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Generative AI in the Financial Industry

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Abstract:

In recent years, Generative Artificial Intelligence (GenAI) has become an emerging technology with the potential to revolutionise various industries. The financial services sector represents one of the most promising domains for GenAI implementation. Despite the rapid advancement of GenAI technologies, current academic literature lacks a comprehensive understanding of practical applications, implementation strategies, and real-world challenges within the financial industry context. To address this knowledge gap, this thesis explores the current applications, potential capabilities and value propositions for organisations and customers, risks, implementation strategies and challenges of GenAI in financial services. A qualitative research methodology was employed to address the stated research questions through semi-structured interviews with industry specialists with diverse roles within financial institutions. The research approach encompassed interview preparation, data collection, and thematic analysis to identify key patterns and insights from participant responses. The findings provide an overview for GenAI implementations in financial services, identifying primary application domains. The research contributes insights into practitioner perspectives and implementation realities that extend existing theoretical literature. This thesis aims to enhance understanding of GenAI's transformative potential within financial services and provide insights for industry professionals who make technological adoption decisions. The findings offer value for professionals and academic researchers investigating the intersection of artificial intelligence and financial services. By connecting technological capabilities and practical implementations, this research supports decision-making in an AI-driven financial landscape.

Keywords:

Generative AI (GenAI), Large Language Model (LLM), financial industry, applications, values, use cases, challenges, implementation

CERCS: P170 Computer science, numerical analysis, systems, control

Generatiivne tehisintellekt finantssektoris

Lühikokkuvõte:

Viimastel aastatel on generatiivne tehisintellekt (GenAI) kujunenud esilekerkivaks tehnoloogiaks, millel on potentsiaal muuta mitmeid tööstusharusid. Finantsteenuste sektor on üks paljutootavamaid valdkondi GenAI rakendamiseks. Vaatamata GenAI tehnoloogiate kiirele arengule puudub praeguses akadeemilises kirjanduses põhjalik arusaam selle praktilistest rakendustest, juurutusstrateegiatest ja tegelikest väljakutsetest finantsvaldkonnas. Selle teadmislünga täitmiseks uurib käesolev magistritöö GenAI praeguseid kasutusvõimalusi, potentsiaalseid võimekusi ja väärtuspakkumisi organisatsioonidele ja klientidele, riske, rakendusstrateegiaid ning väljakutseid finantsteenuste kontekstis.

Uurimisküsimustele vastamiseks kasutati kvalitatiivset uurimismetoodikat, viies läbi poolstruktureeritud intervjuud erinevates rollides töötavate finantssektori ekspertidega. Uurimisprotsess hõlmas intervjuude ettevalmistust, andmekogumist ja temaatilist analüüsi, mille abil tuvastati osalejate vastustest olulised mustrid ja sisulised tähelepanekud. Töö tulemused annavad ülevaate GenAI rakendustest finantsteenustes, tuues esile peamised kasutusvaldkonnad. Uuring pakub praktilist teavet ekspertide vaatenurkadest ja rakendusreaalsustest, täiendades olemasolevat teoreetilist kirjandust. Magistritöö eesmärk on süvendada arusaamist GenAI muutlikust mõjust finantsteenuste valdkonnas ning pakkuda väärtuslikku sisendit tööstusprofessionaalidele, kes osalevad tehnoloogiliste otsuste tegemises. Tulemused on väärtuslikud nii professionaalidele kui ka teadlastele, kes uurivad tehisintellekti ja finantsteenuste lõimumiskohti. Sidudes tehnoloogilise võimekuse ja praktilised rakendused, toetab see uurimus otsuste tegemist AI-põhises finantsmaailmas.

Võtmesõnad:

Generatiivne AI (GenAI), Large Language Model (LLM), finantssektor, rakendused, väärtused, kasutusjuhud, väljakutsed, teostamine

CERCS: P170 Arvutiteadus, arvutusmeetodid, süsteemid, juhtimine (automaatjuhtimisteooria)

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1 Introduction

In fields like medicine, education, marketing, and finance, Generative Artificial Intelligence (GenAI) is advancing rapidly. GenAI has the potential to impact several domains of the financial industry, including forecasting, fraud detection, risk assessment, trading, market simulations, customer service, and more. The financial sector is one of these areas that responds to technological change the best [31]. Innovative technologies alter how the financial sector controls elements like data security, data sharing, and operational efficiency while also opening opportunities for improvement [32, 18]. GenAI is one such emerging technology that has the capabilities to alter the financial landscape.

Lately, GenAI has gained focus, driven by improved computing technologies and large volumes of data. The breakthroughs have placed GenAI at the centre stage, putting it among the top AI tools used today [22]. AI and automation are not new to the Financial Industry. In fact, for years, trading has been automated, risk management has been modernised, and investment research has been carried out using machine learning/deep learning algorithms and natural language processing (NLP) approaches [6]. However, a substantial portion of operations are being carried out utilising human capital, despite the fact that billions of dollars have been spent automating numerous functions throughout the transaction life cycle [6]. With the advancement of Generative Artificial Intelligence (GenAI), personalisation, and democratization of access to the newest technology are all aided by open-source efforts and frameworks. Open-source initiatives, like OpenAI's GPT models, have made a contribution to the creation of generative models, enabling scholars, programmers, and almost every professional anywhere to investigate and expand upon these developments.

Within the finance industry, open-source projects have an impact on initiatives such as Gemini, ChatGPT, and Claude, which demonstrate how GenAI may be used to solve real-world problems in a faster and more efficient way. These projects serve as examples of how cooperative, community-based efforts can result in the creation of specialised solutions for financial institutions and further the continuous advancement of GenAI technologies in the banking industry.

The findings of recent research on the effects of generative AI on productivity are promising. According to a Stanford University study, generative AI increased a call centre's productivity by 14%. Another study by the Massachusetts Institute of Technology found that generative AI helps marketers, consultants, and data analysts operate more quickly and more effectively. The ability of technology to level the playing field and, in particular, to help lower-skilled workers increase their outputs and productivity is one recurring finding [6]. However, less skilled personnel may initially need to put in more validation effort. Some researches forecast that LLMs and AI will impact the user experience in the banking industry in multiple ways [18]. In order to give customers individualised customer service and support, companies can analyse consumer data to understand their preferences and needs. Using this knowledge, companies can respond

to users' questions and concerns in real-time. Additionally, banks might utilise AI models to deliver targeted product suggestions, fraud detection, and quick support wait times. Through onboarding, identification verification, account setup, and advice on available products, AI can assist clients [18]. Businesses might employ AI to offer a conversational banking experience by integrating models with banking applications to provide consumers with a single point of contact for transactions, account information, and notifications through the chat or voice interface in many languages. It could make using banking services more accessible to everyone, including non-native speakers, by streamlining the user experience and reducing the complexity of banking operations [18].

The landscape of Generative Artificial Intelligence (GenAI) in the financial sector is marked by diverse perspectives, reflecting both optimism about its potential benefits and apprehension regarding its associated risks. While some experts consider GenAI as a transformative force capable of revolutionising financial services, others express concerns about regulatory challenges, data security issues, and the perpetuation of biases within AI systems [5, 18]. Despite these varying viewpoints, the existing literature remains sparse in its documentation of the capabilities of GenAI in enhancing financial operations, how to utilise them, its potential for disruption, the implementation strategies, and the challenges during implementation. In light of this, we seek to dig deeper into the nuances of GenAI's integration within the financial landscape. Recognising the importance of gaining a comprehensive understanding of the current state of GenAI in financial domains, this study employs a qualitative survey approach through interviews with individuals possessing expertise in both GenAI and the financial industry, with an intention to fill the gap we identified. By uncovering insights from these sources, this research addresses the existing gaps in understanding and provides insights into the practical applications, value, and challenges associated with the integration of GenAI in financial institutions. Furthermore, the thesis involves a discussion of the findings, including a comparison of them with existing theoretical literature. To fulfil the research objective, I have formulated the following research questions:

- What are the potential applications of GenAI in the Finance sector?
- What value does GenAI bring to the Financial Industries?
- How to deliver the values that GenAI promises for Financial institutions?
- What are the risks and challenges regarding the implementations of GenAI in Financial Industries?
- How will the future of Financial Industries be with GenAI solutions?

1.1 Research Contribution

This thesis seeks to bridge the gap between the theoretical potential of GenAI and its practical application within the financial industry. To achieve this, we utilise a qualitative research methodology, employing semi-structured interviews with domain experts. These interviews delve into the current landscape of GenAI utilisation within finance while also exploring its potential applications.

By analysing the data gathered from these interviews, we aim to reflect on the findings, which will serve a dual purpose:

- For engineers and researchers: It will provide a foundational roadmap for the development of innovative GenAI-powered solutions tailored to the needs of the financial sector.
- For financial institutions: It will act as a practical guide for the successful implementation of GenAI solutions within their organisations, maximising the potential benefits and mitigating potential risks.

The key contribution of this research lies in its ability to bridge the knowledge gap between the GenAI potential and its application in finance. This will empower both technology developers and financial institutions to harness the power of GenAI.

1.2 Thesis Outline

The thesis unfolds in six main sections. Section 2 (Background), we establish a foundation in GenAI, exploring core concepts, key models, and open-source initiatives. We then start to analyse the financial sector and identifying areas for GenAI disruption. Section 3 (Methodology), to bridge theory and practice, we employ qualitative research. This section details our interview process with industry experts, including selection criteria, interview questions, and data collection and analysis methods. Section 4 (Results), building on the methodology, this section presents the key findings gained from the expert interviews. Section 5 (Discussion), we delve deeper, analysing the research findings, discussing on them and comparing with the literature. This section explores the structure, purpose, and potential impact on GenAI integration within finance. We also have a subsection here to reflect on the limitations we had during the research process. Section 6 (Conclusion and Future Work), the final section, summarises the key points in the conclusion of the thesis and discusses the possibilities of future work.

