, 24/7 access*, and *faster responses.* Both these quotes from the data discuss how customers will benefit from the responsiveness GAI potentially can provide: *"Customers will benefit from 24/7 service"* (A216), "*generative AI offers prompt, precise responses."* (A216).

4.1.4 Security and regulatory compliance enhancement

The last coding sub-category for the drivers which we interpreted from the collected data is *security and regulatory compliance*. This sub-category has three different first order constructs which involve *protection, management,* and *navigation*.

Protection

Protection implies different ways GAI can be used to enhance *cybersecurity measures, fraud detection, anomaly detection,* and *threat protection*. Some quotes from the data provides insights into what the discourse have been about regarding protection: "*using it to identify suspicious activities."* (B23), "*Adopting generative AI not only strengthens a bank's defense against cyberattacks but also enhances its overall risk management and* *response efficiency, ensuring the protection and integrity of critical data and financial transactions."* (A162).

Management

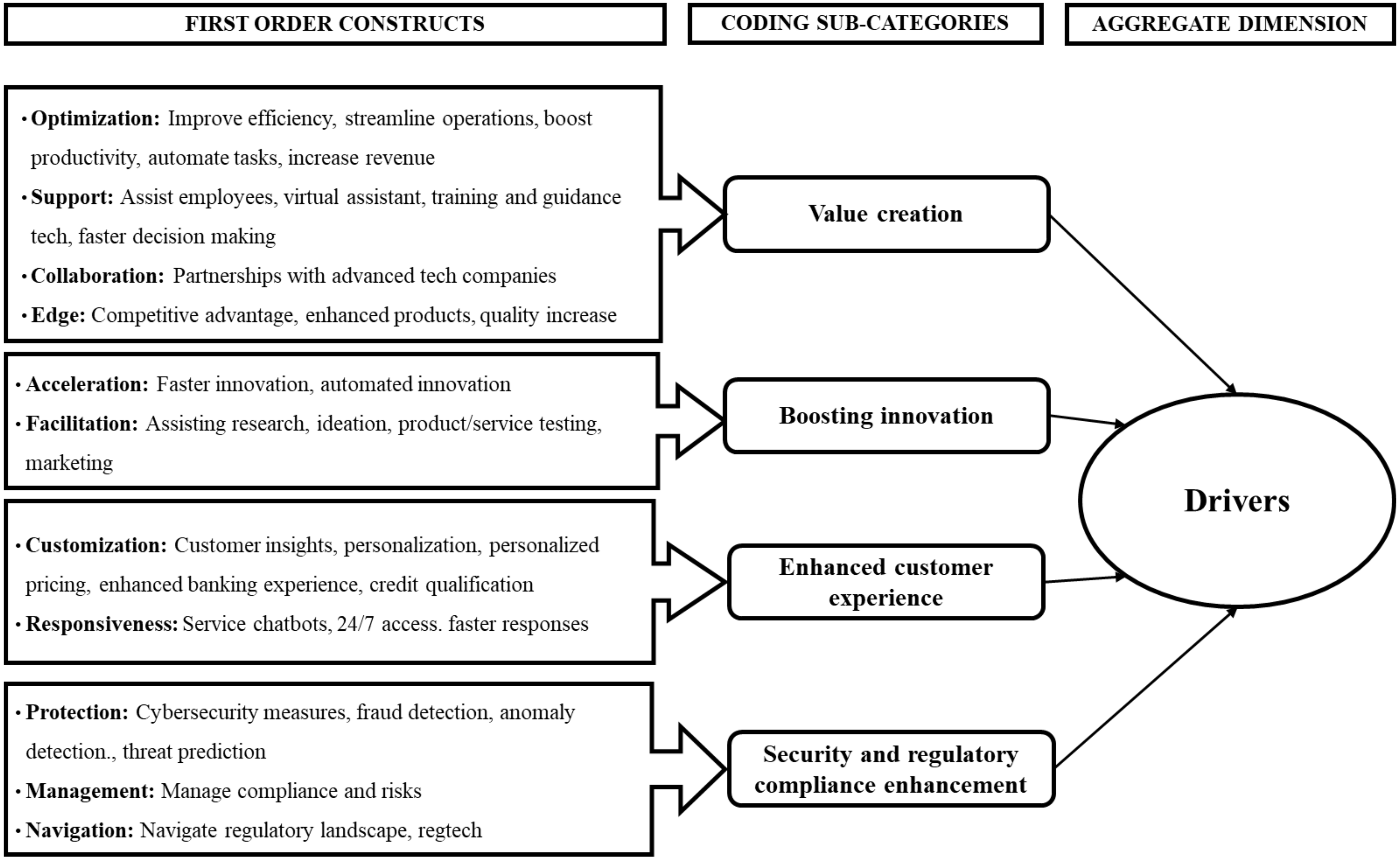
The second first order construct in the security and regulatory compliance enhancement sub-category involves *management*, and it details how this new technology can be used to enhance compliance management and risk management. *"Compliance Management: Generative AI streamlines compliance processes by analyzing vast amounts of data, ensuring adherence to regulations, and minimizing compliance risks."* (A167), and "*groundbreaking advancements in risk management, fraud detection, and regulatory compliance."* (A449) are some of the multiple quotes from the data that discuss how GAI can be used in enhancing management of security and regulatory compliance.

Navigation

Navigation is the last first order construct, and it involves discussions on the technology's potential to *navigate regulatory landscape* and mentions of regulatory technology. These are some examples of where this first order constructs emerged from: *"Generative AI stands as a beacon of innovation, offering a more efficient and effective approach to manage this burgeoning regulatory landscape"* (A153), *"The use of AI and machine learning by financial institutions known as Regtech"* (B468).

Figure 7: *Data structure for drivers.*

Template from Gioia, Corley, and Hamilton (2012).



4.2 Barriers

In this data structure are the aggregate dimensions *Barriers*, which are made from the coding sub-categories *Risk*, *Negative employee impact*, *Implementation challenges*, and *Ethics and regulatory challenges*. These coding sub-categories are created using the first order constructs. *Risk* is caused by *Uncertainty*, *Divergence*, *Stagnation,* and *Exaggeration*. *Upskilling* and *Displacement* creates the earlier mentioned *Negative employee impact*. The third coding sub-category, *Implementation challenges,* comes from *Integrity*, *Cost*, *Human resources,* and *Strategy*. Finally, *Ethics and regulatory challenges* are based on *Trustworthiness* and *Governance*. Figure 8 provides a comprehensive overview of all barriers that emerged during the media discourse analysis.

4.2.1 Risk

The risks which emerged while analyzing the collected data were uncertainty, divergence, stagnation, and exaggeration. These are important for financial institutions to address to reduce negative valence and achieve higher net valence.

Uncertainty

Many underlying uncertainties come with the use of GAI, one of these that was discussed and warned about in the articles and video during the search was "hallucinations". *"Information accuracy is another concern. Generative AI can sometimes produce inaccurate or "hallucinated" information."* (A9) We can also find articles and videos talking about the underlying threats, such as "*if your baseline data isn't optimized to be fully efficient, well your journey AI capability is also not going to be fully efficient*." (B12).

Divergence

Another risk we can see is the danger of creating a gap. *"Adopting generative AI in banking and the financial market can make room to widen the digital gap between developed and developing economies."* (A21).

Stagnation

People who choose not to use GAI stand in danger of becoming laggard or falling behind. *"What is clear is that people who use generative AI are going to be fundamentally more efficient than people who don't."* (B270).

Exaggeration

It is also important not to exaggerate GAI, and to have a realistic view of where we are with the technology and what its capabilities are at the moment. *"We really have to* *scrutinize what are the technological offerings on display, what is differentiated here"* (B121).

4.2.2 Negative employee impact

The coding sub-category named negative employee impact, refers to the first order constructs upskilling and displacement. These terms encapsulate the collected data that mentioned negative ways employees were impacted, which is a barrier that financial institutions can experience when implementing GAI use.

