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Transformative Evolution: A Comprehensive Study on FinTech's Transformation with Emphasis on Leveraging AI Copilot for UX Enhancement.

Investigating User Experience in Fintech System with AI Copilot in Collaboration with SimCorp.

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ABSTRACT

The thesis explores the integration of Artificial Intelligence (AI) technologies to enhance Product Development in the transition of Simcorp, a leading fintech company, from legacy software to modern frameworks. The research aims to identify potential AI applications, assess their feasibility, and impact, and understand the challenges and opportunities associated with their implementation. This research explores the perspectives of financial institutions, specifically Simcorp, on the effectiveness and challenges of integrating AI technologies, such as Azure OpenAI, into their modern web solution. The study is grounded in qualitative data collected from interviews with Product Manager, Portfolio Manager, and a Software Engineer involved in the AI integration process at Simcorp.

Through a comprehensive literature review, desk research and observation key AI techniques and tools relevant to product development and portfolio management are identified. Through thematic analysis, key challenges and insights were identified, providing a comprehensive understanding of the obstacles and potential benefits associated with AI adoption in financial software. The findings reveal several critical challenges. Firstly, both the Product Manager and Software Engineer emphasized performance issues, particularly the need for consistent performance of AI models to ensure user adoption. High data volumes and complex calculations often result in slow performance and top of that not having appropriate technology stack often hinders the effectiveness of the AI tools. This performance challenge and to leverage the company's transition to the modern engineering, the need of AI tool is seen in the organization. The management team believes the integration of AI into their new web solution would highly benefit the users/clients in making the informed decision and saving the time.

Data privacy and security emerged as another significant concern. The Product Manager highlighted the importance of educating clients about data privacy to alleviate fears of their data being used for model training. Ensuring that client data is not shared across clients or with external parties like OpenAI is crucial for building trust. The Software Engineer supported this view, stressing the need for a secure platform, such as Azure, which guarantees not sharing prompts or embeddings for future model training.

Through interview with the Portfolio Manager, it was found that while AI can enhance decision-making by providing valuable insights and recommendations, there are significant concerns regarding the trustworthiness of AI-generated data. These concerns include the reliability of AI training data, the clarity of AI suggestions, and the potential for AI to make errors or exhibit biases. Despite the potential benefits and ability, portfolio managers often prefer manual execution of decisions due to lack of convincing explanations from AI systems. This study highlights the need for improving AI transparency and trustworthiness to better support portfolio managers in their roles.

The study also uncovered challenges related to the limitations of AI models. Addressing hallucinations in AI responses by using precise prompts and performing calculations on the API side is essential to ensure the accuracy and reliability of AI-generated outputs. Additionally, evaluating whether AI is the best solution compared to traditional development methods and estimating the cost of using AI models based on token usage present significant hurdles.

Further, the transition from legacy systems to AI-integrated solutions poses considerable difficulties. The Software Engineer pointed out the extensive effort required for transitioning from a long history of legacy systems, which are massive and often have outdated UIs. This transition requires significant resources and time, making it a challenging but necessary step towards modernizing financial software.

Despite the challenges, the study found that AI technologies offer promising benefits, such as speeding up investment decision-making and enhancing the user experience by providing outcome-based solution. The AI copilot tool, for instance, simplifies information retrieval and graph generation, assisting portfolio managers in

the decision-making process. The AI copilot is looked as a central information hub/provider which has power to fetch all the relevant data or say information at one point and top of that it has the ability to summarise the data, helping clients and users make informed decisions more efficiently.

This research contributes to Simcorp's journey towards AI-driven portfolio analysis within its evolving software landscape, drawing insights from information science, computer science, finance, and business management.

Keywords: Fintech, Product Development, Artificial Intelligence, User Experience, Qualitative Data Analysis, Interview, Observation, Think-aloud, Retrieval-Augmented Generation (RAG).

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1 INTRODUCTION

While the concept of financial technology, or fintech is not a novel concept (Berger, 2003; Mareev, 2016; Shim & Shin, 2016; Razzaque & Hamdan, 2009), recent developments have pushed it into a new era. fintech serves as a bridge between the financial industry, information technology (IT), and innovation (Siddiqui & Rivera, 2022). The term *FinTech* is derived from the fusion of finance and technology, encapsulating the essence of its meaning – the use of technological advancements and innovative ideas to strengthen financial services. It encompasses the broad spectrum of technologies such as cloud computing and mobile internet, and their integration into financial services like loans, payments, and money transfers. It is presumed that fintech competes with banks because its services and offers include new and creative services that replace those offered by banks (Puschmann, 2017).

Numerous scholars have delved into the phenomenon of fintech, exploring its historical roots, evolution, and underlying concepts. Despite extensive research on fintech or financial institutions and also on banking sector, existing scholars have not immensely delved into the integration of AI in these sectors especially in the fintech sector, where my interest lies. Thus, this research has made an attempt to provide insights into this matter.

The rapid evolution of technology in the product development fields, be it software development, web development, strategy development or any others, has prompted fintech companies like Simcorp to reassess their software infrastructure and explore new avenues for innovation. As Simcorp continues to utilize its existing backend technologies such as .NET and APL, alongside XAML/GUI and Excel frameworks, it is also taking steps in adopting and adapting to its frontend technologies. The company is now embracing modern front-end technologies like Angular and Micro Frontends Architecture, while also adopting Micro Services Architecture to organize its software into smaller, more manageable pieces. Additionally, Simcorp is transitioning towards Azure Dev Environment and implementing SCSS for enhanced web user interface (UI) design. Concurrently, the company is embarking on an exploration of integrating AI into its portfolio analysis and management processes. This transition marks both opportunities and challenges for the company. On one hand, there is the potential to significantly enhance portfolio analysis capabilities through better enhanced UI/UX and backed up by AI-driven insights. On the other hand, Simcorp must navigate the complexities of adapting to the changing technological landscape and ensuring a smooth integration of AI technologies.