2 Background

This section contains a synopsis of the key ideas regarding generative AI and the financial sector, as well as a review of relevant research and a clarification of the terms used throughout this thesis. It aims to provide a thorough framework for comprehending the essential components that serve as the foundation for this study.

2.1 Financial Sector

The financial sector is a vital and dynamic segment of the global economy that adopts emerging technologies to improve its services and operations. The financial industry includes banking, investing, insurance, and other elements that support business activities [3]. However, the financial sector is not immune to challenges. The ever-evolving landscape demands constant adaptation. Concerns around fraud prevention, risk management, and streamlining operational efficiency are ever-present. Additionally, the rise of new technologies like blockchain and cryptocurrencies necessitates a forward-thinking approach to remain competitive. By automating routine tasks, AI can lighten the workload of finance teams – potentially by up to 20%. This frees up employee time and expertise for more complex and strategic pursuits within the financial institution. Given the concern over workplace burnout, AI presents a game-changing opportunity for financial institutions [8]. One of the latest McKinsey reports [12] states that 75% of the respondents who are already using AI in their companies plan to increase their investments in AI moving forward. In this dynamic environment, GenAI emerges as a potential game-changer. This AI technology holds promise for revolutionising the financial sector by automating tasks, enhancing decision-making capabilities, and innovating financial products and services [1]. The following sections will delve deeper into the world of GenAI, explore its core concepts and key models, and examine the existing open-source initiatives shaping its development. We will then shift our focus to the financial sector, identifying areas where GenAI can be harnessed to address existing challenges and propel the industry forward.

2.2 Generative AI

At its core, what sets GenAI apart from other machine learning techniques is its capacity to produce information that nearly resembles human-created data. Using algorithms and computer power, this technology can generate realistic data that resembles the patterns and structures present in the huge datasets on which it has been trained [13]. The two most popular generative AI models are Transformer-based models and Generative Adversarial Networks (GANs). GANs produce multimodal and visual outputs and show adaptability in managing both textual and image input data. Transformer-based models, such as the GPT language models, on the other hand, use textual sources, such as the Internet, to produce textual content [22].

Transformer-based Models - Transformer-based models, exemplified by the Google-developed GPT (Generative Pre-trained Transformer) series, have emerged as trailblazers. The introduction of Transformer-based models, as pioneered by the seminal work "Attention is All You Need" by Vaswani et al. (2017) [39], marks a paradigm shift in sequence transduction architectures. Departing from traditional recurrent neural networks (RNNs) and convolutional neural networks (CNNs), Transformers leverage multi-headed self-attention mechanisms to capture global dependencies between input and output sequences without relying on sequential computation. This innovation enables significantly improved parallelisation during training, addressing the limitations associated with sequential processing, especially in tasks with extended sequence lengths. The Transformer architecture, with its encoder-decoder structure comprising stacked self-attention and feedforward layers, has demonstrated high performance in various natural language processing tasks. Notably, the model's ability to learn long-range dependencies and its computational efficiency have positioned it as a cornerstone in the evolution of generative models, influencing subsequent advancements in diverse applications, including machine translation and constituency parsing. The success of Transformers underscores their potential for reshaping the landscape of artificial intelligence and inspiring future developments in both research and practical implementations. These models exploit textual sources, including the expansive realm of the Internet, to produce coherent and contextually rich textual content. The transformer architecture has become a cornerstone in natural language processing, influencing the development of language models like GPT-4, Claude 4 anthropic. Additionally, open-source initiatives such as OpenAI's GPT and successors like ChatGPT and Claude have further propelled the democratization of generative AI. These platforms enable developers and researchers to explore the potential of transformer-based models in diverse applications, fostering an ecosystem of collaborative innovation.

Generative Adversarial Networks (GANs) - In parallel, Generative Adversarial Networks (GANs) constitute another powerhouse in the generative AI landscape. GANs exhibit versatility in handling textual and image input data, producing multimodal and visually compelling output. Generative Adversarial Networks (GANs) represent a framework in the realm of generative models, proposed by Goodfellow et al. [20]. The fundamental idea underlying GANs is an adversarial process involving the training of two models concurrently: a generative model tasked with capturing the data distribution and a discriminative model aimed at distinguishing between samples originating from the training data and those generated by the generative model. This approach frames the training procedure as a minimax two-player game, where the objective for the generative model is to maximise the probability of the discriminative model making errors.

2.3 Use Cases in the Financial Sector

Generative AI's impact on the financial sector is profound, reshaping traditional practices and introducing innovative solutions. The following section provides an overview of the most prevalent use cases we came across through relevant researches.

Fraud Detection and Risk Assessment - GenAI's ability to prevent fraud is one of its most important uses in the banking industry. Generative models play a role in fraud detection and risk assessment by analysing large datasets to identify anomalous patterns and potential risks, bolstering the security infrastructure of financial institutions [33]. Cybercrime Magazine reported that by 2021, the worldwide cost of cybercrime had reached \$6 trillion, and by 2025, it is predicted to reach \$10.5 trillion [7]. The need for banks to prioritise data security in order to protect their operations is highlighted by this growing threat. Generative Artificial Intelligence (GenAI) mines synthetic data continually and updates its detection algorithms, providing a transformative solution. By using a proactive and dynamic approach, banks are able to keep up with the most recent fraud schemes and prevent fraudulent acts from happening in the first place. This not only overcomes the drawbacks of conventional methods but also increases the effectiveness of fraud prevention.

Compliance - Anti-Money Laundering (AML) regulations are essential for safeguarding the financial ecosystem against activities like money laundering and terrorism financing. Generative AI provides a mechanism to enhance compliance processes by analysing transactional datasets to detect anomalies of suspicious behaviour [19]. Generative AI models can learn and evolve from historical and real-time data, unlike traditional rule-based systems, which may struggle with adaptability and scalability, enabling a better understanding of fraudulent patterns. This adaptability not only ensures higher accuracy in detecting irregularities but also reduces the rate of false positives, which is a challenge for financial institutions. By minimising false alerts, organisations can allocate resources more effectively. Similarly, these models can generate reports tailored to meet the requirements of international regulatory bodies, reducing the operational burden on compliance teams.

Customer Service Automation - Natural language processing (NLP) gives GenAI chatbots the ability to provide human-like customer care around the clock. These chatbots are excellent at responding to more complex consumer inquiries in addition to performing standard duties like answering questions, providing account updates, starting transfers, and updating profile information [4]. In the realm of customer service, generative AI powers virtual agents like LangChain, facilitating automated interactions, answering queries, and providing personalised assistance.

Financial Forecasting - Open-source platforms enable the development of generative models for financial forecasting, assisting analysts in predicting market trends and making informed decisions. This comprehensive overview sets the stage for a nuanced exploration of the intersection between Generative AI and the financial industry, en-

compassing not only the fundamental models but also the collaborative landscape of open-source initiatives and the transformative impact on financial practices.

2.3.1 Related work

Due to the emerging nature of GenAI technology, the volume of academic research specifically addressing its applications/values in financial services remains relatively limited. However, as industry interest and practical implementations have accelerated, the number of publications exploring GenAI in finance has begun to increase rapidly over the past year. The application of GenAI in fraud detection has attracted attention. [27] and [40] proposed a novel approach using generative models to simulate potential fraud patterns, enabling financial institutions to proactively identify emerging threats before they appear in real transactions. Their methodologies demonstrated improved detection rates compared to traditional machine learning approaches. There are studies that have investigated GenAI's capabilities in financial forecasting and market analysis. The book [24] analysed the personalisation of financial services through GenAI, and a future where financial advice and strategies are as unique as the individual investors. It discusses the limitations of current AI technologies in financial forecasting and AI's expected influence on the finance industry's structure. Bloomberg engineers have developed BloombergGPT [41], which is capable of doing multiple services, including financial report generation, trading ideas, trend prediction, risk assessment and client communication. They did a huge resource investment to deliver a model that outperforms existing ones on financial tasks without sacrificing performance on general LLM benchmarks. Until this point, the most researched, mentioned and practical product developed application of GenAI in finance is in the customer service scope. Cem Dilmeghani and Sena Sezer researched the use cases that include conversational finance with chatbots, which are accurate and explaining interactions with users [14]. According to them, conversational finance has use cases to provide the customers with improved customer support, personalised financial advice, payment notifications, and document generations like investment summaries or loan applications.

3 Methodology

To address the existing gaps in understanding regarding the integration of Generative Artificial Intelligence (GenAI) within the financial industry, this study sets out to achieve several research objectives. The primary goal is to gain insights into the practical applications, values, risks, and challenges associated with GenAI in financial institutions. In pursuit of these objectives, qualitative survey methods will be employed through expert interviews. The choice of interviews as the methodological approach is motivated by the need to gather detailed and contextually rich data. Interviews are well-suited for this purpose as they facilitate in-depth exploration and understanding of the subject matter, allowing for a thorough investigation into the use cases, values, and challenges related to the integration of GenAI in financial institutions. [38]

The three key steps of the methodology are interview preparation, data gathering, and data analysis. Figure 1 shows the general components of the methodology. In the preparation stage, the interview questions will be created, and interview candidates will be searched. The online interviews will take place and be recorded during the following data collection phase. The process of data transcription and data coding is included in the data analysis step, and it, in the end, helps in our ability to respond to the research questions.