Upskilling

During the research, the authors of the thesis found a noticeable number of articles and videos discussing the negative impacts employees might feel from GAI, such as the need for upskilling and the chance of displacements. One article discovered during the research period gives a warning. "*In terms of impact on jobs, my message to everyone is if you are not using generative AI, it will replace you with someone who is.*" (A67). Another important challenge for the employees is the need for reskilling, this is why rapid training such as the like of KPMG is implementing. The focus on this is crucial so the companies do not fall behind. (A119)

Displacement

If companies and management do not do as KPMG and start training themselves and their employees, then they do stand the risk of being displaced from their jobs. *"As many as 57% believe that the technology will lead to job losses within the next three years with an average headcount reduction of 30%."* (A548)

4.2.3 Implementation challenges

There are many implementation challenges experienced by financial institutions when considering adopting GAI use, the ones that emerged from the data are integrity, cost, human resources, and strategy.

Integrity

The integrity of the data is a vital point when implementing GAI, as shown in the article is emphasized, *"If your baseline data isn't optimized to be fully efficient, well, your journey AI capabilities is also not going to be fully efficient." (B12).* We are also informed that "*Generating this generative AI journey for customer is getting your data platform figured out right. Aking sure your data is in one place."* (B232).

Cost

"A consideration of costs must be part of the road map. Every step of developing gen AI." (A14). This sentence shows concern about GAI implementation that showed itself in several articles during the research process. Articles like A206, and A240 are examples of this.

Human resources

Another important first-order construct that was discovered was human resources, and one of the key aspects that was talked about regarding this was human oversight. It was mentioned in A219, *"Humans in the loop will be needed."* (A219). Skilled workers will also be needed for this, in A222 it is mentioned, *"need cross-disciplinary teams to implement and manage generative AI."* (A22).

Strategy

Finally, for implementation challenges, have we strategy, and how business operating models are going to go through a transformation, with examples such as, *"Generative AI serves as a vital digital guide, facilitating a profound transformation across the industry."* (B243). This implementation can also be an opportunity for banks, *"Opportunities created by generative AI are really transformational banking."* (B5). Lastly, we can tell that even if we are in the initial stages the pace is evolving rapidly, *"Even the impact the generative AI is going to have on enterprise very early in the cycle. So, you know, in such a scenario where you´re seeing the pace of transformation evolve so rapidly, how does one really craft a strategy."* (B252)

4.2.4 Ethics and regulatory challenges

According to the collected data, the ethics and regulatory challenges experienced by financial institutions when considering adoption of GAI use are trustworthiness, and governance.

Trustworthiness

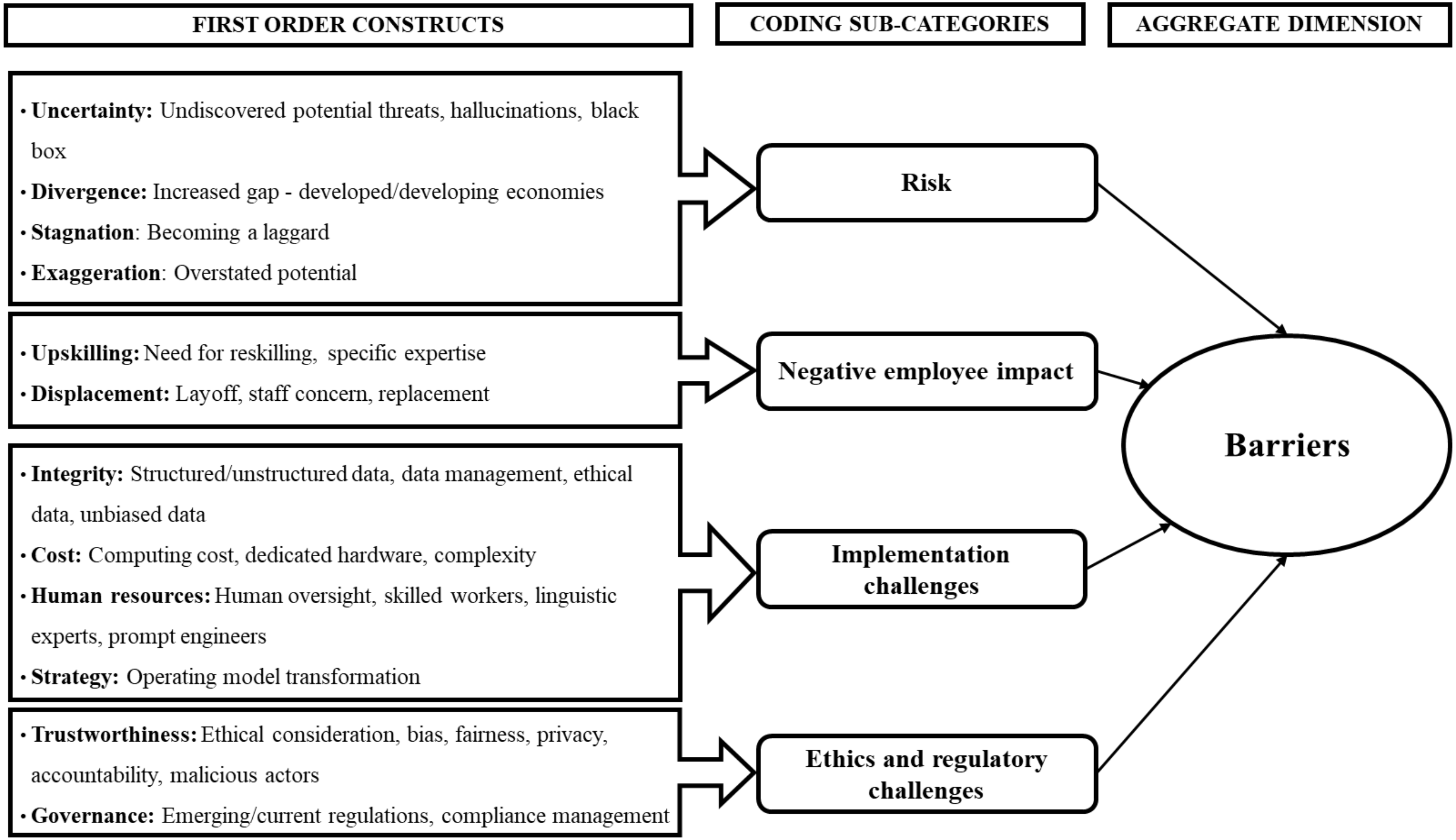
When it comes to trustworthiness and the consumer's faith in GAI can we see that there are some concerns, especially amongst the consumers, *"30% of UK consumers said they do not trust Gen AI at all. This sentiment increases for older age groups, with 44% of Boomers expressing a total lack of thrust, compared to o30% of Gen X, 21% of Millennials, and just 12% of the Gen Z consumers."* (A24). *"It found that 74% of UK consumers have no idea if their bank uses the technology within its operations. Half of the respondents in the* *study expressed that they would be either somewhat, very, or extremely comfortable with their bank using Gen AI, while the other half expressed varying levels of discomfort."* (A24). These articles show a broad degree of trust and mistrust toward GAI and significantly a difference between the different generations of people.

Governance

The emergence of GAI comes with the difficulty of regulations in an already heavily regulated industry. As shown in the articles, *"Finally, the financial services industry is highly regulated, and gen AI likely will only add to that scrutiny. Already, full regulation of AI by the government is under consideration, around the world and here in the United States, both on a federal and individual state level."* (A5). This is why it is important to start early and evolve the regulations with the technology as it develops and don't fall behind, *"Evolving regulations create uncertainty about compliance requirements and the liability risks banks could face"* (A7). This comes both in the interest of the governments, but also for the public who have high privacy standards when it comes to banking and their banking details. *"Governments are starting to, in response to public concerns, are starting to implement a lot of regulations associated with foundational generative AI."* (B48).

Figure 8: *Data structure for barriers*

Template from Gioia, Corley, and Hamilton (2012)



4.3 Future Development

Future Development has been stapled as our last aggregate dimension due to the content of our data. This dimension is made up of three coding sub-categories, which are *roadmap, governance initiatives,* and *technology-based advancements.* Each category has its own set of first order constructs. There is a total of eight first order constructs which creates three coding sub-categories that makes the aggregate dimension of future development. Figure 9 provides a comprehensive overview of all future developments which emerged during the media discourse analysis.

4.3.1 Roadmap

The first sub-category for future development is roadmap. The roadmap consists of needs, experimentation, and assistance. These first order constructs are what media articles in the qualitative data discussed as important steps, which are necessary to successfully implement GAI in a safe and efficient manner.