The idea of AI has an interesting history, starting with Alan Turing in 1945 (Long, Lin, Cai & Nong, 2020; Cai, 2019). John McCarthy is credited with envisioning the term 'AI' in 1955 (McCarthy et al., 2006). Essentially, AI refers to systems that can learn by themselves, get better over time, and process lots of information quickly (Plastino & Purdy, 2018). The main aim of AI is to help make decisions by finding important insights from big and complicated sets of data (O'Leary, 2013). AI is a big deal because it is changing the way things work in many industries (Brock & Von Wangenheim, 2019). Advances in AI, especially in prediction, are making it possible to make decisions in situations where it was hard or expensive before (Agarwal, Gans, & Goldfarb, 2019; Cao, 2022). Machine Learning (ML) is a part of AI that is all about finding connections between different things (Lehr & Ohm, 2017; Zhongzhi, 2019). The number of ML products is growing super-fast because we have more data and better ways to analyse it (Kreuzberger, Kühl & Hirschl, 2023).

Looking at the big picture, the AI market is expected to grow a lot in the coming years, reaching half a trillion U.S dollars by 2024 and 1.5 trillion U.S dollars by 2030 (Thormundsson, 2022). It is predicted that AI will boost the global economy by 10% by 2030 (Gillham, 2017, pp. 6-8), 16% by 2035 (Bughin et al., 2018), and increase productivity by 40% by 2035 (Purdy & Daugherty, 2017). According to a study by Reilly, Depa, and Douglas (2019), 84% of executives believe that implementing AI is crucial for achieving growth goals, even though 76% say they face challenges in doing so.

1.1 ABOUT SIMCORP

Simcorp operates within the financial technology sector, specializing in providing software solutions for asset managers, investment managers, portfolio analysis and other financial institutions including banking sectors. Established with a vision to streamline and optimize investment management processes, Simcorp offers a range of innovative software solutions tailored to meet the diverse needs of its customers/clients worldwide. With a focus and effectiveness, Simcorp has consistently adapted to the evolving landscape of technology and finance.

In around 2019, Simcorp recognized the importance of modernizing its user-interface and user-experience, as well as adopting modern engineering frameworks like Angular and embracing cloud computing and DevOps practices. This strategic decision was aimed at aligning with current industry trends and ensuring its products remain competitive in the market and at the same time embracing the practice of continuously improving from the decades long legacy GUI. Recently, Simcorp has taken steps to further enhance its offerings by integrating Artificial Intelligence (AI) technologies. Collaborating with Microsoft, Simcorp aims to leverage Azure OpenAI to improve its software's market presence and enhance user experience. This initiative reflects Simcorp's commitment to innovation and its dedication to providing cutting-edge solutions to its users/clients.

1.2 AI CONTEXT IN SIMCORP

In the AI Context at Simcorp, the company aims to integrate AI technology as a co-pilot to assist portfolio managers in their daily tasks. Initially, Simcorp plans to utilize features provided by Microsoft to develop an AI-assistant powered by Azure OpenAI. This AI-bot will act as a virtual assistant for portfolio managers, helping them with various tasks related to portfolio management or asset management.

For example, a portfolio manager could ask the AI co-pilot to provide an overview of how a specific portfolio or equity has evolved over the last six months. The AI co-pilot would then generate charts and visualize it on the screen or summarize it in simple human readable text indicating the performance and changes in the interested portfolio that was queried for. Similarly, the co-pilot could be tasked with retrieving relevant documents or information to a particular investment decision. Meaning, it can be asked to find and provide any necessary documents or information that might be relevant to a specific investment decision. This could include past performance reports of any portfolio, analysing the portfolios in the system at the moment, doing market analyses, retrieving latest relevant news from reliable dedicated sources, or simply asking the copilot to stimulate the orders.

The primary goal of integrating AI as a co-pilot is to provide portfolio managers with quick and reliable assistance in generating essential responses or data. By leveraging Microsoft Azure OpenAI, Simcorp aims to empower its users with tools that facilitate informed decision-making in the dynamic world of investment management.