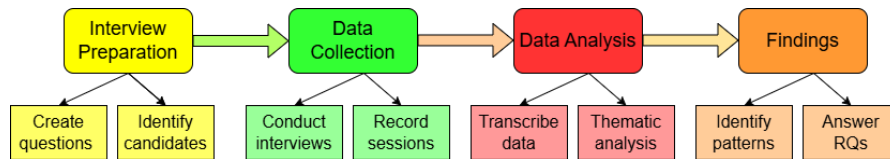


Figure 1. High-Level Methodology Workflow

3.1 Research Questions

This thesis aims to address the research questions presented in the introduction section in order to understand the impact of Generative Artificial Intelligence (GenAI) on the financial sector. The selection of research questions is informed by an analysis and inquiry aimed at bridging the recognised gap in existing research.

- **RQ1. What are the potential applications of GenAI in the Finance sector?** Exploring the various financial applications of GenAI. A detailed analysis of the reasons for GenAI's growing popularity and the ways in which its different aspects potentially transform financial procedures has been neglected in previous studies.
- **RQ2. What values does GenAI bring to the Financial Industries?** Quantifying and explaining the contributions and inherent advantages of GenAI in the financial

industry. The purpose of this study is to provide a deeper understanding of the ways in which GenAI benefits financial institutions.

- **RQ3. How to deliver the values that GenAI promises for Financial Institutions?** Elaborating on the starting point and strategic roadmap of the implementation process of GenAI solutions.
- **RQ4. What are the risks and challenges regarding the implementations of GenAI in Financial Industries?** Evaluating the risks and challenges of applying GenAI in the financial sector. To responsibly implement GenAI in finance, it is imperative to identify possible threats and ethical issues.
- **RQ5. How will the future of financial industries be with GenAI solutions?** Exploring the possible scenarios of the context: How will tomorrow be different from traditional solutions or workflow.

3.2 Interview Preparation

To find answers to the research questions, pertinent interview questions will be created as part of the preparation phase. Designing interview questions is a crucial part of our research approach. We will leave the questions open-ended to solicit thoughtful comments from experts while giving them flexibility in how they respond. These carefully crafted questions are going to be used to create an interview guide before every interview, guaranteeing a planned and directed discussion. Adding extra questions to the interview questions will be a beneficial addition that enables us to obtain a variety of viewpoints and, more precisely, explore the use cases that were highlighted. These follow-up questions will give us a chance to examine specific aspects of the research topic that the primary set of research questions may not have covered. It is essential to formulate questions strategically and set guidelines to conduct focused and productive interviews [11]. Additionally, the methodology's preparation phase includes the search for interview candidates.

3.2.1 Interview Guide

While preparing the interview guide, guidelines of Empirical Standards were also followed [10].

As mentioned in the previous subsection, the interview guide will be formulated based on the predefined set of research questions, as its purpose is to assist the researcher in obtaining comprehensive responses [11]. The phrasing of questions will undergo refinement during the interview process. The interview guide is structured into five main sections: an introduction, questions related to RQ1, questions related to RQ2, questions related to RQ3, and a conclusion. Initial questions serve as an icebreaker,

facilitating a deeper understanding of the interviewee's professional background and their involvement with Generative Artificial Intelligence (GenAI). Subsequently, the section dedicated to research questions follows, aiming to delve into elements of each inquiry. For instance, questions such as "What developments in GenAI do you observe within the financial industry?" and "How can GenAI impact different aspects of financial services, products, and processes?" will be posed to gather insights for addressing RQ1(What are the potential applications of GenAI in the Finance sector?). To address RQ2(What value does GenAI bring to the Financial Industries?), queries like "In what ways can the implementation of GenAI solutions benefit companies or organisations within the financial industry?" will be explored, with potential follow-up questions focusing on the value brought to customers within the financial industry. These inquiries aim to elucidate specific values of GenAI in financial industries. For RQ3 (How to deliver the values that GenAI promises for Financial Institutions?), a question such as "Can you outline the key steps involved in successfully integrating GenAI solutions into existing financial systems and workflows?" was included to uncover practical strategies for effective implementation. This question focuses on identifying steps and strategies to bridge the gap between conceptual GenAI solutions and their practical deployment. Addressing RQ4(What are the risks and challenges regarding the implementations of GenAI in Financial Industries?), "What challenges do you perceive in the implementation of GenAI within the financial industry?" will prompt discussions on challenges associated with GenAI in the financial sector. If the participant does not naturally address use cases that other researchers have brought up in the existing literature, optional questions will be asked in the conclusion section. The interviewee might address any more relevant points that were not addressed by the previous questions during these conclusion questions. Finally, for RQ5 (How will the future of financial industries be with GenAI solutions?), questions like "How do you think these implementations will change the future of financial industries?" and "How would these solutions differ from today's approaches?" will explore the transformative potential of GenAI and its long-term implications for financial workflows and customer experiences.

3.2.2 Interview Participants

The research will involve semi-structured interviews conducted with a carefully selected pool of participants. This pool will encompass professionals working in diverse roles within financial institutions, including data scientists, compliance officers, risk analysts, and technology executives. Interview participants will be selected based on the following criteria:

- Having experience in the Finance Sector
- Having experience or knowledge of concepts with Generative AI

LinkedIn will be the primary platform used in the selection procedure to identify participants. Additional routes like Twitter and direct email outreach will be investigated to improve outreach. The search parameters will be guided by keyword combinations such as "Generative AI", "finance", and "bank". The search results will be carefully sorted according to users or postings, making it possible to identify all possible participants. The objective of this strategy technique is to guarantee the incorporation of varied viewpoints from proficient individuals in the technology and financial domains.

Table 1. Interview Participants

Interviewee ID	Role/Position	Experience
I-00	Senior Manager (Bank)	13y
I-01	Data Scientist (Finance Researcher)	2y
I-02	Head Data Science (Bank)	8y
I-03	Data Analyst (Bank)	2y
I-04	Strategic Lead (Bank, Insurance, AI book co-author)	13y
I-05	Senior ML Engineer (Bank)	3y
I-06	Senior Fraud Analytics Consultant (Bank, Insurance, Taxation)	7y
I-07	Mid Software Engineer (Bank)	2y
OpenAI(GPT-4.1)		
Claude 3.7 Sonnet Thinking		

3.3 Data Collection

The data collection phase involved conducting expert interviews to gather qualitative data on the integration of Generative Artificial Intelligence (GenAI) in the financial industry. Following the preparatory work in the earlier phase, this stage focused on executing the interviews and recording the data that was collected.

To conduct the interviews, we used the Zoom platform, with prior consent from the interview participants for recording the sessions. This ensured the availability of a dataset for the analysis in the subsequent stage. In addition to video conferencing, supplementary tools were utilised to streamline the data collection process. All interviews were transcribed using speech-to-text software, providing a written format that facilitated the analysis phase.

The interview process adhered to the pre-defined question guide developed during the preparation phase. Each session lasted approximately 30 minutes on average. We agreed on times verbally most of the time, as the interviewees were not willing to use a tool to schedule the time. The goal was to interview experts until we reached the

saturation point. After interviewing 8 technical people, we decided that the answers were becoming redundant. Finally, we interviewed 2 LLMs from different sources to get their descriptions on their capabilities. Arguably, our approach to interviewing LLMs was different than humans, because we were aware that follow-up or distracting questions could easily manipulate the answers of these language models. Therefore, we only asked directly predefined questions and took the transcripts of the first answers. As a result, the transcripts of the LLM interviews were significantly (50% on average) smaller than those of humans. Table 1 provides an overview of the interviewees, their current roles, and their expertise in GenAI and the financial sector.

Participants were primarily identified through LinkedIn. Additionally, experts who had published articles on the topics were contacted via email. While eight interviews with participants were completed, it was observed that after this point, data saturation occurred, with subsequent responses becoming repetitive. Finally, two large language models (LLMs) were also interviewed to gather insights regarding their and based on their data, other finance-specific LLMs' capabilities in the financial sector.

This phase marked the transition to the data analysis phase, where the collected data was systematically coded and analysed to gather insights addressing the research questions.

3.4 Data Analysis

The final phase of the methodology, **Data Analysis**, focused on extracting insights from the data collected during the expert interviews. This phase employed a systematic approach involving transcription, coding, and thematic analysis to explore the research questions.

3.4.1 Transcription and Data Cleaning

The first step in the analysis was transcription, where recorded interviews were converted into a textual format using the AI tool *TurboScribe.ai*. To ensure high accuracy, all initial transcriptions were manually reviewed and corrected for any errors or omissions.

3.4.2 Data Categorisation and Coding

Once transcription was complete, the data were organised into manageable categories for analysis. Each transcript was segmented into smaller units of meaning, such as sentences or phrases, that corresponded to specific ideas or discussion points. This step involved categorising the responses based on the key themes relevant to the research questions, allowing the identification of patterns and trends across the dataset.

The coding process was iterative and unfolded in two cycles:

1. **First-cycle coding:** This phase involved assigning codes to data segments, focusing on high-level themes such as *Applications*, *Values*, *Implementation*, *Challenges*, and *Future Impact*, as outlined in Table 2. These themes were directly derived from the research questions.
2. **Second-cycle coding:** In this phase, the initial codes were refined, grouped, or expanded into specific sub-themes. For example, within the *Challenges* theme, sub-themes such as *cost barriers*, *data privacy*, and *lack of expertise* emerged from the participant responses. This refinement ensured a more granular analysis while maintaining alignment with the research questions.