Needs

The *needs* are defined as *strategic change, integration initiatives, investment, and partnership with tech/data companies.* Media from the qualitative data agrees that these needs are important, for creating a roadmap for future development: *"a lack of strategic roadmap (including investment priorities) and governance are major challenges around Generative AI."* (A316).

Experimentation

The second factor we have deduced from the data is *experimentation*, which is made up from the keywords *exploratory approach, use cases,* and *innovation*. This quote from the data mentions an exploratory approach when utilizing the technology: *"A number of banks have announced plans to experiment with the technology"* (A27). Another media article mentions exploring further use cases: "*The company is exploring further use cases"* (A54).

Assistance

The final factor that goes into the roadmap sub-category is *assistance*, which involves data that discusses supporting a transitioning workforce. One of the articles says: *"it will require investments to support workers as they shift work activities or change jobs."* (A208).

4.3.2 Governance initiatives

In the second sub-category of the third data structure, the findings suggest that *governance initiatives* are important for the future development of GAI in banking. The first order constructs contain, *regulatory initiatives,* and *ethical initiatives.*

Regulatory initiatives

Regulatory initiatives are defined in the data structure as regulatory or compliance frameworks, and policies. The creation of *regulatory initiatives* as a first order construct is backed up by qualitative data suggesting that, *"Creating a governance framework around policies, ethics and usage is crucial*" (A222).

Ethical initiatives

The second first order construct relating to *governance initiatives* is *ethical initiatives*, which involves the implementation of ethical guidelines, and removal of potential bias GAI can be prone to. The collected data suggests that *"managing risks around AI ethics and biases."* (A201) is on the to do list for banks that plan on implementing the technology.

4.3.3 Technology based advancements

The last sub-category for future development is *technology-based advancements.* This sub-category is made up of three distinct first order constructs, *reliability, usability,* and *equity*. This sub-category defines the technological advancements needed for GAI to be suitable for commercial use by financial institutions.

Reliability

Reliability relates to the future development on *increasing the dependability*, *transparency*, and *trust* of GAI models. Improvements to transparency are already in progress according to media: *"Organizations, on the other hand, are focusing on developing tools to manage the risks associated with generative AI, particularly in areas of model explainability"* (A21). A video from the qualitative data mentions "*focus on trustworthy AI*" (B423), insinuating that trust is an important technology-based advancement for future development.

Usability

The second first-order construct is *usability*, which refers to *user-friendliness*, *convenience*, and *accessibility*. This construct is based on insight from the data such as: *"I happen to think that generative AI is going to change every customer experience, and it's going to make it much more accessible for everyday developers, even business users to use."*

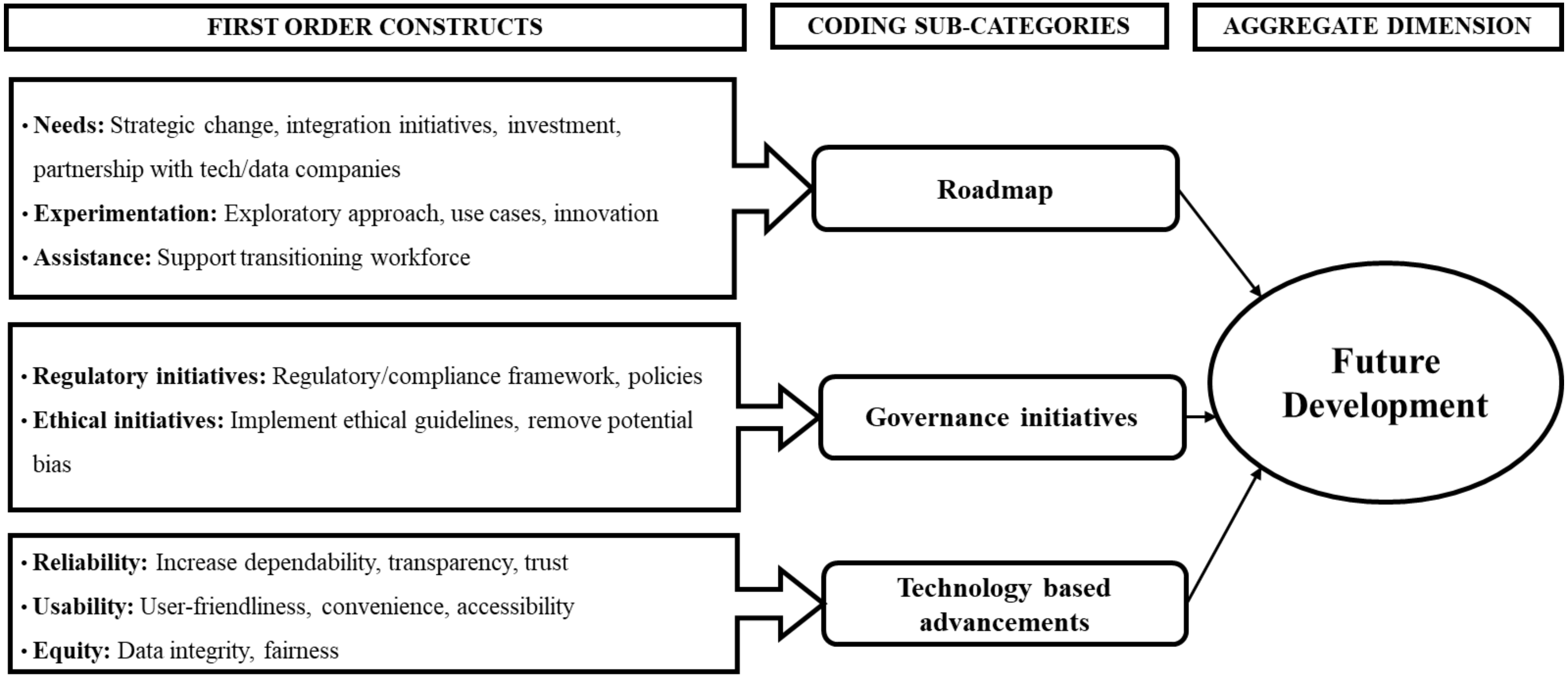
(B134), and “*more personalized services and greater convenience and efficiency for customers”* (B375).

Equity

According to the collected data, it is important to conserve the data integrity and promote fairness when utilizing GAI in financial institutions. Facilitating fair use, and high integrity will potentially increase positive valence and reduce negative. *“Generative AI serves as a vital digital guide, facilitating a profound transformation across industry. Safeguarding integrity and progress while propelling innovation to unprecedented heights”* (B243). *“Risk surrounding data leakage, data integrity, privacy, and the impact of the customer.”* (A245).

Figure 9: *Data structure for Future Development*

Template from Gioia, Corley, and Hamilton (2012)



5. Discussion

In this section, the authors integrate the study's findings with the previously presented literature and theoretical framework. The authors also connect the findings, prior literature, and theoretical framework with the research questions (RQs) and objective.

This research is important in understanding the concepts that can have significant implications for the sector's efficiency and regulatory compliance. The topic of Generative Artificial Intelligence (GAI) use in finance has had a surge in interest in the last two years, and many concerns have arisen regarding responsible and efficient implementation. This study provides government officials, researchers, policymakers, CTOs, CEOs and other officers, and managers with a comprehensive overview of current and emerging drivers, barriers, and future developments on GAI use in financial institutions.

When looking at the drivers of implementing GAI use in financial institutions, the authors conducted a media discourse analysis (MDA). This research method enabled the authors to systematically analyze 571 news articles and 615 videos on GAI in different aspects of finance. After analyzing the media discourse, the authors discovered and presented five key categories that have the potential to drive the implementation of GAI use in financial institutions. After conducting a thorough literature review on 95 articles and papers from Web of Science, the authors argue that prior literature does not contain extensive and sufficient research on all these drivers simultaneously. However, there is a clear alignment between this study's findings and prior literature in recognizing the potential of value creation and enhanced customer experience caused by GAI use in financial institutions.

The findings on drivers show that recent the narrative from recent media as well as prior literature is supporting the transformational potential of GAI and that financial institutions are portrayed as harnessing GAI to streamline workflows, personalize customer interactions, and develop new financial products that better meet consumer demands. During the research for this thesis, the authors found a clear link between the already existing literature and the findings from the MDA regarding the barriers. From the data gathered and the literature, the authors identified several barriers. From the data gathered by the authors, the first-order constructs and the coding sub-categories create a consistent impression of the barriers experienced by financial institutions while implementing GAI.