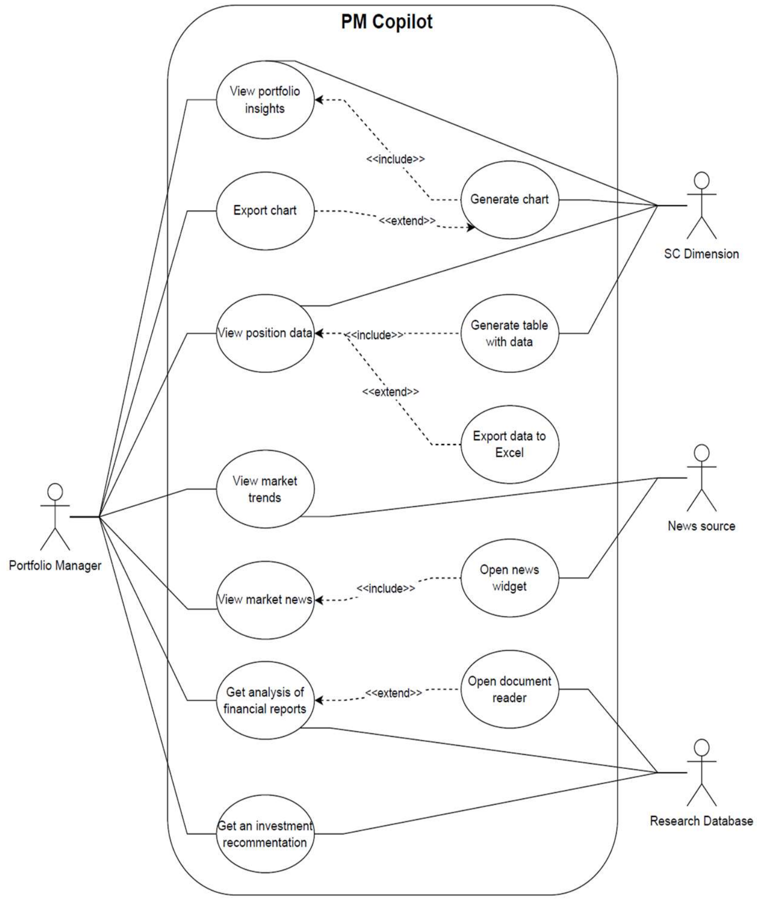

Fig:1, PM interaction with PM-copilot, Use Case Diagram. Generated through *draw.io*.

The use case diagram (UCD) above outlines how portfolio managers (PM) can interact with the system through a chat panel in the new web solution. The PM-copilot serves as an interface where portfolio managers can request various types of information and assistance related to their tasks. PMs can use the copilot to view market trends, access their position data, and obtain portfolio insights. They can also generate charts and grids with the data fetched through APIs from their legacy Simcorp Dimension (SCD) solution. The generated charts or grids then can also be exported to excel for further analysis.

Additionally, the PM-copilot allows the users to open a news widget on command to stay updated with the latest market news and get detailed analyses of financial reports from the news itself or from the internal data warehouse. The tool can also open a document reader for reviewing important documents and provide investment recommendations. However, while the PM-copilot offers a wide range of functionalities to support decision-making and streamline tasks, it does not allow portfolio managers or any users to release orders directly though the chat panel, which we will talk about in the later section of this report.

1.3 PROBLEM DEFINITION AND RESEARCH AREA

In the realm of financial technology, business leaders face a tough decision: whether to use artificial intelligence (AI) or not. Some leaders are really excited about AI and only focus on its intriguing and ever evolving features, forgetting about what employees and customers actually need. Others don't want to try any new innovations and ignore AI altogether, which could make their company fall behind in the fast-changing FinTech world (Pedersen, 2023).

However, prioritizing the client aspect and giving the utmost importance to improving the ergonomic experience for both clients and staff, including fund managers and portfolio managers, is crucial. The digital financial service industry, particularly in the realm of investment decision-making software, is witnessing a continuous evolution. Nevertheless, the need to systematically analyse the current state of user experience and understand its evolution remains vital. In the financial institution's sector, design and user satisfaction is often relegated to a lower level on the scale of priority (Cordeiro & Weevers, 2016, p.36). Investing in user experience (UX) and user interface (UI) design is crucial for financial institutions. With their fund managers, product owners, and portfolio managers navigating complex financial data and workflows, a seamless and intuitive UI/UX is essential for enhancing productivity, efficiency, performance, and overall user satisfaction. Moreover, in a landscape characterized by rapid technological advancements, staying abreast of UI/UX best practices ensures that financial institutions remain competitive and adaptable to ever-evolving market demands.

This thesis work aims to explore how AI can improve/enhance the user experience and decision-making processes at the fintech company Simcorp. Recognizing the importance of balancing technological innovation with improved customer satisfaction, Simcorp serves as a prime environment for this research. My focus as a thesis researcher is on integrating AI copilot that is based on Large Language Model (LLM) and Natural Language Processing (NLP), such as Chat GPT, and engaging with development-related tasks to investigate how Simcorp can assist users/clients and portfolio managers with complex tasks related to making informed decisions. By exploring how LLM-based AI can improve the UX, this study aims to provide insights into streamlining financial processes and increasing user satisfaction.

1.4 PROBLEM STATEMENT AND RESEARCH QUESTIONS

Looking at the rapid growth of AI in almost every aspect of human lives be it at the personal or corporate level, I will aim to explore and provide insight to the following problem statement:

How is AI currently being used in fintech or financial institutions in terms of enhancing the user/client experience, and how AI integration can enhance user satisfaction, user experience and decision-making in the dynamic fintech landscape, particularly within financial institutions like Simcorp? What challenges or risks are associated with AI integration in this context?

The focused research questions that the research aim to address are:

RQ.1) How do financial institutions, specifically Simcorp, anticipate the effectiveness and challenges of incorporating AI technology, into their modern software?

RQ.2) How might AI, particularly Large Language Models (LLMs) like Chat GPT 3.5/4, be leveraged to assist portfolio managers in performing their tasks within the portfolio management/analysis domain?

RQ.3) How do portfolio managers perceive the recommendation generated by AI, and usability of the AI-integrated prototype for viewing portfolios? Are there any challenges in the AI-integrated prototype?

RQ.4) How do stakeholders perceive the trustworthiness of AI-generated content in their financial software solution, and to what extend this perception influence their decision-making processes?