Table 2. Coding Framework and Corresponding Research Questions

Code Category	Corresponding Research Question
Applications	RQ1: Potential applications of GenAI in Finance
Values	RQ2: Value proposition of GenAI for Financial Industries
Implementation	RQ3: Delivering GenAI value to Financial institutions
Challenges	RQ4: Risks and challenges of GenAI implementation
Future Impact	RQ5: Future outlook for Financial Industries with GenAI

3.4.3 Thematic Analysis

Thematic analysis, following the guidelines of Braun and Clarke [15], was employed to identify recurring topics and themes across the dataset. This method provided a structured approach to uncover, analyse, and report patterns within the data. The thematic analysis process involved the following steps:

1. **Familiarisation:** Immersion in the data by thoroughly reading and re-reading the transcripts.
2. **Initial coding:** Coding of data features relevant to the research questions.
3. **Theme identification:** Collation of codes into themes and sub-themes.
4. **Theme refinement:** Review and refinement of themes to ensure clarity, coherence, and alignment with research questions.
5. **Theme definition:** Defining and naming each theme to capture its essence and scope.

3.4.4 AI-Assisted Analysis

To complete the manual analysis, an AI-assisted thematic analysis was also conducted using LLM tools such as ChatGPT and Claude for verification and as a support to catch if something was missed. The AI was guided by instructions to:

- Identify key points and patterns within the transcripts.
- Assign initial codes to segments of text corresponding to specific themes.
- Organise codes into broader themes and sub-themes.
- Generate summaries of identified themes with supporting quotes.

This AI-assisted approach supported the analysis process by improving the finding accuracy, enabling faster identification of patterns and themes. Table 3 illustrates how the AI analysis connected themes to specific quotes from the interviews, creating a foundation for comprehensive thematic analysis.

Table 3. Example of AI-Assisted Thematic Analysis with Quote Mapping

Primary Theme	Sub-theme	Supporting Quote(s)
Applications	Customer Service Automation	"I think the most obvious application would be in customer support. We're already seeing chatbots that can handle basic inquiries and troubleshooting, but with GenAI they can be advanced to much more complex issues." (I-03)
Values	Cost Efficiency	"In terms of return on investment, we're looking at potential cost savings of 30-40% in certain departments where repetitive tasks can be automated using these technologies." (I-00)
Challenges	Data Privacy	"The biggest challenge we face is ensuring client data remains secure while still leveraging it to train the models. Financial data is extremely sensitive, and regulations around it are strict for good reason." (I-04)
Implementation	Strategy	"You can't just drop GenAI into already existing workflows. There needs to be a step-by-step process that involves re-training staff, adapting to technology." (I-02)
Future Impact	Role Transformation	"I don't see GenAI replacing financial analysts entirely, but I do see their roles evolving. They'll become more like supervisors and strategy thinkers rather than report generators." (I-04)

4 Results

This section presents an overview of the data collected and the findings obtained through thematic analysis. The aim is to report and interpret the key results in relation to the research questions (RQs) of this study. Each subsection addresses a specific research question, detailing the main themes and insights that emerged from the interviews and are supported by illustrative tables and direct quotes from participants.

Findings are presented in a way that highlights both common patterns and unique perspectives across participants. By directly linking the analysis to the research questions, this section has subsections that focused on: (RQ1) the potential applications of Generative AI in the financial sector, (RQ2) the value that GenAI brings to financial institutions, (RQ3) how these values can be effectively delivered, (RQ4) the risks and challenges associated with GenAI implementation, and (RQ5) the anticipated future impact of GenAI on the financial industry.

4.1 Applications

The interviews revealed 13 distinct application areas of GenAI in finance, with customer service automation emerging as the most frequently mentioned use case (cited by all participants). Thematic analysis discloses that Generative AI applications in finance cluster into three primary domains: customer service applications, operations efficiency, and advanced analytical capabilities. These domains represent separate value pathways through which financial institutions can take advantage of GenAI technologies. Table 4 provides an overview of the themes identified in 10 interviews.

Table 4. Applications

Application Theme	Occurrence	Participant References
Customer Service & Chatbots	10	I-00, I-01, I-02, I-03, I-04, I-05, I-06, I-07, GPT-4.1, Claude
Document Processing	8	I-00, I-02, I-03, I-04, I-06, I-07, Claude, GPT-4.1
Financial Copilots	8	I-00, I-02, I-04, I-05, I-06, I-07, Claude, GPT-4.1
Fraud Detection	5	I-02, I-04, I-06, Claude, GPT-4.1
Risk Assessment	4	I-04 I-06, Claude, GPT-4.1
Compliance Monitoring	4	I-04, I-06, Claude, GPT-4.1
Knowledge Management	3	I-02, I-04, Claude
Credit Scoring	3	I-07, Claude, GPT-4.1
Loan Processing	3	I-03, Claude, GPT-4.1
Investment Analysis	3	I-04, Claude, GPT-4.1
Tax Preparation	3	I-00, I-04, I-06
System Monitoring & Reporting	3	I-04, I-07, Claude
Financial Forecasting	2	I-00, I-04

4.1.1 Customer Service Applications

This domain represents the most mature and wide application area, with chatbots dominating implementations. I-03 noted: *We have virtual assistants that are more human-like... performing 24/7 queries without human intervention.* Claude added: *Conversational interfaces enable natural interaction without navigating complex menus.* Our analysis revealed three value pathways:

Intelligent Service Automation: The transition from scripted responses to contextual understanding represents a paradigm shift. I-03 described this evolution: *We've moved from menu-driven IVR systems to chatbots that understand natural queries about account anomalies.* Claude noted the underlying technology shift: *Transformer architectures enable contextual understanding of financial terminology that rule-based systems couldn't achieve.*

Proactive Advisory Services: Beyond reactive support, GenAI enables anticipatory guidance. Claude explained: *Systems can now analyse spending patterns against income fluctuations to alert customers before overdrafts occur.* GPT-4.1 highlighted the scalability: *Personalised wealth management advice, previously reserved for high-net-worth clients, becomes economically viable at scale.*

Unified Customer Experience: Participants noted significant improvements in

cross-platform experience. I-04 observed: *Customers receive stable advice whether they use mobile or web platform, or kiosks in banks, because all channels use the same knowledge base.* This integration eliminates the frustrating experience of having to repeat information when switching channels. Claude elaborated: *GenAI maintains conversation context across touchpoints - a customer can start an inquiry via chatbot, continue it through a mobile app, and complete it in-branch without restarting the conversation.* GPT-4.1 quantified the benefit: *Financial institutions implementing channel integration reduce customer effort scores by 35% while increasing satisfaction metrics by 28 %.*

4.1.2 Operational Efficiency

This domain demonstrates how GenAI transforms background functions. LLM drives operational efficiency primarily through the transformation of labour-intensive jobs into automated processes. We divided the domain through the following dimensions: *Document processing and automation, resource optimisation, and error reduction.*

Document processing and automation: In terms of efficiency, document processing has undergone fundamental changes. Most of the interview participants have agreed on how GenAI significantly reduces the time consumed while processing across operations in several scopes. To support with quotes from experts, I-00 described: *GenAI can extract semantic meaning from various formats such as PDFs, images, etc., and convert financial data into a standard format. This will reduce the manual work from, for example, 30 minutes to seconds.* Claude quantified benefits: *Automated loan approvals and compliance monitoring significantly speed up operations. Mortgage application processing time reduced from 45 days to 72 hours through automated document verification.*

Resource Optimisation: Our participants reported on reductions in resources for human effort required for routine tasks. Quotes from I-06 on compliance gains: *In our team now we are implementing GenAI tools which are capable of automatically flagging relevant changes, and this cuts manual review time by 60%.* Similarly, I-03 mentioned efficiency in risk management: *What previously required three analysts manually reviewing transaction patterns, now runs automatically, and just one specialist will be enough for validating the outputs.* and similar example from GPT-4.1 in a different scope: *Loan underwriting processes that required 17 manual handoffs now execute in straight-through processing pipelines with GenAI validation checkpoints.* Claude emphasised the scalability: *Once trained, GenAI systems handle volume spikes without additional staffing costs—particularly valuable during market volatility.*

Error Reduction: The idea of "AI reduces human error in data-intensive processes or calculations" is not new or came together with our research, but as it was expected, this idea is also backed up by our experts during our research. I-00 explained: *Before, on average, we had 8-12% error rates while extracting manual data from financial documents, now our GenAI has taken this below 1%.* I-07 mentioned consistency in GenAI work: *AI-generated reports maintain consistent formatting and calculation*

standards that we were struggling before, to achieve across global offices. GPT-4.1 added: Automated reconciliation of transaction data across systems eliminates manual matching errors that previously caused 30% of operational delays.

As GPT-4.1 summarised: *"Faster processing enables more iterations, lower errors reduce rework, and freed resources can focus on exception handling—creating compound efficiency gains."*

4.1.3 Advanced Analytical Capabilities

Expert insights on the scope of fraud detection and risk assessment led us to create and classify this domain category. Traditional modelling approaches are being enhanced. I-06 noted: *Our experiments show us GenAI can identify fraud patterns across millions of transactions in real-time.* Claude supported: *Multimodal GenAI applications provide comprehensive investment insights by analysing various data types simultaneously. Generative models simulate thousands of economic scenarios for stress testing, revealing vulnerabilities that conventional models overlook.* However, after mentioning similar opinions, I-05 added: *For now and for us, these remain as supplementary tools, yet human validations are still needed for model validation.*

Fraud Detection: Especially, the majority of the participants have mentioned new emerging methods utilised by GenAI applications for fraud prevention. One example from I-06: *In our pre-GenAI structures, the algorithms were mostly catch-known patterns, GenAI identifies novel fraud typologies by learning from graph structures.* Supporting GPT-4.1 stats: *Real-time analysis of payment networks reduces false positives by 40% while increasing true detection rates.*

Credit scoring & Risk assessment: Credit evaluation was also a popular nuance. I-03 gave us a sample with explanation: *If a customer is doing transactions and then again cancelling it and then again doing it... it makes the customer's trust score go down. All these kinds of things can actually help the generative AI model to generate a credit score for a customer.* I-07 said: *I would like to mention dynamic credit scoring. Right now credit decisions are based on math formulas. GenAI can bring in alternative data to calculate credit score, like payments, rent invoices, etc. It may help young people or people who don't have credit to access fair credit.* However, in reality from I-02, I-04 and I-05's perspective, there are implementation and ethical constraints. In summary, they noted that we cannot use LLM for this scope, we should explain from the legal side how our model works, but we cannot explain how the vast language model works.