The authors argue that the literature and data collected consistently overlap on risks, negative employee impact, implementation challenges, and ethics and regulatory challenges.

The similarities consist of the same overall topics and talks for the categories. However, the similarities are also differences. It's clear that many news articles don't go as in-depth as the researchers in the literature, but that can be expected. The authors have utilized the same method to analyze the media discourse on future development as for understanding the drivers and barriers. When comparing the findings from the analysis with prior literature, it becomes apparent that the narrative media presents is similar to what the literature shows. The literature shows an interest in determining which organ should create the regulatory and privacy frameworks in which GAI use in financial institutions must be compliant. Meanwhile, the findings from the media discourse analysis, suggest that governance initiatives such as regulatory and ethical initiatives are important considerations when planning the implementation of GAI use in financial institutions.

RQ1 examines different drivers of implementing GAI use in financial institutions. In this study results, the authors find out that the drivers are as follows. Firstly, the potential for value creation through optimization, supporting and enhancing employees, partnerships with advanced tech companies, and the potential to gain an edge over competition. Secondly, the potential for GAI to facilitate and accelerate innovation. Thirdly, an enhanced customer experience through personalization, customer insights, and the responsiveness of customer facing GAI use drives implementation of GAI use in financial institutions. Lastly, GAI has the ability to protect against fraud, anomalies, cyberattacks, and navigate strict compliance and regulatory frameworks while managing exposure to risks.

RQ2 examines different barriers experienced by financial institutions while implementing GAI use. The findings developed through the MDA suggests the following. Firstly, the findings identify several risks, these are uncertainty, divergence, stagnation, and exaggeration. Secondly, negative employee impact, in which there is a need for upskilling of employees, or displacement through layoffs, or replacements. Thirdly, implementation challenges, where integrity of the data, costs, human resources, and strategy can be barriers experienced by financial institutions. Lastly, ethics and regulatory challenges, such as trustworthiness and governance. These barriers are comprehensively presented in Figure 8.

RQ3 examines what considerations are relevant to shaping the future development of GAI use in financial institutions. The study findings suggest these answers. Firstly, a roadmap consisting of needs, such as strategic change and investment in GAI technology, experimentation on where and how to use GAI to be most efficient, and support transitioning workforces. Secondly, governance initiatives such as regulatory or compliance frameworks, and ethical guidelines are important considerations to support a successful and efficient implementation process. Thirdly, technology-based advancements, such as an increase in reliability, usability and equity are an important consideration.

5.1 A valence perspective on GAI adoption and implementation in financial institutions

Valence theory is used as a theoretical lens in this study because this theory is ideal for understanding valence between risks and benefits. In this study the risks refer to barriers, and benefits refers to drivers. According to valence theory, if any financial institutions want to adopt and implement GAI, they need to ensure that the valence effect of perceived benefits, in this case, drivers, are stronger than the valence effect of perceived risks in this case, barriers. Valence theory considers both the positive and negative aspects of technology adoption and has provided the study with a structured approach to understanding the interplay between the factors influencing GAI implementation by financial institutions.

The findings illustrate that the drivers of GAI align with the positive valence described by the framework. The drivers are value creation, boosting innovation, enhanced customer experience, and security and regulatory compliance enhancements. The drivers are perceived as significant motivators for financial institutions to pursue GAI technology by both prior literature and the media discourse. On the other side, the barriers identified by the study showcase various negative valences. These are risks, negative employee impact, implementation challenges, and ethical and regulatory challenges which are experienced by financial institutions. These barriers align with the theory's perspective that negative perceptions can significantly impede technological adoption. In terms of future developments, these function as a moderator for the drivers, and barriers. Whereas if the considerations described in future development, such as if governance initiatives were in place, it would potentially remove some of the concerns and issues from barriers and boost the drivers. Making the balance between drivers and barriers to shift, and the intention to implement GAI use in financial institutions to become more present. The concept of future development consists of roadmap, governance initiatives, and technology-based advancements.

Figure 11 shows samples of some of the future developments identified by the findings of the study, and how these affect the relationship between drivers and adoption, and barriers and adoption. The authors suggest that if regulatory and compliance frameworks, and ethical guidelines are developed, it will reduce the perceived risks which are conceptualized as barriers, and increase the perceived benefits, conceptualized as drivers. And that the same will happen if GAI technology has increased dependability, transparency, and trust, or it is more user-friendly, more convenient, and accessible to everyone, as well as if advancements are made in data integrity and fairness.

Using this framework allows the study to account for the complexities and dualities in the adoption of GAI technologies. It emphasizes the need for balanced considerations and underscores the necessity of addressing both the drivers and barriers, as well as encouraging and facilitating the future developments this study provides. Viewing not only one or the other, but all three dimensions simultaneously when considering implementing GAI use, or doing theoretical research on GAI use in finance, will foster an environment of potential innovation while mitigating the risks and concern associated with GAI technologies.

The authors have developed 5 propositions based on the operating variables. **Proposition 1:** the governance initiatives, in particular development of regulatory and compliance frameworks, and implementation of ethical guidelines if properly implemented, will have a positive impact on the net valence of drivers and barriers. **Proposition 2:** the authors propose that technology-based advancements, such as making GAI more reliable in the financial use context, by increasing dependability, transparency and trust will increase positive valence from drivers, and reduce negative valence from barriers, which then has positive impact on net valence from drivers and barriers. **Proposition 3:** making the technology more user-friendly, and increase the convenience and accessibility, will positively impact the net valence on adoption and implementation of GAI in financial institutions. **Proposition 4:** The authors propose that advancements in data integrity and fairness of GAI models, will have a positive impact on drivers and reduce barriers experienced by financial institutions. **Proposition 5:** the authors propose that if the future developments are all properly addressed, it will have a significant positive impact on the valence and intentions of adoption and implementations.

Figure 10: *Proposed association between valence of perceived risks and benefits*

Figure inspired by Dhir et al. (2021)