2 STATE OF THE ART

State-of-the-art literature reviews offer a concise overview of the current state of knowledge on a topic, how it's changed over time, and where it might go next (Barry, Merkebu, & Varpio, 2022). This section of the report provides an overview of the current knowledge and advancements in the field of AI integration within the financial technology (fintech) sector. This section is divided into two parts: literature search and literature review. In the literature search, I will explore existing research and publications related to AI implementation in fintech or financial institutions, aiming to gather insights into the latest trends, challenges, and best practices. Following this, the literature review critically examines the findings from the literature search and is compiled as a knowledge build-up, presenting a structured and coherent synthesis of insights that serves as the foundation for the report. Together, this section attempts to offer a comprehensive understanding of the current state of AI integration in fintech, laying the groundwork for my research and analysis in subsequent sections.

2.1 LITERATURE SEARCH

For conducting the literature search, I primarily utilized the AAU library database, Google Scholar, and Elsevier, complemented by searches on online platforms like Medium, LinkedIn, Springer, O'Reilly, ProQuest and other similar blogs/posts/platforms. This approach ensured access to a diverse range of academic and non-academic articles and journals related to AI integration in fintech and on user experience (UX) in financial institutions. The titles and abstracts scanned carefully and quickly to find the relevant literature/content in reasonable time as checking the title and abstract of the title is one of the simplest methods to find contents that is of our interest (Adams et al., 2007, p.49; Fink, 2019). Additionally, I also took documents and exclusive research materials including the huddles (recordings) done internally by the host company to gain the required insight and relevant context.

To ensure relevance and currency, I set the demarcation criteria for articles published within the last 5-7 years, focusing on recent research to capture *enough* content with *broader* contextual information as proposed by Fink (2019). I mostly prioritized *peer-reviewed* studies and research that address AI implementation/integration or those discussing similar contexts. Search terms included topic such as *"UX/UI in financial institutions", "Integration of AI in financial institutions", "UX in FinTech", "AI integration in portfolio analysis and portfolio management", "Future of FinTech", "Challenges and opportunities of AI in FinTech", "Internet of Things*" OR "Smart products*" OR "digitalization" OR "Machine Learning in finance *" OR "Big Data finance", "Trading algorithm*", "Smart products*" OR "Cloud computing", "Deep learning" OR "Neural Networks*", "AI copilot in finance*", "UX in data analytics*", "User experience fintech*".* This comprehensive approach aimed to collect up-to-date and relevant information/literatures to help with researching how AI is used in fintech.

In doing so, I found about 150 articles to begin with that looked related to my research aim. Then, I carefully checked the titles, abstracts, and content of these research materials. I only kept the ones that were closely related to my research topic and provided meaningful insights or citation power. This step narrowed down the list to 50 articles in the final pool, which I aimed to study for my detailed research. Additionally, I referred to relevant books as well and selected chapters that matched my research focus.

2.2 OVERVIEW OF AI

In the first two decades of the twenty-first century, we have seen incredible technological advancements, especially in AI. AI is a part of computer science that makes smart machines capable of doing things like thinking, learning, acting, and understanding speech: tasks that were typically seen as only human abilities. AI includes lots of different technologies and fields and is considered a super important type of technology that is spreading everywhere, getting better all the time, and sparking new ideas and inventions (Frankenfield, 2021). So, it is not surprising that it is common to find different interpretations of what AI actually means (Van Roy et al., 2020). Acemoglu and Restrepo (2020) offer a detailed definition, describing AI as the study and creation of intelligent machines or software that can understand and react to their surroundings. This broad field includes various technologies like machine learning, deep learning, natural language processing (NLP), predictive APIs, image recognition, and speech recognition (Martinelli et al., 2021).

We can see the enormous rise of AI in almost every aspect of human life in the present context. The rapid growth of AI technology in recent years can be attributed to several key factors, including the availability of vast unstructured databases, the availability of data and information in abundance, advancements in computing power, and increased investment from venture capital firms (Ernst et al., 2019; World Economic Forum, 2018). Unlike traditional industrial robots or say machines programmed to perform repetitive tasks in manufacturing settings, AI technologies have the unique ability to learn autonomously from their environment. For example, they can process visual and tactile data from sensors and use this information to guide their actions without explicit programming (Raj & Seamans, 2019). Additionally, AI technologies are capable of performing complex cognitive tasks that were once considered exclusively human, such as problem-solving and decision-making (Ernst et al., 2019).

Various researchers have explored the concept of intelligence in AI systems (Schank, 1980; Van der Maas et al., 2021). Schank talked about how important it is for AI to learn from new situations, which was a problem for AI in the past (Schank, 1980, p.12). On the other hand, Legg & Hutter (2007) defined intelligence as an AI's ability to achieve goals in different situations. This definition is similar to Schank's idea, saying that AI needs to adapt and learn in different scenarios. They also mentioned how this adaptability sets humans apart from many AI systems (Legg & Hutter, 2007).

Van der Maas et al. (2021) echoed Schank's idea, highlighting that intelligence involves generalization, a weakness still present in AI systems. However, they pointed out that modern AI techniques like transfer learning have significantly improved AI's ability to generalize. These techniques, including deep learning and reinforcement learning, have transformed how AI learns. Van der Maas et al. (2021) suggested that these advancements may necessitate a redefinition of intelligence and how we measure it (Van Der Maas et al., 2021). Reflecting on Legg & Hutter's definition, they acknowledged that while AI excels at solving specific problems and achieving goals, it struggles when facing entirely novel situations.