As a result, our analysis revealed a tension between technical potential and operational reality. While GenAI enables modelling capabilities through pattern recognition using alternative data, some experts noted to maintain human oversight concerning regulatory and explainability sides.

4.2 Values

Our analysis revealed that the values that GenAI brings, proposes or is capable of bringing to the financial institutions are through fundamental transformations rather than just improvements. We have identified and headlined the following values that are mentioned by our experts: customer experience, operational efficiency, and risk reduction. We concluded that these dimensions are interconnected, which means they form a value ecosystem where improvements in one area often catalyse benefits in the others. Table 5 quantifies value occurrences across participants.

Table 5. Value Propositions

Value Dimension	Occurrence	Participant References
Customer Experience	9	I-00, I-01, I-02, I-03, I-04, I-05, I-06, Claude, GPT-4.1
Operational Efficiency	8	I-00, I-02, I-04, I-05, I-06, I-07, GPT-4.1, Claude
Risk Reduction	6	I-04, I-05, I-06, I-07, Claude, GPT-4.1

4.2.1 Customer Experience

As Claude noted, this creates "the new norm of personalisation" for every customer, previously only available to high-net-worth clients. The transformation extends to proactive relationship management, where systems anticipate needs based on transaction patterns rather than reacting to requests. I-07 noted convenience: *"Faster document processing means faster approvals and reduced frustration."* This shift reduces customer effort while building trust, such as fraud alerts before damage occurs or credit advice before applications. Specialists who work in banks reported some secondary benefits too: *"results can increase interest for customers to buy more products, give better satisfaction scores, etc."*

4.2.2 Operational Efficiency

Human experts highlighted efficiency improvements across document processes. As previously mentioned, I-00's note on concrete time savings: *"reducing manual work from 30 minutes to seconds."* I-06 has summarised: *"This way of document processing boosts efficiency, reduces manual labour, and speeds up the delivery."* Participants noted resource optimisation benefits, with I-07 observing: *"Generative AI solves simple problems through automation, freeing staff for complex issues."* According to I-02, this also creates scalability: *"...reduce operational costs while providing 24/7 support."*

4.2.3 Risk Reduction Capabilities

GenAI introduces predictive risk management capabilities that alter security and compliance scopes. Summarising what I-06 explained, in fraud detection, the technology's value is not only faster pattern recognition, but also in simulating novel attack vectors before they happen. I-06 termed this as "preemptive security". In the regulatory compliance scope, I-04 identified: *"generative AI can help also in terms of compliance, to process policies and identify compliance risks."*

4.3 Implementation

Our analysis of implementation strategies identified four dimensions for implementing GenAI value in financial institutions: implementation process, prerequisites, timeframe considerations, and stakeholder alignment. The data revealed a consensus on the importance of methodical and iterative approaches rather than attempting comprehensive transformations. Table 6 is a visual summary for the implementation dimensions we defined across interviews.

Table 6. Implementation Dimensions

Implementation Dimension	Occurrence	Participant References
Implementation Process	8	I-02, I-03, I-04, I-05, I-06, I-07, Claude, GPT-4.1
Prerequisites	8	I-00, I-02, I-03, I-04, I-05, I-06, Claude, GPT-4.1
Timeframe Considerations	5	I-03, I-05, I-06, Claude, GPT-4.1
Stakeholder Alignment	5	I-02, I-04, I-06, Claude, GPT-4.1

4.3.1 Implementation Process

The participants emphasised a disciplined approach for implementation; we have to begin with identifying the problems rather than technology-first thinking. I-04 provided a clear framework: *"First, you need to identify the problem you want to solve. Because if you just start with the technology, you will go nowhere."* This idea was also mentioned by GPT-4.1: *"Start with clear use cases, check data readiness, run small pilots, ensure secure integration, collect feedback, and scale gradually while monitoring outcomes."*

The data showed a framework for phased implementation with internal testing preceding applications. I-03 noted: *"The first step milestone should be testing it internally, I guess. For the internal people, that could be the first step. We implement it, and then we test it internally for the results. And if we are satisfied with it, then we can open it up a*

little to the next step." We had the same idea by I-02 mentioning this is the preliminary step before checking the legal entanglement and the legal aspect of the deployment.

Iterative development is advocated by the participants consistently, with regular evaluation. I-04 explained: *"And then you need to start small and iterate. Because you will never get the perfect solution first."* And Claude elaborated more: *"Develop proof-of-concept implementations in controlled environments with rigorous evaluation metrics. Design an integration architecture that addresses security, scalability, and compliance requirements. Implement human-in-the-loop workflows where AI augments rather than replaces human decision-making."*

An important point mentioned by several participants was the necessity of accepting potential failure. I-04 stated: *"And then you need to also accept you could fail. This is the trickiest one, probably. Because you will invest money, and suddenly you will see, oh, but that doesn't work. And then you continue investing money, but that won't work, right? So you need to be able to say stop"*

4.3.2 Prerequisites

From the analysis, we identified four prerequisites for a GenAI implementation: technical infrastructure, data quality, and governance frameworks.

Technical Infrastructure: Participants highlighted some of the substantial computing resources that are required for a deployment. I-05 gave us some insights also containing premature costs: *"Finding the amount of GPUs, which is the, for example, about a million dollars one server, if you use on premise, or if you use the cloud solutions, it's also very costly, because the training one model is the more than the \$15,000 one time, and hosting also very costly, hosting for the one month is the around the \$20,000."*

Data Quality: In this subsection, data remains the top and most critical prerequisite. The concerns included finding just enough data for training and methods to process it. I-04 stressed: *"Data, data, data, data, data, and data, right? It's easy to do a prototype, right? I can, I'm doing myself, but if you think about how can you put it in production, when do you have enough data..."* I-05 elaborated on the challenge: *"Finding this type of data, very hard amount of data. If you use speech, a version of task, it's, of course, it's also hard, because you should think when you design a system, where you will save your data, and how you will stream this data to your model."*

Governance Frameworks: Participants highlighted the importance of governance structures. Claude noted: *"Regulatory preparation involves creating documentation frameworks for model transparency and explainability. Process preparation requires mapping existing workflows and identifying integration points for GenAI solutions."* I-02 emphasised legal considerations: *"You want to check the legal entanglement and the legal aspect of it. So you want to be sure that if you're using private CCIO or secure information, this information is not saved on a different server or the technical aspect of this technology, where it is going to run, which server it is going to run on, and which*

information is going to be shared."

4.3.3 Timeframe Considerations

However, our outcomes did not fully confirm the precise timeframes that were mentioned in interviews. For now, in this subsection, we will illustrate insights from the interviews, and will keep the discussion for the next and dedicated section. At this point, I-05 was also cautioned against precise estimates: *"You cannot say which time, because in engineering, especially in the computer science fields or software engineering or in machine learning, you cannot give an exact estimation with days or months."* He added: *"It's dependent on the qualification of the engineers in your team, because I will find the engineers, which can sound like egoism, but if I can't find engineers with my qualification, I can't say that I can do this project during three months or five months."* But in general, agreement was noticeable that substantial implementations require extended periods. Claude provided the most specific estimate: *"A basic financial copilot can be implemented in 6-9 months, starting with targeted use cases like research assistance or customer inquiry support. However, a comprehensive enterprise-grade solution integrated across multiple departments typically requires 18-24 months. The timeline depends significantly on data readiness, existing AI infrastructure, and organisational change capacity."* I-03 also offered a broader timeframe: *"I think it will take like around two, three years more to overcome these kinds of challenges."*

Participants emphasised that implementation should be viewed as an evolutionary process rather than a one-time project. Claude noted: *"The implementation should be viewed as an evolutionary process rather than a one-time project, with continuous improvement cycles built into the roadmap."* GPT-4.1 advised: *"A pilot can be ready in 6-9 months; a fully integrated system across departments may need 18-24 months."*

4.3.4 Stakeholder Alignment

Securing stakeholder support emerged as a critical success factor in our analysis. I-04 emphasised: *"Yeah, for sure, you need sponsorship, but I guess this is, you know, this is always the case in any project. But since we are talking about new technology experimentation, probability of failure, then probably you need to have executive sponsorship."*

Claude highlighted the importance of strategic alignment: *"Start by aligning GenAI initiatives with specific business objectives for each department rather than pursuing technology for its own sake. Develop clear ROI models showing tangible benefits in terms meaningful to different stakeholders—cost reduction for operations, revenue enhancement for sales, risk reduction for compliance."*

LLM participants recommended demonstrating early value to build momentum. Claude advised: *"Create early proof-of-concept demonstrations that address recognised*

pain points. Establish a cross-functional steering committee with representation from all key departments. Implement phased deployment approaches that demonstrate value quickly before scaling." GPT-4.1 concurred: *"Align GenAI projects with business goals, show early results, involve all departments from the start, and communicate benefits clearly."*

I-02 recommended a structured approach to customer adoption: *"Then you can start to have a better version for a selected section of customers. Then you perform A-B testing. And then once you are satisfied with the results and the performance, you can scale up and go to a higher, to more segment of your customer. And then eventually you open to all your customers."*

4.4 Challenges

The thematic analysis shows us strong participant consensus when we try to define risks and challenges. This is evidenced by high occurrence intensity and references. The identified challenges include data privacy and security concerns, legal compliance requirements, model hallucination issues, integration barriers, skill gaps, and cost considerations. Table 7 illustrates categorised challenge occurrences. These findings cluster into technical, regulatory, and legacy domains that require coordinated mitigation strategies.