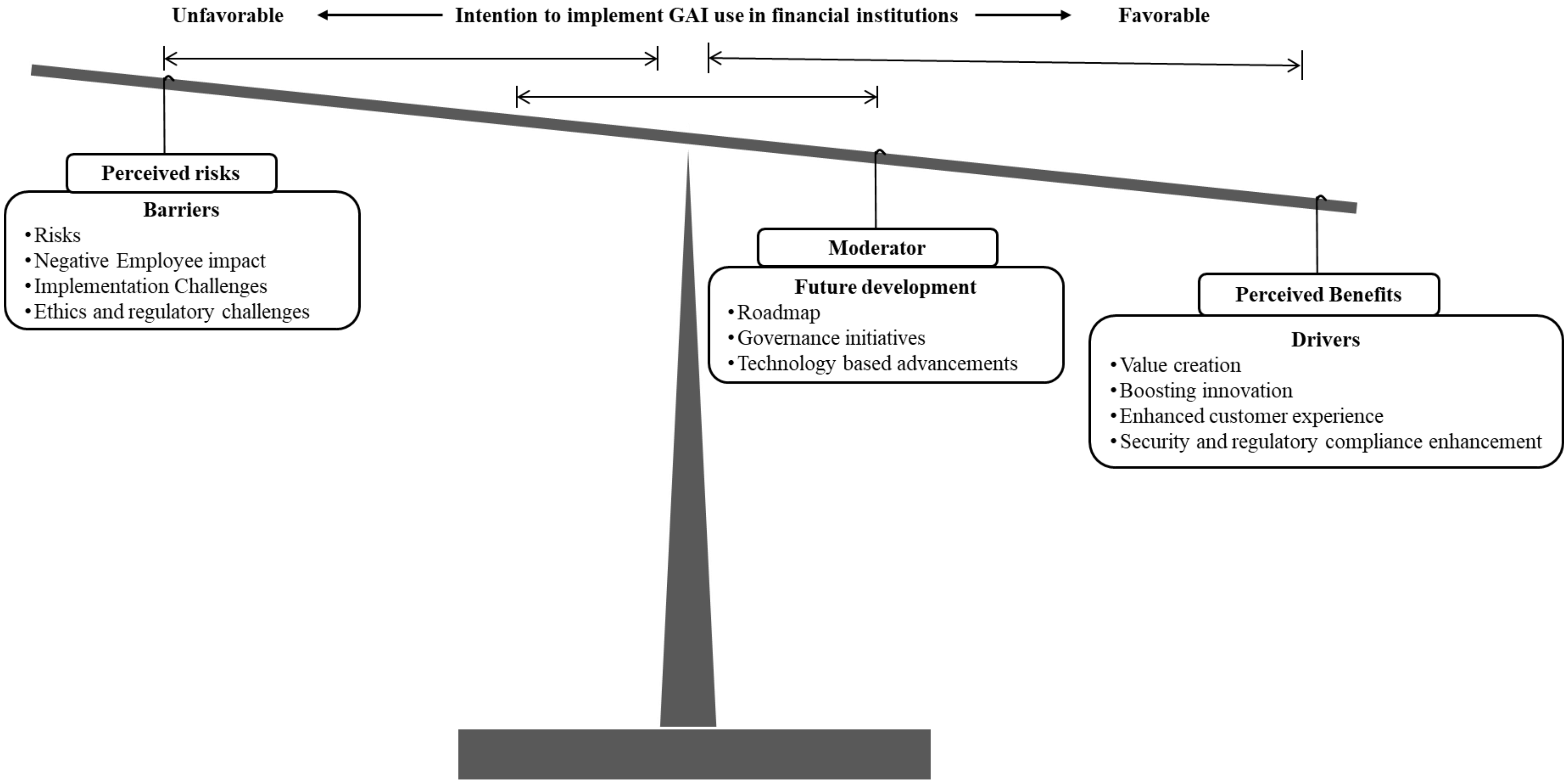
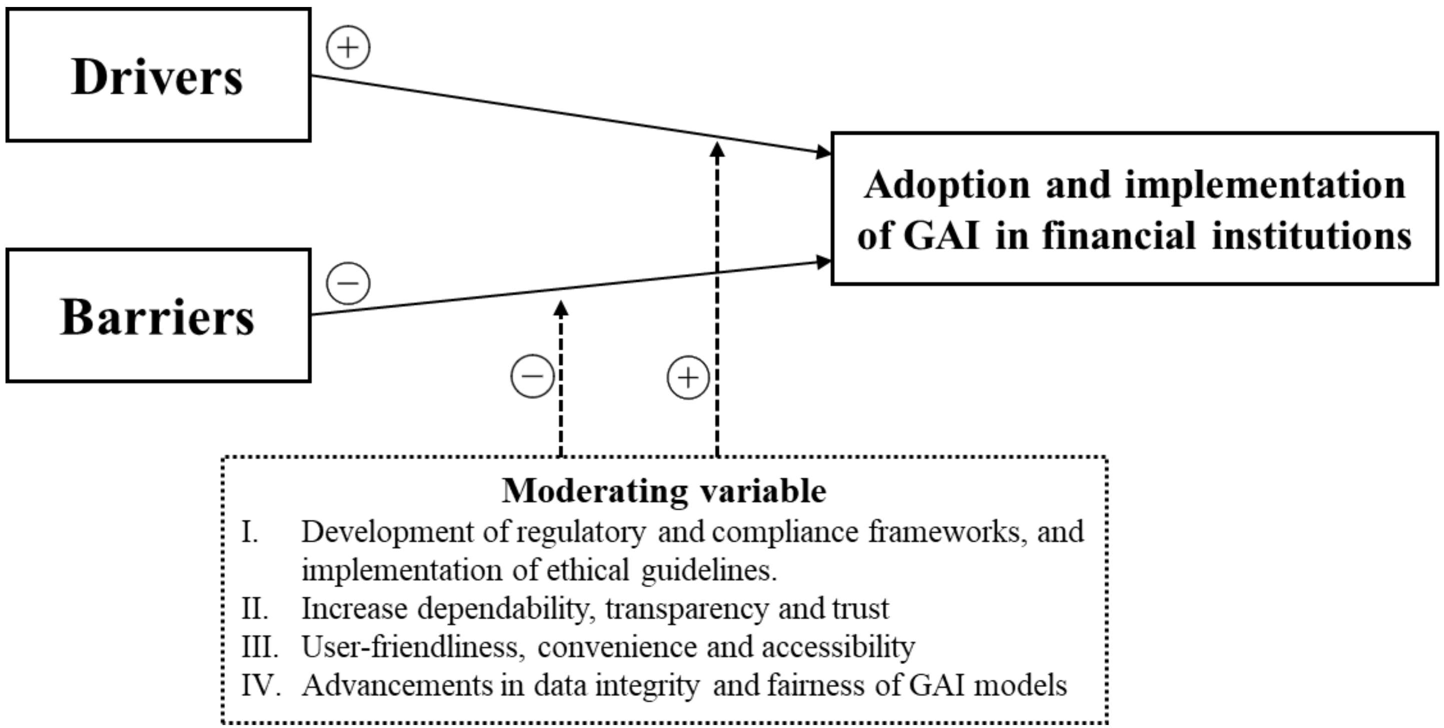


Figure 11: *Valence perspective on adoption and implementation of GAI in financial institutions*



6. Study Implication

In this section, the authors present different theoretical and practical implications associated with the findings and objective of this study. The theoretical implications enrich the academic discourse on Generative Artificial Intelligence (GAI) use in financial institutions, and the practical implications present stakeholders with practical applications of the study.

6.1 Theoretical Implications

In this section, the authors propose four theoretical implications, which are as follows. Firstly, this research contributes to an emerging area of theory on GAI use in financial institutions. Prior literature has commonly consisted of determining use cases and identifying challenges associated with GAI in specific areas of finance (e.g., Gill, et al., 2023; Neilson, 2023) The authors did not find any prior literature which provided a comprehensive overview of drivers, barriers and future development, and how perceived risks and benefits would affect financial institutions intention to adopt and implement the technology. Some studies only view certain elements of GAI adoption, such as computational costs and that GAI inaccuracy is bad for decision-makers (Roychowdhury, 2024; Samsi et al., 2023). As such, there is a gap in prior literature which this study remedies by providing a comprehensive overview of drivers, barriers, and future developments, as well as contributing to understand how the dynamic relationship between drivers, and barriers with future development as a moderator using valence theory.

Secondly, by providing a comprehensive overview of GAI use in financial institutions, the research encourages further research into more specific fields in finance. Researchers can use this overview to gain insights into drivers, barriers, and future developments in specific areas of technology adoption in finance, as well as other disciplines considering adopting GAI use. Furthermore, the authors have not found that prior studies have used a technology acceptance model, such as valence theory, to gain insights in the adoption and implementation on GAI use in financial institutions. As such, this study contributes to the area of literature on GAI adoption with a theoretical framework, extended with the incorporation of future development, which other researchers can use to gain insights into technology acceptance and adoption in finance along with other industries or disciplines.

Thirdly, this study finds socioeconomic implications regarding GAI adoption in financial institutions as a whole, such as the potential displacement of jobs and the need for ethical considerations. Highlighting the importance of balancing technological advancement with social responsibilities allows practitioners and researchers to understand further the complexities caused by GAI implementation. This also counterbalances the insights from prior literature being primarily focused on specific use cases and intricacies regarding GAI use, without regard to social responsibility and human resources (e.g., Barrington, et al., 2023; Lakkaraju, et al., 2023).

Lastly, by emphasizing what drives the use of GAI in financial institutions, such as value creation and boosting innovation, through streamlining operations and facilitation of innovation, the research provides theoretical insights into the mechanisms which contributes to organizational performance and competitive advantage. These insights can provide insights for further theoretical work on value creation and innovation in the context of GAI. In addition, by emphasizing the barriers experienced by financial institutions on GAI use, such as the risks and negative employee impact, through uncertainty and the need for reskilling, among other. The study offers valuable insights to researchers which they can use to further investigate how these barriers might change, due to technological advancements in the future.

6.2 Practical Implications

In this section, the authors present three practical implications, these implications create a comprehensive understanding of the use of this thesis and why drivers, barriers, and future development are important when implementing GAI in financial institutions. These implications are as follows.