Most of the AI systems we have today fall under the category of narrow AI, such as those used for speech-to-text, translation, object detection, facial recognition, and web search (Kore, 2022). Narrow AI refers to AI designed to excel at specific tasks like translation or search. This distinction exists because broad AI possesses additional abilities like knowledge transfer, adaptability, reasoning, and efficiency (Hochreiter, 2022).

AI can be divided into five main subdomains: Machine Learning (ML), Natural Language Processing (NLP), Computer Vision (CV), Artificial Neural Networks (ANN), and AI robotics (Williams et al., 2021).

2.3 AI IN USER EXPERIENCE (UX)

Yang et al. (2020) describe UX as the complete experience involving everything a user does with a product or service. When creating a digital product or service, designers must ensure that the overall user experience (UX) meets the needs and expectations of the end-users (Chen et al., 2018). End-users of digital solutions have high expectations for the applications they use, and the success of software/product often depends on how well designers understand and implement user requirements, functionality, and design aesthetics (Baker, 2017; Knight, 2018). In their literature review, Enholm et al. (2022) discuss various definitions of AI, noting that it generally involves giving computers abilities akin to humans, such as performing tasks that typically require human intelligence. Due to the diverse strengths of AI showcased in recent practical applications, there is growing interest in leveraging AI to improve or even revolutionize the design process of digital solutions (Agner et al., 2020). AI is praised for its ability to offer numerous benefits, including facilitating extensive customization, providing more precise analysis of digital solution usage, and assisting designers in their creative endeavours (Oh et al., 2018). Recent advancements in AI and machine learning (ML) have significantly influenced UX practices, leading to the development of solutions with enhanced UX (Lu et al., 2022). There is a noticeable trend where AI capabilities are increasingly utilized to improve UX design processes (Abbas et al., 2022; Chen et al., 2019), creating new opportunities for professionals in this field (Holmquist, 2017).

The recent rise of AI has stirred up discussions about how designers can improve the user experience (UX) design process. This includes providing designers with tools that help them create better digital products more efficiently and cost-effectively. Researchers are exploring practical applications and conducting studies on how AI can enhance UX design. For example, AI can analyse user data or graphical user interface (GUI) elements to automate design tasks. It can also assist in developing adaptive interfaces that adjuHost dynamically based on changing user needs. These advancements aim to streamline the design process and ultimately improve the usability of digital products (Oh et al., 2018; Johnston et al., 2019; Yang, 2017). This paradigm shift towards AI-supported UX design is revolutionizing digital product creation. By using AI, designers can improve various aspects of UX design processes, such as personalization, automation, predictive analytics, and adaptive interfaces, ultimately leading to more user-friendly and intuitive experiences. With so much data available, AI can learn a lot and make smart guesses about what users want. For example, it can stimulate heat maps of digital pages or products. These heat maps show which parts of a page/content people focus on the most or click on. This valuable insights aids in user testing and product enhancement, ensuring a better experience for users on the end-product. Furthermore, the integration of AI-driven chatbots and speech recognition chat copilots in user experiences has extended the scope of interactive interfaces. These features enhance user engagement by offering responsive and intuitive channels for interaction.

With AI offering diverse applications across various domains, there are abundant opportunities to develop data-driven solutions that optimize UX processes. Despite this potential, there remains a significant gap in understanding how AI influences UX design. We still don't fully understand how AI affects the design of user experiences. UX practitioners are finding it challenging to explain AI concepts effectively (Q.V. Liao et al., 2023). They are experimenting with AI models to understand the potential risks and benefits associated with integrating AI into their designs (Satterfield & Abel, 2020). While UX designers often use pre-trained models, they lack support for generating UX-focused ideas. They are actively seeking a better grasp of AI models and transparency to make well-informed decisions about using AI in their work. This underscores the importance of further research in this area, especially in the field of information systems, where the success of digital tools depends on meeting what users expect (Chatterjee & Kar, 2017).

2.4 AI IN FINANCIAL INSTITUTIONS

AI technology has made its way into various industries, with significant changes happening in finance. Financial institutions, using vast amounts of data, heavily reliant on Big Data and automation, find themselves uniquely positioned to lead the adoption of AI (PwC, 2020). This adoption offers various advantages, such as facilitating the automation of manufacturing processes, ultimately leading to improved efficiency and productivity. Additionally, AI offers accurate and unbiased predictive analytics and trading strategies (*depending on the data and model it is trained upon)*, as machines are not prone to human errors or influenced by psychological factors. It also drives innovation in business models and transforms customer relationships through personalized digital finance, leading to improved service efficiency and cost savings (Cucculelli & Recanatini, 2022; Chui et al., 2023; Cao et al., 2020). Furthermore, AI is expected to significantly impact financial regulation and supervision, aiding in the identification of potential violations, and assisting regulators in anticipating the effects of regulatory changes (Wall, 2018).

Moreover, advanced AI machine learning algorithms enable fintech lenders to quickly make credit decisions, benefiting both lenders and consumers (Jagtiani & John, 2018; Yin, Wu, & Kong, 2022). Intelligent devices in finance serve various purposes, such as detecting fraud, trading algorithms, managing portfolios, making credit decisions based on scoring models, predicting bankruptcies, managing risks, analysing behaviours through sentiment analysis, and ensuring regulatory compliance. The use of AI in financial institutions has brought about significant changes across different areas (Yin, Wu, & Kong, 2022). One key focus is how AI is shaping financial markets and stock trading. Studies show that algorithmic trading (AT) improves market liquidity by reducing costs for listed companies. Algorithms trade faster and more efficiently than humans, adapting quickly to new information and making better timing decisions, ultimately leading to higher profits (Frino et al., 2017). Additionally, advanced neural network models like Long Short-Term Memory Networks (LSTM) are proving to be highly accurate in predicting stock price movements, especially when considering online investor behaviour (Zhang et al., 2021).