Table 7. Challenge Categories

Challenge Category	Occurrence	Participant References
Data Privacy & Security	9	I-00, I-01, I-02, I-04, I-05, I-06, I-07, Claude, GPT-4.1
Legal Compliance	9	I-00, I-01, I-02, I-04, I-05, I-06, I-07, Claude, GPT-4.1
Legacy Resistance	6	I-02, I-04, I-05, I-06, I-07, Claude
Model Hallucination	6	I-00, I-01, I-02, I-03, I-05, I-07
Integration	6	I-02, I-03, I-05, I-06, Claude, GPT-4.1

4.4.1 Technical Challenges

We decided to group technical challenges into 2 core domains: model reliability, integration.

Model Hallucination: Participants consistently reported accuracy concerns. I-01 warned: *"The model sometimes will get hallucinated... it is pretty thing like which is not going to be the real."* I-05 also explained hallucination: *"Hallucination is not good... if the model is generally trained with less amount of data and if you're asking critical questions it will end up in hallucination."*

System Integration: Integration from existing infrastructure created obstacles. I-05 described: *"Integration process is very, very painful because you have the existing system, you have the existing architecture."* Claude also commented on the technical ecosystem that needs to be prepared: *"The deployment of generative AI models in financial environments presents substantially greater operational complexity than traditional software implementation. Financial institutions must establish a comprehensive machine learning operations infrastructure on cloud platforms, which encompasses not just the technical deployment but also robust governance frameworks, model monitoring systems, and specialised data pipelines. This expanded operational footprint creates significant integration hurdles when merging GenAI capabilities with existing financial systems and workflows."*

4.4.2 Regulatory Challenges

Compliance requirements created complex implementation constraints across two domains.

Data Privacy: *"The legal aspect is still a nightmare and there are still lots of discussions."* Answers related to data privacy concerns were the most dominant during discussions. We got lots of similar occurrences to support the quote by I-02 mentioned in the beginning. As a result, we can fairly set *"Data privacy concerns"* as the primary barrier.

Legal Compliance: According to most participants' mentions about legal compliance, we can say that explainability requirements conflicted with technical capabilities. In addition to what I-05 warned us earlier about how *"we cannot use vast language models for risk assessment"*, we got confirmations from the majority of the experts similar to: *"Regulatory constraints create tension with the black-box nature of many GenAI models."*

4.4.3 Legacy Challenges

From the results of the analysis, we can divide organisational challenges into human and cultural factors.

Legacy Resistance: The legacy barrier was the first answer of I-02 whilst asking about the challenges: *"The difficult part is the legacy part ... banks or this kind of old corporate company, they might tend to be very conservative for safety reasons, for security and other bureaucratic reasons"*. We understood that the biggest challenges include data privacy concerns and a lack of explainability in model decisions. We came to this summary as a result of what was also extensively explained by the participant I-06 during the interview. Institutional inertia hampered implementation. I-07 also had supportive notes: *"Managers say we do not need it... people think generative AI could*

cost a lot of jobs." Claude added: *"There's resistance from internal stakeholders unsure of the technology's reliability."*

Skill Gaps: As far as we understood, because the tech is still very new, there are expertise shortages causing limited execution. I-05 identified: *"Lack of knowledge in the engineers... all engineers should know how work recurrent neural networks, LSTMs, GRU, etc."*

Cost Considerations: In contrast to what we were expecting before conducting interviews, economy-related answers were not the top hit by the experts. However, mostly by LLM participants we observed that uncertainty relating to this challenge is slowing down the investment and consequently the development. GPT-4.1 noted: *"The uncertain return on investment timeline further complicates budget justifications, as the operational efficiencies promised by GenAI implementations typically materialise over extended timeframes rather than providing immediate financial returns. Organisations frequently encounter unanticipated scaling costs when moving beyond pilot programs, as computational requirements for large language models can increase exponentially with deployment scope. Furthermore, financial institutions face unique cost considerations related to regulatory compliance, where establishing robust governance frameworks for AI systems demands significant investment in validation processes, documentation systems, and audit mechanisms."*

4.5 Future Impact

"What will be different tomorrow?" based generic question led us to get most of the answers on the future impact of GenAI in financial industries. The analysis based on those answers revealed four dimensions for the impacts: the transformation of human roles, democratization of financial services, hyper-personalisation, and competition conditions. The results demonstrate to us that the next generation of financial services delivery will have fundamental changes with GenAI implementations, though participants differed in their timeframe projections and emphasis on specific aspects of this transformation. Table 8 summarises the future impact dimensions identified across participant interviews.

Table 8. Future Impact Dimensions

Impact Dimension	Occurrence	Participant References
Evolution of Human Roles	8	I-00, I-02, I-03, I-04, I-05, I-07, Claude, GPT-4.1
Competitive Landscape	6	I-01, I-02, I-04, I-07, Claude, GPT-4.1
Democratization	5	I-00, I-04, I-07, Claude, GPT-4.1
Hyper-Personalization	5	I-01, I-03, I-04, Claude, GPT-4.1

4.5.1 Human Role Evolution

The most consistent prediction centred on evolving human functions. Claude outlined this transformation: *"Human roles [will shift] toward higher-value activities... Decision-making will become more data-driven but paradoxically more human-centred as AI handles routine analysis, freeing humans to focus on relationship building and complex judgment."* This idea was supported by the expert I-02 with an example case: *"You can reduce 100 people, 100 personnel to 30 personnel. And these 30 personnel can focus on the most difficult question that ChatGPT is not able to answer or is not able to answer properly with the right level of precision... And then you can keep paying 30% of the people which are going to do a better job because they are not working on the stupid question that can easily get answered. Moreover, I-05 added a caution: "We cannot remove human moderators completely due to hallucination risks - this requirement stays for the foreseeable future."*

I-07 noted how employees would develop new competencies: *"As employees learn to work with GenAI tools, they gain skills in data engineering, and digital confidence."* This perspective indicates that while some job functions will be automated from the current industry, new skills will be required within the industry of the future.

4.5.2 Democratization of Financial Services

Some participants predicted democratization to be a transformative outcome in financial expertise. I-04 was one of them, and his answer to the question above was: *"Democratization of finance. Meaning that I did an experiment on medium. I mean, this was just a prototype. But if you want to invest in a portfolio, you have different ways of investment, depending on the context of certain criteria. And right now, these models are very proprietary, or you have to pay a lot of money to get the financial advisor to help you, right? So, probably generative AI will help to democratize this kind of financial advice, tax advice."* To understand the democratization in finance better, we

will summarise the quote and the remaining conversation that has an example case. In the pre-GenAI scenario, personalised investment advice is restricted to individuals who can afford dedicated financial advisors. And the typical customers with modest savings had access only to generic advice. However, in the post-GenAI scenario, a bank implements a GenAI-powered financial copilot that is capable of analysing individual customer financial data to generate personalised investment strategies for every customer.

Claude expanded on this theme: *"Financial expertise will become more democratized, reducing the advantage of scale while increasing competition based on service quality and customization."* GPT-4.1 highlighted specific impacts: *"GenAI will make services more efficient and personalized, help smaller players compete, and shift human roles to more strategic work."*

4.5.3 Hyper-Personalization

The dimension anticipated the next generation of customisation. I-03 predicted: *"Generative AI would learn from datasets to improve answers continuously, creating truly personalised guidance."* Claude described: *"Interfaces will adapt to individual knowledge levels and specific financial situations."* GPT-4.1 contrasted current limitations: *"Future solutions will anticipate needs and deliver clear, tailored guidance unlike today's generic support."* Claude detailed how this would impact customer experience: *"Key benefits include true personalization beyond simple segmentation, with recommendations and interfaces adapting to individual customer needs and preferences. Conversational interfaces will enable natural interaction with financial services without navigating complex menus or forms. Proactive guidance will replace today's reactive support models, with systems identifying potential issues or opportunities before customers are aware of them."* I-04 predicted that this emerging feature will become the next competitive field in banking.

4.5.4 Competitive Landscape

Our research showed that the use of GenAI would change the competitive dynamics of the financial industry. I-02 predicted that those who are not using GenAI will have a disadvantage in the long term, because those who implemented the GenAI solution properly will benefit from the values mentioned earlier in the changing dynamics of the financial services.

Claude elaborated on how competitive dynamics would shift: *"Financial expertise will become more democratized, reducing the advantage of scale while increasing competition based on service quality and customization. The investment is absolutely worthwhile—institutions that successfully implement these technologies could see 15-30% improvements in efficiency ratios and significantly enhanced customer satisfaction."*

Those that delay risk falling irreparably behind as customer expectations evolve toward AI-enhanced experiences."