Firstly, for financial institutions contemplating integrating GAI technology, this research provides an important and comprehensive overview of the drivers of implementing GAI use in finance, the barriers financial institutions might experience, as well as what considerations are relevant to shaping the future development of GAI use. The data gathered and analyzed in this study further strengthen the already little existing literature on the subject and will come to good use for further research on the topic. Furthermore, CEOs of financial institutions can use this study to learn important considerations when deciding when, how, and if they should strategically implement GAI in their business model. This includes understanding drivers for adoption, such as value creation, innovation acceleration, enhanced customer experience, and improved security and regulatory compliance. Comparing the thesis with previous literature (e.g., Gill, et al., 2023; Neilson, 2023), it is apparent that there is a lack of studies comprehensively showing different drivers, barriers, and future development.

In contrast, this study does this, while also investigating the relationship between the concepts using valence theory, which can be a great advantage for CEOs of financial institutions.

Secondly, the study gives policymakers and regulators a fundamental framework highlighting key insights on the governance initiatives needed for a responsible implementation strategy. Furthermore, government officials can potentially make better decisions on which organ should regulate GAI use in and outside of financial institutions. The research can also be used to develop comprehensive governance frameworks. These frameworks should include ethical and regulatory challenges, ensuring responsible GAI implementation, and mitigating risks associated with data privacy and security. The financial institutions must look into the regulatory aspect of the service they provide and how it impacts technology (Ooi, et al., 2023). Even though the study by Ooi et al. (2023) suggest that each institution must look into its own service and make changes accordingly, this thesis also urges institutions to work together and make a standard of a regulatory framework that can apply to all.

Lastly, the final practical implication proposed by the authors comes from analyzing the findings. The authors found that there is a need for upskilling employees to handle new GAI technologies (Gill, et al., 2023). Financial institutions should rapidly invest in training programs to prevent job displacement and ensure that their workforce is equipped to work alongside AI systems. Furthermore, GAI can streamline operations by automating routine tasks and providing insightful analytics for decision-making (Ooi, et al., 2023). This efficiency increase of the decision-making process can potentially lead to higher profits. Also, financial institutions can use GAI to improve customer service and implement GAI into their systems to gain strength in their defense against cyberattacks and fraud. GAI customer service offers personalized interactions and responsive chatbots, which can lead to significantly enhanced customer satisfaction and loyalty by providing constant service and tailored financial products. GAI cybersecurity and fraud detection technology can identify suspicious activities and enhance overall risk management, ensuring the integrity and critical financial data and transactions.

7. Conclusion

The thesis initially set out to explore Generative Artificial Intelligence (GAI) in financial institutions, noting a rapid increase in interest and adoption. A comprehensive media discourse analysis has identified GAI drivers, barriers, and future development. The data has been gathered, organized, and studied by the authors, to give an overview of the media discourse and complemented with a literature review. Drivers have been shown as transformative tools capable of enhancing efficiency and customer experience. Barriers have brought a picture of ethics and compliance with regulatory requirements. The extensive adoption of GAI is poised to streamline operations through automation and assist in complex decision-making processes by providing insightful analytics and forecasts.

Value creation and innovation boosting are among the primary drivers for financial institution's adoption of GAI technologies. These technologies offer significant advantages in terms of optimizing operational efficiency and enhancing the scope for innovation within the financial sector. For example, GAI can analyze vast datasets faster than traditional methods, leading to quicker decision-making and potentially higher profits. Furthermore, GAI applications in customer service, such as chatbots and personalized financial devices, contribute significantly to improving customer interaction and satisfaction.

Despite the potential benefits, implementing GAI faces several barriers. A major concern is the ethical and regulatory challenges associated with GAI. Issues such as data privacy, security risks, and the need for transparency are significant hurdles. Additionally, integration into existing systems is challenging and can be both technically and financially demanding. The thesis also highlights the potential negative impact on employment, as automation may displace jobs, creating resistance from within the organization.

This thesis underscores the need for a clear roadmap for the adoption of GAI technologies, guided by governance frameworks and ethical considerations. It further recommends increased collaboration between tech developers, financial institutions, and regulators to establish standards and frameworks that guide GAI use. Such collaboration could also facilitate sharing best practices and innovations, accelerating the responsible deployment of GAI technologies.

In conclusion, while GAI presents significant opportunities for financial institutions, its integration requires careful consideration of various drivers, barriers, and future development. Financial institutions must develop robust strategies that address the technical and socioeconomic implications of GAI adoption. This comprehensive approach will ensure that the benefits of GAI can be maximized while minimizing potential risks, leading to more innovative, efficient, and inclusive financial services.

7.1 Limitations and Future directions

While the study offers valuable insights into the drivers, barriers, and future developments, several limitations must be acknowledged. The first is the scope of the data. The research primarily analyzed English-language media sources, which may not fully represent the global perspective on GAI in financial institutions. Because the keywords used by the authors when collecting data were in English, the algorithm used by the search engine showed mostly English-language news articles and videos. A small number of videos were in different languages, but because of issues with the transcribing software, the translations did not provide valuable insights.

Secondly, relying on media discourse analysis, while it does provide valuable insights into the discourse on GAI use in financial institutions, the perceptions and narratives might not align with the actual state of GAI adoption in the industry. Also, because the nature of the data in discourse analysis is secondary, the authors cannot control the relevance and accuracy of the analyzed data, such as some sources interchangeably describing GAI, Artificial Intelligence (AI), and machine learning as the exact same tool.

Thirdly, the field of GAI use in financial institutions is rapidly evolving, which can significantly impact current literature and how the technology is perceived in media. Thus, some findings may become outdated as new technologies, frameworks, and literature emerge.

Fourthly, despite the author's efforts to mitigate researcher bias through reflexivity and methodological rigor, this study provides interpretive qualitative insights that can potentially reflect the authors' perspectives. Also, because of the interpretive nature of qualitative research, the findings might not be generalizable to all financial institutions globally.

To further build on this study, future research could address the limitations and explore several key areas, such as including media sources in other languages and use primary data from financial institutions worldwide to provide a more comprehensive view of GAI implementation. Another suggestion for future research is to use longitudinal studies to understand the evolving nature of GAI. Tracking changes in media narratives and their alignment with advancements of GAI technologies when more media has emerged.

Because this study is qualitative, it could possibly provide valuable insight to conduct a quantitative analysis to complement and help validate the findings from this study, providing a broader generalization. Lastly, the authors suggest future studies to focus on specific segments within financial services, such as investment banking or insurance, to detail the unique drivers and barriers of GAI use in these areas.

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Appendix

This section includes supporting material for the master thesis, such as data and coding process, as well as two discussion papers.

Appendix I: Data

All data analyzed for the purpose of this thesis, are available through the hyperlinks connected to Google docs below.

News

News articles can be accessed here.

Open codes for news articles can be accessed here.

Axial codes for news articles can be accessed here.

Selective codes for news articles can be accessed here.

Video

Videos can be accessed here.

Open codes for videos can be accessed here.

Axial codes for videos can be accessed here.

Selective codes for videos can be accessed here.

Other

Other material can be accessed here.

Open codes for other can be accessed here.

Axial codes for other can be accessed here.

Selective codes for other can be accessed here.

Combined

Combined selective codes can be accessed here.

Data structures

Data structures for news media and other separately can be accessed here.

Appendix II: Discussion Paper – International - Lars Erik Amundsen Steen

Introduction

This discussion paper is taking a short look at the concept "international", with the use of the master thesis myself and my colleague have written this semester. The thesis covers the use of Generative Artificial Intelligence (GAI) in financial institutions. The thesis is titled "Generative Artificial Intelligence Use in Financial Institutions: Drivers, Barriers and Future Development." The authors of the thesis have used a substantial amount of time to analyze media representations and the discourse about GAI in financial institutions. This thesis is highly relevant for the theme of "international", as what is happening right now with GAI applies on a global scale, not just a national. Another key point to underline is that my colleague and I first got our interest in the topic while on a study abroad program in Perth, Western Australia, while doing a course on Financial Technology (Fintech), so from the very beginning, this has been an international topic for us.

Research Question and Objective

When writing this thesis, my colleagues and I set some research questions and an objective for the thesis. These research questions were research question 1: "What are the drivers of implementing GAI use in Financial institutions.", research question 2: "What are the different barriers experienced by Financial Institutions while implementing GAI use.", research question 3: "What considerations are relevant to shaping the future development of GAI use in financial institutions.". As stated in the thesis, the main research objective was twofold. One is to understand drivers and barriers in the implementation process of GAI use in financial institutions, and two, to understand the moderating aspect of future development on shaping the future of GAI in financial institutions.