In the realm of portfolio management, AI-driven approaches have changed how assets are allocated and managed. Researchers are using clustering techniques paired with risks analysis to improve portfolio constructions (Soleymani and Vasighi, 2020). Moreover, deep learning models, as highlighted by Dixon et al. (2017), boast robust predictive capabilities, boasting an impressive accuracy rate of 68%. These advancements are instrumental in optimizing portfolio performance by mitigating tracking errors (Kim and Kim, 2020). Additionally, methods such as the symmetric copula model are playing a pivotal role in further enhancing the efficiency of portfolio allocation strategies (Zhao et al., 2018).

Fund managers are confronted with a significant challenge in effectively harnessing the vast amount of available data to make well-informed investment choices (OECD, 2021). This data encompasses critical insights like market trends, economic indicators, and company-specific risks, all crucial for informed decision making. However, traditional fund management methods struggle to swiftly and efficiently process this flood of information (Deloitte, 2023). Advanced AI algorithms offer a solution by swiftly analysing large datasets, providing valuable insights beyond what human analysis alone can achieve (World Economic Forum, 2018). These AI-powered tools automate repetitive tasks, granting fund/portfolio managers more time to focus on strategic activities. Moreover, AI algorithms can spot patterns and trends, guiding the development of optimized investment strategies, potentially leading to higher returns and mitigated risks (Bartram et al., 2020)

Similarly, investor sentiment has become a crucial factor in predicting stock market movements. To gauge this sentiment, analysts use sentiment analysis techniques to extract opinions from social media platforms like StockTwits and Yahoo Finance. By employing natural language processing and data mining methods, they categorize these opinions as either positive or negative (Yin et al., 2020). In terms of predicting market behaviour, daily news often influences stock returns over a few days, while weekly news can impact returns over longer periods, ranging from one month to one quarter. This ripple effect on stock prices is particularly evident around significant corporate events, such as earnings announcements. Consequently, investor sentiment emerges as a critical variable when evaluating the role of AI in financial markets (Heston & Sinha, 2017).

2.5 SPECULATION ON THE FUTURE OF AI

Previous studies have developed AI models capable of mimicking stock market indexes' performance, a strategy known as index tracking. These models are designed to construct portfolios efficiently without human intervention. Kim and Kim (2020) emphasize the importance of enhancing AI algorithms to improve index-tracking performance. Additionally, Soleymani and Vasighi (2020) highlight the significance of clustering algorithms in portfolio management. They propose using a clustering approach, specifically fuzzy clustering, to select assets that are less risky yet profitable. Chen and Ge (2021) suggest incorporating deep learning analysis of asset volatility into portfolio selection models to further enhance their effectiveness.

The integration of AI into UX design or research within the financial institutions is poised to undergo significant evolution. With advancements in Machine Learning and Natural Language Processing, AI-driven UX solutions are anticipated to become more personalized, intuitive, and contextually aware. Financial institutions are likely to leverage AI algorithms to analyse vast datasets of user interactions, preferences, and behaviours to tailor user experiences in real-time. The progress we see today in AI and its methods largely stem from the evolution of Artificial Neural Networks (ANNs). These networks are computerized models initially inspired by how our brains work i.e., biological neural networks (Van der Maas et al., 2021). Reinforcement learning techniques excel in learning adaptive behaviour, allowing systems to outperform humans in specific tasks (Van der Maas et al., 2021).

Additionally, Natural Language Processing models are revolutionizing AI assistants like Siri and Alexa, enabling machine translation and speech-to-text capabilities. These advancements in AI, particularly in the field of Generative AI (Gen AI), are shaping the future of UX design. These advancements allow AI systems to create contents and artifacts out of mere texts. For instance, AI can now generate realistic images-videos (e.g., *DALL-E and Midjourney)* and produce human-like language output (Van der Maas et al., 2021; J. Sun et al., 2022), showcasing the potential of AI in shaping user experiences.

2.6 CHALLENGES OF AI AND UX INTEGRATION

In exploring the realm of user experience design, Agner and team (2020) undertook a comprehensive examination of how users interact with recommendation algorithms, uncovering gaps in their understanding of how these systems function and process data. They emphasized the need for improved transparency and user empowerment to enhance the overall experience. Their research sheds light on the evolving landscape of recommendation systems and underscores the ongoing efforts required by UX designers. There are various aspects involving AI, such as AI-assisted design, systems for artificial design intelligence, and designing user experience for AI products (Li, 2020). However, despite the potential of AI in design, the field is still fragmented or say it is lacking cohesion. This fragmentation makes it hard to fully understand how AI is currently used in design, how we can make the most of its use, and how AI might completely change the design process in the future.

Researchers have identified several challenges and areas for future work regarding the integration of AI into UX design. One major obstacle is in UX/UI prototyping, where adopting an AI-centric approach complicates the conventional or the usual design process. Designers find it difficult to convince leadership to embrace innovative designs due to the significant volume of data required for AI-based prototyping. This poses challenges in demonstrating the value of their designs through functional prototypes, diverging from conventional practices. Additionally, there is a lack of integration between UX and AI, making it challenging for UX designers to collaborate with data scientists and prototype effectively with AI tools (Abbas et al., 2022).