I-01 and I-07 had similar answers to the question, "Would it be worth spending money/resources to deliver this technology?" to get the ideas on whether the substantial investment cost would be redeemed. Their answer was positive, just as all the other participants, and their supportive argument was: *"If you don't want to be a step behind than the other competitors."*

GPT-4.1 summarised the competitive rationale: *"The investment is justified as it drives both cost savings and better customer experiences."* This perspective underscores that while GenAI implementation requires substantial upfront investment, competitive pressures may ultimately make adoption necessary for institutional survival.

5 Discussion

This thesis section discusses the results and presents a framework correlating applications, their values, implementation strategies, challenges, and the future of the sector.

The first research question of this thesis is: "What are the potential applications of GenAI in the Finance sector?". The results show that the use cases could be grouped under three categories: customer service, operational efficiency, and improved analytical capabilities. Customer service was the most widely mentioned (by all participants) and implemented application domain, with chatbots representing the foundational use case. This aligns with industry reports identifying conversational AI as the most mature implementation area [23]. Traditional chatbots have historically relied on rule-based decision trees with limited ability to respond to queries. According to our findings, GenAI brings an evolution at the fundamental level to improve beyond this paradigm. As I-03 noted, these systems now perform *"24/7 queries without human intervention"* with a level of human-like interaction previously unattainable. This advancement supports the idea that it is not just an incremental improvement; it is a paradigm shift from scripted responses to contextual understanding. However, while customer service applications showed high adoption consensus, there was variation in how participants viewed their sophistication. Technical specialists (I-05, I-02) expressed more cautious opinions about current capabilities, while those in strategic roles (I-04, I-06) described more advanced implementations. This suggests a gap between aspirational use cases and reality that warrants further research. The operational efficiency domain encompasses applications that transform internal workflows and processes. Document processing was a frequently mentioned application in this domain. What distinguishes GenAI document processing from traditional solutions is its semantic understanding capabilities. Traditional automation required structured templates and was not flexible with variations in document format, while GenAI's contextual understanding accommodates variations [36, 35]. This represents an advancement over previous generations of automation technology. The resource optimisation pathway demonstrates how GenAI is transforming the economics of knowledge work in financial institutions. By encoding institutional knowledge that previously resided only with human specialists, organisations can ensure consistent application of complex rules while reducing the dependency on individuals [21]. The discussion reveals GenAI's potential to make institutional knowledge more accessible and deployable. An observation is that operational efficiency applications appeared most mature in document processes, rather than transaction processing. This shows that GenAI's current strengths align better with unstructured data processing than with structured data manipulation, where actions by specialists may still hold advantages in applications. The advanced analytical capabilities domain represents the most technically sophisticated yet least widely implemented application area in our findings. Although fraud detection, risk assessment, and compliance monitoring were mentioned by multiple participants, there was divergence in how participants viewed

their maturity and appropriateness. Counter-ideas emerged between technical potential and operational reality in this domain. While some participants described applications where GenAI identifies "novel fraud typologies" and "simulates thousands of economic scenarios," others cautioned that these remain "supplementary tools" requiring human validation and are subject to discussion on the legacy and legal levels.

It seems that GenAI applications in finance suggest that transformation is occurring rapidly in domains with lower regulatory barriers and where the technology's strengths in processing unstructured data and natural language provide advantages over previous technologies. The observed patterns indicate that GenAI is not only accelerating existing processes, but fundamentally transforming the way financial institutions deliver value to customers.

The second research question was structured as: "What values does GenAI bring to the Financial Industries?". We classified the value proportions into 3 groups: customer experience, operational efficiency, and risk reduction. As already mentioned in the previous paragraphs, participants consistently mentioned customer experience enhancement as GenAI's widest application, as well as its value proposition. This dimension transcends simple chatbot implementation by representing a paradigm shift in financial service delivery. Institutions utilise GenAI to overcome traditional accessibility barriers through 24/7 multilingual support systems that eliminate wait times. This is valuable for time-sensitive financial decisions. More profoundly, the technology enables hyper-personalisation at scale, moving beyond demographic segmentation to behaviour-based customisation of advice and products. We can see that another value that GenAI delivers is efficiency, and the key point of this achievement is reengineering the fundamentals of financial workflows. GenAI achieves time savings by replacing manual work with contextual understanding. Specifically, participant I-00's explanations about the 30 minutes of gain on the expert work automated to seconds with higher accuracy, are supportive notes for this result. The risk reduction value extends beyond loss prevention to strategic advantage. Institutions using GenAI for credit scoring reported expanded markets through alternative data analysis while maintaining portfolio quality [2]. We also observed cross-dimensional value relationships such as improved fraud detection (operational efficiency) enhances security (risk reduction), and this reduces false declines (customer experience). However, participants emphasised this requires careful calibration; I-05 warned that unexplainable models create risks from a legacy perspective, even though they are statistically superior. The consensus view positions GenAI as enhancing rather than replacing human judgement in risk contexts, creating layered defence systems where algorithms handle pattern recognition while experts focus on anomaly investigation [25].

The third research question was formulated as: "How to deliver the values that GenAI promises for Financial Institutions?". To discuss the results, we grouped the findings under four dimensions: implementation process, prerequisites, timeframe considera-

tions, and stakeholder alignment. The difference in the implementation from traditional IT deployments is that participants emphasise a problem-first approach rather than a technology-first approach. I-04's framework that "you need to identify the problem you want to solve, because if you just start with the technology, you will go nowhere" represents a departure from conventional technology implementations where solutions are often predetermined. This finding aligns with the literature on AI implementation that emphasises business-problem orientation over technology capability [28]. It seems that iterative, phased approaches need to be taken into consideration, with I-04 noting "you need to start small and iterate because you will never get the perfect solution first." This approach contrasts with traditional waterfall methodologies common in financial services implementations. One aspect of the implementation process seemed to be the acceptance of potential failure. I-04's observation that "you need to also accept you could fail... you need to be able to say stop" represents a challenge for risk-averse financial institutions. This requirement for an experimental mindset suggests that successful GenAI implementation may require fundamental changes in organisational culture rather than simply acquiring new technology capabilities. Prerequisites revealed that implementation success depends more on organisational readiness than technical barriers. Although computing resources were acknowledged, I-05 mentioned "million dollar servers" and "\$20,000 monthly hosting costs"—the most critical barriers centred on data quality and governance frameworks. I-04's repeated emphasis on "data, data, data" highlights how GenAI implementation is constrained by data availability rather than computational power. This finding challenges assumptions that GenAI implementation is primarily a technology challenge, revealing instead that organisational data maturity represents the primary success determinant [30]. The prerequisite of the governance framework appears to be complex due to legal requirements [9]. I-02's emphasis on "legal entanglement and legal aspects" reflects how compliance considerations must be built into GenAI systems from the initial design phase, rather than being added later, which distinguishes GenAI implementation in finance from technology deployments in less regulated industries. The findings on timeframe considerations were controversial between human experts and LLM participants. While humans are cautious about precise estimates, LLMs could predict timeframes. According to research on LLM performance on timeframe forecasting, LLMs can lack formal mechanisms for uncertainty quantification and may struggle to improve accuracy across diverse application domains [26]. At this point, we can discuss that while LLM predictions on this domain may not be 100% accurate, it may only help to have a general idea. To remember the uncertainties, we can look into I-05's observation that "you cannot give an exact estimation" due to the experimental nature of the processes, while implementing a fundamental challenge for institutions. Stakeholder alignment emerged as requiring value creation rather than achieving buy-in. A recommendation to develop clear ROI models showing benefits in terms meaningful to different stakeholders, reflects the challenge that organisational functions evaluate value using different metrics

and timeframes. The distributed ownership approach, illustrated by another recommendation to assign people within each department as ambassadors, suggests that successful implementation requires new organisational structures for cross-functional collaboration rather than traditional mandates.

The fourth research question is: "What are the risks and challenges associated with GenAI implementation in Financial Industries?". The results reveal three barrier types: regulatory (data privacy, legal compliance), organisational (legacy resistance, skill gaps), and technical (hallucination, integration). The regulatory barriers appear fundamental, restricting applications regardless of technical capability. Organisational barriers are persistent, requiring cultural transformation that may take years to achieve. Technical barriers, while important, seemed to be more amenable with technology and engineering development. Data privacy and security emerged as the most frequently cited challenge, together with legal challenges, mentioned by all participants, reflecting the sensitive nature of financial data. This finding is consistent with financier report identifying regulatory compliance as the primary barrier to the adoption of AI in financial services [34]. The explainability paradox represents a core challenge where financial regulations demand transparent processes while GenAI models operate as "black boxes" with limited interpretability. I-05's warning that "we cannot use vast language models for risk assessment" because institutions cannot explain model decisions reflects how regulatory constraints create barriers to GenAI deployment in banking [29]. Legacy resistance represented an organisational challenge, with I-02 identifying the "legacy part" as a primary implementation barrier, noting that banks might tend to be conservative for safety reasons. The evidence suggests that this resistance operates on multiple levels, encompassing both technological inertia and cultural reluctance to embrace change. What emerges from the data is that conservatism in financial institutions, traditionally considered a strategic advantage for maintaining stability, has now become a disadvantage when implementing GenAI technologies. The technical barriers covered both model reliability and system integration challenges that undermine the feasibility of GenAI deployment. Model hallucination seemed as a reliability concern. According to a study by Oxford researchers, LLMs are likely to generate plausible but incorrect information. This advancement could mitigate risks in applications in the finance domain, where inaccuracies can have serious consequences. [17]. The integration complexities compound these technical challenges. From the results, integration challenges extend beyond system connectivity to require architectural transformation of existing financial infrastructure. The implication is that institutions face the choice between maintaining existing systems with limited GenAI integration or undertaking larger changes that may be expensive and risky.