Theoretical Framework

For the theoretical framework, we used the concept of the Valence Theory, which explores financial institution's willingness to engage (Peter & Tarpey, 1975), the theory has integrated insights from both economics and psychology to provide a comprehensive model for human behavior (Kim, et al., 2009). We found the Valence theory highly relevant to the study because it is a behavioral theory that, at the same time, views the perception of risk and benefit, giving a better evaluation of the adoption dilemma facing financial institutions (Peter & Tarpey, 1975) (Dhir, et al., 2021).

Methodology

A media discourse analysis (MDA) was decided as the best methodology for the thesis. MDA, being an inductive qualitative research method, is useful for analyzing interactions through a broadcast platform, for example, news articles or publications, videos, and podcasts (O'Keefe, 2011). The study itself is inductive in nature (Streefkerk, 2019), in other words, the researchers has conducted the research without relying on existing literature, this is because the topic is so new that there is little already existing literature.

Findings

The results of the findings are represented in the thesis with three Gioia Data Structures, showing three aggregated dimensions, and eleven different coding sub-categories. These were used to interpret the findings. The aggregated dimensions were Drivers, Barriers, and Future Development. The whole thesis can be applied to the theme international, as all the literature and data gathered for the thesis comes from all over the globe, and what has been found essential discuss the attempt of institutions to implement GAI, and what drives them to do so, the barriers they face, and what can be worked at towards the future, to improve, and further drive the implementation of GAI.

Relevance to International Trends and Forces

Drivers

When looking into the relevance of international trends and forces related to GAI, a few key concepts stand out. Firstly, global adoption and interest. During the research, it has been clear that a surge in GAI technology has exploded into the market and financial institutions. All over the world, financial institutions are working on implementing GAI into their operations at some level. On an international level, financial institutions can highly benefit from shared insights and technological advancements. The importance of value creation and innovation can be seen on an international level, with global cooperation driving the trend of GAI for financial institutions.

GAI enables personalized customer experience on a global scale. Financial institutions have a long history of data containing what they need to analyze, learn, and develop what they want GAI to do so they can provide the ideal customer experience. The new trends and expectations for what customers want will also drive international trends in customer preference and behaviors, influencing how GAI is utilized to meet diverse needs.

There is a race in the world to implement GAI and reap the benefit that follows. McKinsey research has found out that GAI has the potential to add up to 4.4 trillion to the global economy, annually (McKinsey & Company Corporation, 2023). Countries worldwide are investing in GAI to boost innovation and enhance competitive advantage, making global collaboration and knowledge sharing essential. Secondly, international collaboration is something to be desired and should be used to drive further global innovation and efficiency with GAI. As of right now, the focus for the financial institutions is to develop their own GAI technology, but they should make further efforts into cross-border partnerships to leverage GAI technologies. Thirdly, International regulatory frameworks will play a crucial role in shaping GAI adoption. Standardizing global standards will help financial institutions navigate regulatory challenges and ensure compliance across different jurisdictions. It is crucial for GAI adoption to adhere to international security standards and regulatory compliance. The thesis findings emphasize the need for a robust governance framework to address these drivers.

Barriers

Continuing regulation, it also faces some barriers that translate over to the global business dynamic. GAI implementation faces significant ethical and regulatory hurdles on a global scale. Different countries have varying regulations and standards, creating complexities for multinational financial institutions. Another barrier with relevance to the broad concept of international is data privacy and security. Cross-border data flow raises concerns about privacy and security. International regulations influence how financial institutions manage and protect data, impacting GAI deployment strategies. Lastly, the global impact of GAI on employment varies across regions. In some countries, there is a fear of job displacement, while others see opportunities for upskilling and new job creation. These variations will affect how GAI is perceived and adopted internationally (Gill, et al., 2023).

Future Development

The future development of GAI is essential for international GAI. International bodies and governments need to work on creating governance frameworks for GAI. These initiatives must aim to establish ethical guidelines, regulatory standards, and best practices for responsible GAI use globally. In the thesis, the suggestion of the need for a roadmap came up, this translates also over on a global scale (Li, et al., 2023). Developing a global roadmap for GAI integration involves international cooperation to address common challenges and leverage shared opportunities. This roadmap should include strategic planning for technology advancement, regulatory compliance, and ethical considerations. Finally, international research collaboration drives technological advancements in GAI. These advancements enhance the capabilities of GA, making it more reliable and efficient for financial institutions worldwide.

Theoretical and Practical Implications

This thesis provides a holistic view of GAI adoption and contributes to the theoretical understanding of GAI, which translates to the international scene just like the national scene. The valence theoretical framework also applies to an international context as well, and the thesis enriches the theoretical model, making it more applicable to global technology adoption studies.

We can also find practical implications on the international scene. Business managers can use the findings and the study as a whole to develop strategic plans that consider international trends and challenges in GAI adoption. This approach ensures a more effective and globally aligned implementation strategy. Government officials can also leverage the insights to create comprehensive regulatory frameworks that address global ethical and security concerns associated with GAI. Finally, the thesis can aid brand managers in enhancing customer experience by understanding international trends and leveraging GAI to meet diverse customers' needs across borders.

Conclusion

The concept of “international” is integral to understanding the adoption and impact of GAI in financial institutions. This discussion highlights the importance of considering global trends, regulatory standards, and collaborative efforts in shaping the future of GAI. By integrating international perspectives, the thesis provides valuable insights for academics, policymakers, and business managers, contributing to the responsible and effective implementation of GAI on a global scale.

The importance of considering international trends and forces in the context of GAI in financial institutions cannot be overstated. Global collaboration, regulatory framework standardized, ethical considerations, economic impacts, technological advancements, and strategic governance are all critical factors that influence the successful adoption of GAI (Dwivedi, et al., 2023). Financial institutions should embrace a global perspective, this can help navigate the challenges and opportunities presented by GAI, ensuring that they remain at the cutting edge of financial technology while promoting the responsible and ethical use of AI. A holistic approach not only benefits institutions themselves but also contributes to the broader goal of fostering a sustainable and inclusive financial system.

In the future, researchers should look more into the underlying topics and how they can be related to an international context. This can, for example, involve researching how development, upskilling, regulatory challenges, and other categories discussed in this thesis are framed on an international scale. These are interesting and highly relevant topics for the future and state of the international market for financial institutions and are in desperate need of further research. by addressing these areas, future research can significantly contribute to the advancement of knowledge and practice in the field of GAI in financial institutions on an international frontier. The study of these categories will help ensure that GAI is harnessed effectively, ethically, and sustainably, driving innovation and growth in the financial sector all over the world, and safeguarding against potential risks.

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Appendix III: Discussion Paper – International - Sindre Revheim Vevle

1. Introduction

As the world is increasingly interconnected, the concept of "international" fits the topic of Generative Artificial Intelligence (GAI) use in financial institutions. The thesis explores the media discourse about GAI and its use in financial institutions, uncovering barriers, drivers, and future developments. Furthermore, the thesis uses Valence Theory (Pelster & Val, 2024) to explore the interplay between the perceived benefits, and risks associated with GAI adoption.

The thesis begins with reviewing existing literature, and identifying key drivers, barriers, and future developments discussed in prior research. The concepts that encapsulate the term drivers were, value creation, enhanced customer experience, and security and regulatory compliance. The barriers were risk, negative employee impact, implementation challenges, and ethics and regulatory challenges. Lastly, the future development were governance initiatives, roadmap, and technology-based advancements. By critically reviewing twenty-one relevant results, several gaps in prior literature emerged. One of the essential gaps is that GAI use in financial institutions is a recent phenomenon, and as such, there is not much existing literature.

The next chapter presents the methodology used in the thesis, which is a media discourse analysis. The authors analyzed in total 1200 articles and videos to discover what the discourse on GAI use in financial institutions are. After analyzing the authors were left with three different aggregated dimensions, compiling the essence of all relevant articles. These are showcased comprehensively in the findings, and are drivers, barriers, and future development. The drivers are comprised of four coding sub-categories, which are value creation, boosting innovation, enhanced customer experience, and security and regulatory compliance enhancements. The barriers are made up from four coding sub-categories, which are risk, negative employee impact, implementation challenges, and ethics and regulatory challenges. The last aggregated dimension future development consists of three coding sub-categories, these are roadmap, governance initiatives, and technology-based advancements.