Furthermore, most AI research projects have mostly benefited academia, and not industries. They have not really been useful for real-world practices. We do not fully understand how AI can make UX better, so we need more research to figure out what designers and industry people need and to help them use new technology better. Current AI-based prototyping tools are primarily tailored for software developers, presenting a challenge for UX designers with limited AI knowledge. Extensive research is necessary to develop prototyping tools specifically for UX designers, enabling rapid prototype development and early identification of design issues (Jiang et al., 2022).

On top of these, there is another angle to the challenges that AI incorporates when it comes to integrating AI. This angle can be viewed as cultural barriers. Sometimes companies encounter challenges when trying to implement AI technology due to their organizational culture. According to Fountaine et al. (2019), many companies/organizations struggle with this because they think AI is easy to install and will bring immediate benefits right away. However, they found that achieving the desired customer experience with AI takes time and effort, and it needs to be implemented across the entire company, not just in isolated projects. It is not just about the technology; it is about changing the way the company works, which can be quite complicated and can bring complexities along the process.

3 THEORY & PHILOSOPHY OF SCIENCE

In this part of the thesis, I will outline the view on theoretical framework and *Philosophy of Science (PoS),* that I have attempted to dissect and justify for this research. Additionally, I will explain how I gain knowledge and the philosophical assumptions I make throughout the process.

In the theory section of my report, it is crucial to understand the insights shared by Adams et al. (2007) regarding theories, concepts, and hypotheses. According to their perspective, a theory is like a roadmap that helps us navigate through complex phenomena. It is made up of interconnected concepts, definitions, and propositions that work together to explain and predict facts or events. One key takeaway from their insights is the importance of hypothesis. These are specific propositions that can be tested through empirical research. In other words, hypotheses are statements about the relationship between variables that we can actually investigate in the real world. Theory generation involves two main approaches: deductive reasoning and inductive reasoning. Deductive reasoning starts with general statements and narrows down to specific assertions, while inductive reasoning begins with observing specific facts and generalizes them into broader propositions. These methods, outlined by Adams et al. (2007), help researchers in developing theories whether at a conceptual or empirical level.

Throughout the research journey, it is also crucial to recognize the philosophical ideas guiding our understanding of knowledge (Creswell & Plano Clark, 2018, p.38). Research philosophy revolves around two main concepts: *ontology and epistemology*. Ontology delves into the essence of reality, prompting us to question our assumptions about how the world functions and our commitment to particular perspectives. The discussion often leads to exploring the viewpoints of objectivism and subjectivism among social sectors (Saunders et al., 2012, pp. 129-131). In ontology, there are three basic viewpoints that shape our understanding of reality:

Realism: Realism asserts that there is an objective reality that exists independently of our thoughts, perceptions, or beliefs. In other words, according to realists, the world exists as it is, regardless of whether we perceive it or not. They believe that there are certain truths and facts about the world that exist independently of human perception or interpretation. For example, a realist would argue that the existence of natural phenomena such as mountains, rivers, and moon etc., exist independently of human observation. They argue that these entities have objective existence, regardless of human awareness. Realism values scientific inquiry and empirical evidence, suggesting that through observation and experimentation, we can better understand the world around us. Realism aligns with *objectivism*, as it posits the existence of an *objective reality* that is independent of individual perceptions.

Anti-realism: Anti-realism, also known as idealism, argues that reality is dependent on human perception or consciousness. According to this view, reality is constructed by our minds and is not independent of human experience. Anti-realists often question the existence of an objective reality separate from our perceptions, emphasizing the role of subjectivity in shaping our understanding of the world. For example, an anti-realist might argue that concepts like beauty or justice are not inherent qualities of the external world but are instead constructs created by human minds. They suggest that different individuals or cultures may perceive reality differently based on their unique experiences and perspectives. Anti-realism challenges the idea of a single, universal truth and instead highlights the diversity of human interpretation and experiences. Anti-realism aligns with *subjectivism*, as it emphasizes the *subjective* nature of reality and knowledge.

Relativism: Relativism suggests that truth and reality are relative and can vary depending on different perspectives, contexts, or cultural frameworks. According to relativism, what is considered true or real may differ from one person or culture to another. There is no universal truth or reality that applies to everyone. For example, relativists might argue that moral values vary across cultures and societies and that there is no absolute standard for determining right or wrong. Instead, ethical judgements are influenced by cultural norms, beliefs, and values. Relativism encourages tolerance and open-mindedness towards differing perspectives, recognizing that there can be multiple valid interpretations of reality based on individual or cultural contexts. Relativism aligns more closely with *subjectivism*, as it acknowledges the *subjective nature* of truth and reality, which can vary depending on individual or cultural perspectives.

On the other hand, epistemology focuses on the nature of knowledge itself, determining what qualifies as valid or acceptable knowledge within a specified field of study (Saunders et al., 2012, p.132). One of the basic viewpoints in the realm of epistemology is *pragmatism.* Pragmatists believe that knowledge is not static or absolute. Instead, they think it can change over time depending on how helpful it is and if it works well practically to solve the problems in hand. They care more about how useful knowledge is in the real world than whether it matches up with some objective truth.