The last research question addressed in this thesis is: "What will be the future impact of GenAI implementation in Financial Industries?". The findings reveal a transformation underway in financial services. We can discuss the findings under four dimensions: hu-

man role evolution, democratization, hyper-personalisation, and competitive realignment. Participant consensus indicates these changes represent not incremental improvements but a paradigm shift in how financial services are structured, delivered, and consumed. The evolution of human roles is predicted to be the most consistent transformation. It is predicted that human roles will shift toward higher-value activities. Decision-making will become more data-driven but paradoxically more human-centred. It is expected to have AI-driven job transformation, but to extend it, a dual-path evolution will occur: while junior roles are automated, mid-career professionals are being upskilled into hybrid AI supervisors. Supporting idea also raised by I-05 due to hallucination risks suggests a permanent human-AI co-dependency. The democratization of financial services represents a transformative outcome that could reshape industry access patterns. I-04's observation about making financial advice accessible reveals how GenAI could eliminate barriers to personalised financial guidance. The data suggests that democratization makes financial analysis capabilities available to customers regardless of their wealth levels or location. This challenges the traditional economics of financial advice, where personalised guidance has been viable only for clients with high asset levels. Democratization will alter dynamics by enabling smaller institutions to offer services previously available only from large institutions [16]. Hyper-personalisation represents the most technologically certain but ethically complex shift. GPT-4.1's contrast between "*today's generic support*" and "*anticipatory guidance*" was operationalised by Claude's examples of interfaces adapting to individual literacy levels. However, I-04's prediction that this becomes "*the next competitive battlefield*" raises questions about data ethics absent in current literature. The implementation of such systems (e.g., adjusting advice based on spending behaviour) could create personalisation divides where customers receive service, an inverse discrimination effect requiring regulatory attention. The competitive landscape transformation appears inevitable based on participant answers about GenAI's strategic necessity. I-02's prediction that "those who are not using GenAI will have a disadvantage in the long term" reflects the belief that GenAI adoption represents a competitive imperative. For now, it seems like competitive advantages will compound over time for those who invest for the long term rather than those who save costs in the short term. Claude's projection of "15-30% improvements in efficiency ratios and enhanced customer satisfaction" suggests that GenAI benefits will be substantial enough to create gaps between early adopters and laggards. This dynamic suggests that GenAI implementation may follow a pattern similar to previous financial technology adoptions where late movers face difficult catch-up challenges [37].

5.1 Limitations

This thesis acknowledges several limitations that may affect the interpretation and generalizability of the findings. The relatively small sample of eight human participants plus two LLM models may not provide as comprehensive an overview as a larger study would

offer. GenAI implementation in financial services encompasses diverse organisational contexts and regulatory environments. Although efforts were made to gather participants with various roles and experience lengths, a larger number of participants could reveal different perspectives not captured in this study.

The rapidly evolving nature of GenAI technology presents challenges for research validity. The discussions around AI implementation in the financial industries change continuously, with new regulations, capabilities, and use cases. This dynamic environment makes it difficult to capture all potential applications and ensures that findings may become dated as the technology matures. Several participants could only discuss certain implementations broadly without providing specific details due to confidentiality agreements or proprietary concerns, which can be a limitation on the depth of technical insights available.

Methodological constraints need consideration regarding potential interpretative bias. Having a single person conduct interviews, perform transcriptions, and execute thematic analysis introduces the possibility of human error and misinterpretation of participant responses. To mitigate these concerns, several validation measures were adopted: reflexivity through maintaining detailed notes throughout the analysis to document decisions and reduce bias, triangulation by cross-validating manual checking with AI-assisted outputs, and data presentation where themes were supported by quotes from participants to analyse the depth and context of their responses. However, these measures cannot entirely eliminate the possibility of researcher bias.

Another potential limitation relates to question interpretation during interviews. While the qualitative methodology allowed for clarifying conversations and follow-up questions when responses were unclear, several participants noted the complexity and significance of the research questions. The multifaceted nature of GenAI implementation sometimes required participants to address questions from multiple technical, regulatory, and organisational perspectives simultaneously.

Finally, the study's scope is limited to current perceptions and early-stage implementations. Many participants discussed potential use cases rather than deployed systems, which may not reflect the practical realities of large-scale GenAI implementation in regulated financial environments. The current industry enthusiasm surrounding AI technologies may have influenced participants toward more optimistic assessments than warranted by actual operational experiences, representing a potential response bias that should be considered when interpreting findings.

6 Conclusion

This thesis aimed to investigate GenAI in financial industries, addressing five research questions that examined applications, values, adoption strategies, challenges, and future impacts. Through a qualitative research methodology involving semi-structured interviews with eight industry experts and two AI models, this study sought to provide insights into how financial institutions are navigating the GenAI transformation.

The research methodology employed thematic analysis to examine participant perspectives across diverse roles within financial services, including risk management, technology implementation, compliance, and strategic planning. This approach enabled the identification of key themes and patterns that illuminate both the opportunities and obstacles facing financial institutions in their GenAI adoption journey.

To summarise the findings, GenAI applications in financial services are currently concentrated in four domains: customer service, regulatory compliance support, risk management enhancement, and operational efficiency. These applications demonstrate potential for transforming traditional financial service delivery models, though implementation remains largely in pilot or experimental phases across most institutions.

Values driving GenAI adoption are centred on benefits in operational effectiveness, enhanced customer experience delivery, competitive advantage retention, and adherence to regulatory needs. The research set cost reduction and productivity enhancement as prime drivers, with market positioning and customer satisfaction as strategic priorities guiding investment.

Implementation strategies resulted in a risk-averse, pilot-driven approach in line with the risk-averse nature of financial institutions. Organisations are exploring proof-of-concept pilots prior to wide-scale implementation, with a focus on following regulatory guidelines and addressing risk management throughout the implementation cycle.

Three types of challenges were listed that constrain GenAI deployment: regulatory obstacles encompassing data privacy and legal explainability, legacy resistance encompassing technological inertiality and cultural factors, and technical ones encompassing model reliability and integration complexities. These challenges are seemingly interconnected in that the mitigation efforts require multi-pronged approaches rather than sequential resolutions.

Future impact projections suggest fundamental transformation across four dimensions: evolution of human roles toward higher-value tasks, democratization of financial services through accessible AI-powered advice, hyper-personalisation of customer experiences, and competitive landscape shifts. These changes collectively indicate a paradigm shift rather than incremental improvement in financial services delivery.

This research contributes to the limited academic literature on GenAI in financial industries by providing practitioners' perspectives and implementation experiences. The findings offer practitioner-level guidance to financial institutions developing GenAI strategies while prioritising critical areas that need further study. As GenAI technology

continues evolving and regulatory frameworks develop, further research will be essential to understand the long-term implications of this technological transformation for the financial services industry.

6.1 Recommendation for Future Studies

Based on the findings and limitations, we noticed the need for further studies in certain aspects. Given the small size of human participants in this study, future research would benefit from larger-scale investigations involving more diverse participants. A comprehensive study encompassing participants from different geographic regions, regulatory environments, and organisational sizes could provide more insights into GenAI adoption.

The rapidly evolving nature of GenAI necessitates ongoing research to keep pace with new capabilities. Future studies should establish systematic review processes to evaluate new white papers, industry reports, and technical developments as they emerge. Researchers should consider establishing collaborative frameworks with financial institutions to access real-time implementation data and use cases.

This study revealed disagreements among participants regarding implementation timelines, risk assessments, and strategic priorities. Future research should specifically investigate these viewpoints to understand the factors driving different organisational approaches to GenAI adoption.

While this study captured broad implementation challenges, future research should examine specific technical aspects in detail, including integration architectures, data governance frameworks, and model validation processes.

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Appendix

I. Interview Guide

1. Warm-up questions.

- Where do you currently work and if you can tell about your position and responsibilities?
- How many years of experience do you have with Generative AI and within the financial sector?

2. RQ related questions.

(a) Potential applications of GenAI related questions:

- What recent advancements in GenAI have you noticed specifically within the financial industry?
- Can you provide examples of successful GenAI implementations in finance that have delivered value to both organizations and customers?
- What are the in-progress or potential use cases of GenAI in financial processes or services that you think will deliver value to organizations or customers?
- How can _ use-case (from previous answers) of GenAI impact different aspects of financial services, products, and processes?

(b) The values of GenAI related questions:

- In what ways the implementation of the use-case _ can benefit companies or organizations within the financial industry?
- (Follow-up) More specifically, who, exactly which department benefits and how?
- In what ways can the implementation of the use-case _ benefit customers of the financial industry?
- How do you measure the success or effectiveness of GenAI implementations in financial institutions?

(c) Questions on “How to deliver the values?”

- Can you outline the key steps involved in successfully integrating GenAI solutions into existing financial systems and workflows?
- What background do you think needs to be prepared to deliver the products?
- How can you ensure support from stakeholders across different departments or functions within a financial organization?

(d) Challenges of the implementation of GenAI-related questions:

- What do you think are the challenges that prevent the implementation process of GenAI in the financial industry?
- What do you think are the challenges considering the implementation process of GenAI in the financial industry in a progression state?
- In your opinion, what needs to be prepared or to be done to overcome these mentioned challenges? Feel free to specify multiple strategies for different challenges.
- In your opinion, what time frame is needed to finish up _ solution?

(e) Affection of GenAI implementation in Finance related questions:

- In general, how do you think these implementations will change the future of financial industries? Would it be worth it to spend so much time and resources to deliver the values mentioned?
- What do you think is considered a benefit if GenAI implementation is going to be used to _? How would it differ from today's solution?

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