The discussion revisits the research questions with consideration to the theory and findings. The authors reassure the reader of the link between the theory and findings, while proposing answers to the following questions. **RQ1:** What are the drivers of implementing GAI use in financial institutions? **RQ2:** What are the different barriers experienced by financial institutions while implementing GAI use, and lastly? **RQ3:** What considerations are relevant to shaping the future of GAI use in financial institutions? The questions are comprehensively addressed by referring to the findings and prior literature on the drivers, barriers, and future developments. The authors also propose five propositions based on valence theory regarding based on the operating variables of drivers, barriers, and future developments.

Lastly, the authors provide six theoretical and five practical implications associated with the findings of the thesis. These include, but are not limited to, filling a gap in existing literature, providing insight into technology acceptance models, and providing a comprehensive overview of drivers, barriers, and future development which stakeholders can utilize. The thesis then goes on to discuss limitations and future research directions.

2. Discussion

Adoption of Generative Artificial Intelligence (GAI) technology in financial institutions has global value creation potential. In the banking sector, GAI can potentially increase annual value by up to 340 billion USD, according to estimations by the McKinsey Global Institute (Buehler, et al., 2024). According to a projection from Bloomberg Intelligence, GAI market size will be 1.3 trillion USD in 2032 (Bloomberg, 2023). This increase in value underscores the international drive towards utilizing GAI in financial institutions.

Financial institutions across the worlds, are implementing or planning to implement GAI to streamline operations and enhance decision-making processes. The literature review conducted in the thesis showcase studies published in many different countries. Some of the studies shows intricate problems or solutions, concerning a specific country, while other looks at the whole picture. The study conducted by Zhang & Yang (2023) specificizes the development of a financial chat model specialized for Chinese financial domain (Zhang B. , Yang, Zhou, Babar, & Liu, 2023), while Ullah et al. (2024) explores GAI use in investment decision making in Pakistan (Ullah et al., 2024). However, even though these examples have viewed GAI adoption through singular countries, the findings, and insights they provide, are applicable on an international scale.

Ethics and regulations

The ethics and regulatory challenges experienced as barriers, as well as the security and regulatory compliance enhancements discussed in the thesis shows the importance of understanding and navigating this landscape to globally adopt GAI use in financial institutions. Different countries and regions, have different laws regarding privacy, and use of intellectual property (IP). While doing a study abroad program at UiA, the authors were taught in the subject of global business dynamics, which highlighted the concerns and challenges regarding especially Chinese IP protection, and how foreign organizations have difficulty navigating this landscape when entering the Chinese market. This is something stakeholders who wants to adopt and implement GAI use in multinational enterprises must consider.

Different regions are at a different stage of developing frameworks to govern GAI technologies. European Union has developed The EU Artificial Intelligence Act which is the first comprehensive regulation on Artificial Intelligence (AI) by a major regulator (EU Artificial Intelligence Act, n.d.). However, the United States does not have this type of regulation, and therefore has to rely on already existing federal laws and guidelines to regulate AI (White & Case, 2024). Because of the varying regulatory approaches, to drive international value creation GAI can offer, there is a need for establishing common grounds for the use of GAI, not only in financial institutions, but in any sector.

Emergence and innovation

New progressive financial technologies (fintech) are emerging and bringing financial services across borders, with concepts such as blockchain and open banking. The comprehensive overview on drivers, barriers and future development provided by the thesis is directly relevant to international trends such as these. Stakeholders and regulators globally can benefit and use these insights to further prepare for implementation of these technologies.

GAI is an international trend, as showcased in the thesis. The collected data and literature have emerged from many different regions in the world, and the results are almost exclusively from 2023-2024. This emphasize the global phenomenon which is GAI and puts it into the perspective of financial institutions, offering insights into navigating the challenges and benefits.

Innovation in GAI technologies and financial institutions infrastructure can benefit from global collaboration. Potential partnerships with different regions to build a comprehensive regulatory framework, as well as creating new innovative GAI applications which can further enhance operational efficiencies and customer satisfaction, would be possible. Collaboration between countries and regions in adopting GAI is pivotal for a safe, and inclusive financial industry. This would also encourage further innovation and sharing of knowledge, as well as potentially increase the capacities of the GAI models, which would benefit not only the participating regions, but might also prove to be useful for all nations.

According to an article on Forbes, AI is one of the most important global trends for 2024, and the year will accelerate ethics and regulation on AI, while transforming traditional meeting and office situations (Singh, 2023). This article further enforces that the topic of the thesis is an international trend.

Workforce upskilling

A study conducted by McKinsey reveals over sixty different use cases for GAI across different sectors (Chui, et al., 2023). This could potentially affect workforces across the globe. As found in the thesis, for GAI to be better suited for implementation, reskilling of employees might be required to equip workers with the necessary skill to efficiently utilize GAI in financial institutions. Furthermore, developing countries with less robust educational systems and training infrastructure might become laggard, and fall even further behind.

In the US, initiatives such as the National Artificial Intelligence Act of 2020 (Congress.gov, 2020) aim to promote AI education and workforce development. A similar effort is done by China, with their New Artificial Intelligence Development Plan (Webster, Creemers, Kania, & Triolo, 2017). These efforts show an acknowledgement of the role played by human capital in the successful implementation of GAI in financial institutions globally.

A study conducted by the International Labour Organization address the impact from GAI on job quantity and quality (International Labour Organization, 2023). They state that the largest impact will not be the removal of jobs, but rather the quality of jobs (International Labour Organization, 2023). They also argue that there is a need to create policies as well as training to ensure a fair transition for workers (International Labour Organization, 2023).

Impact of GAI on international financial practices

GAI has the potential to reshape global financial practices. One notable impact is the ability to augment employee performance (Chui, et al., 2023). As mentioned in the previous section, regarding employee upskilling, with enough development, GAI could provide a solution to its own problem, by being able to assist the transitioning workforce on its own. The technology can also be leveraged to enhance employee efficiency by analyzing vast amounts of data at a significantly higher pace than traditional workers (Chui, et al., 2023).

The information and insights GAI can provide can enable decision-makers to take informed and well thought out decisions (Chen, Wu, & Zhao, 2023). Combined with the potential to aid in financial forecasting (Li, Feng, Yang, & Huang, 2024) is valuable in global markets, where fast and accurate analysis can mitigate risk and capitalize opportunities.

GAI as a way to detect fraudulent activities was commonly mentioned in the data as part of the media discourse analysis conducted in the thesis. Enabling financial institutions worldwide to enhance their security and identify suspicious transactions and prevent fraud more effectively (P, n.d.). This could potentially contribute to the overall stability of the international financial system.

3. Conclusion

In conclusion, GAI use in financial institutions is closely linked to international forces or trends. The discussion presents several key points that highlight the global dimensions of GAI adoption. Firstly, the thesis discovers and comprehensively overviews different drivers, barriers, and future development of GAI use in financial institutions. The drivers enable financial institutions worldwide to harness GAI to enhance efficiency, improve decision-making and mitigate fraudulent activities.

Secondly, careful navigation of the ethical and regulatory challenges associated with GAI use is crucial for international implementation. The different progress in developing a regulatory framework in different regions, makes it necessary to come together and do a collaborative approach to ensure compliance and ethical use of GAI. Establishing common grounds for regulation can also drive value creation and increase trust in the technology.

Thirdly, initiatives made in upskilling and reskilling of workforce is important to equip workers with the necessary skills to efficiently use GAI technologies. Ensuring a smooth transition and preventing job placements is in the best interest of everyone. Efforts made by various regions to promote AI education and understanding the potential impact of GAI use on the workforce, reflects the global importance of human capital to successfully implement GAI.

Finally, GAI has the potential to reshape financial institutions on a global scale. By enhancing data analysis, improve decision-making, detect fraudulent activities, and aid in forecasting can significantly impact global markets. In essence, the concept of "international" is integral for understanding the full impact of GAI on financial institutions. To ensure responsible implementation of GAI technology, a collaborative approach in creating guidelines, and frameworks is essential. An international approach is key to maximizing the benefits and mitigating the risks of GAI use in financial institutions.

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