In the following discussion, I will explore four different research paradigms relevant to social sciences, as outlined by Mackenzie & Knipe (2006). I will attempt to channelise thoughts on how each of these paradigms could be applied to the research/project in hand. Which I believe will help me determine the overall philosophical direction. Firstly, a positivistic approach would offer an objective investigation, focusing on empirical (usually quantitative) observations. For example, through positivist experiments, we could measure and gather empirical evidence regarding the effectiveness and productivity of User Experience Professionals (UXPs) when integrating AI in their work.

On the other hand, a constructivist or interpretivist approach would delve into subjective experiences, aiming to uncover the unique human perspectives constructed by research subjects. This approach would allow researchers to explore the perceptions, emotions, and intentions of UXPs or any other stakeholders when integrating AI into their working system, shedding light on their individual viewpoints. Which could allow us to understand not just the practical aspects of AI use but also how it impacts people on a personal level. The transformative paradigm shifts focus to address issues of social injustice, conflicts, and political agendas. By adopting this stance, we could perhaps investigate potential conflicts arising from the integration of AI into UX practices, such as discrimination faced by UXPs if organization enforce AI usage to increase efficiency or whatever other relevant studies depending on one's interest.

Lastly, the pragmatic paradigm takes a problem-centred approach, emphasizing real-world contexts and the consequences of actions. Through this viewpoint, we could immerse ourselves in the day-to-day work practices of actors. It can boost my aim to assess the integration of AI into the prototype and its impact on overall effectiveness. It will help me to delve into how stakeholders/users interact with AI in the prototype and explore whether this integration improves the solution compared to the existing one or provides any hint related to it.

In the realm of information science, theories are usually taken as more specific topic, while paradigms are like looking at the bigger picture (Bawden & Robinson, 2022). Pettigrew & McKechnie (2001) put forward the insight that in information science, there is not just one theory that fits everything perfectly. Information Retrieval Theory (IR) is about finding the best ways to search for and present relevant information from large datasets or documents (Belkin, Oddy, & Brooks, 1982). This empiricist worldview emphasizes the importance of empirical evidence and observation in the pursuit of knowledge and suggests that insights or knowledge about any sort of information retrieval should be grounded in empirical data and observations of user behaviour, rather than speculative or theoretical assumptions. IR approach could help me to study on how stakeholders/users use AI tools to obtain data or to interpret something or simply make decisions more efficiently. Similarly, Cognitive Load Theory (CLT) is an instructional design framework that matches how our brains naturally work, explaining how we manage and deal with information (Kirschner, 2002). This rationalist worldview emphasizes the importance of logic, reason, and systematic analysis in the pursuit of knowledge. CLT suggests that knowledge about cognitive processes should be derived from systematic observation, experimentation, and logical reasoning, leading to the development of evidence-based theories and principles. CLT could be valuable in understanding how stakeholders/users perceive and handle the cognitive load associated with using AI tools to perform tasks such as viewing positions and visualizing data.

In similar manner Human-Computer Interaction (HCI) is one of the most identical theories in the field of information science. HCI has evolved from computers dictating interactions to adapting to users' needs. This shift has led to different design approaches, including technology-centered, business-centered, and user-centered design (Kurosu, 2021). HCI encompasses a variety of philosophical perspectives (Duarte & Baranauskas, 2016), but it often aligns with a pragmatic worldview due to its coupling nature of human and computers. Since, HCI theory explores the interaction between humans and computers, including how users interact with AI-powered tools, it could shed light on the effectiveness and usability of these tools.

Diffusion of Innovation (DOI) is another theory that talks about understanding how new ideas or technologies spread and get adopted by people. This theory is created by Everett Rogers in 1962 (Fahad & Shahid, 2022) and the speciality of this theory is that it helps us gain the knowledge/insights on how something new innovation is adopted and whether it will be successful in a community or in any organization. DOI aligns with a social constructivist worldview, which emphasizes the role of social interactions, norms, and contexts in shaping individual's adoptions of new ideas or technologies. By applying DOI theory, researchers can gain insights into the social dynamics and contextual factors that influence adoption, helping to develop targeted strategies for promoting the successful implementation of AI tools within organisations and communities.

In qualitative analysis approach we have another theory named Activity Theory. AT is a theoretical framework to study and understand how people interact with the tools (Hashim & Jones, 2007). AT, when viewed through the lens of philosophy of science, reflects a socio-cultural worldview. Researchers see the big picture and understand how people do things in different scenarios. It emphasizes how activities are shaped by social, cultural, and historical factors, and how they, in turn, shape individual behaviour and cognition.

In my research, I have found that the pragmatic approach, particularly within the realm of Human-Computer Interaction (HCI) theory, fits best for studying how AI is integrated in the organization and if it is improving user experience in the company's prototype-solution. This approach, rooted in HCI theory, focuses on practical results and real-life impacts, which aligns exactly well with my research concerns shedding light on the aspects of user centered design. Unlike other theories mentioned above which primarily emphasize specific aspects of information processing and cognitive functioning, or social dynamics related to technology adoption, HCI theory provides a holistic perspective on user interaction with technology in its simplest form. It helps me understand how AI tools like Azure OpenAI affects their daily work and help them achieve their goals or simplifies the usual tasks. This approach also lets me use combination of different methods and approaches to get a full picture of what is going on. So, by taking this approach, I am aiming to provide useful insights and suggestions that the company can actually use to reflect on the prototype team's work.

So, considering the research context and questions, a qualitative approach appears to be the most appropriate for this study. Moreover, qualitative study is often adopted by the researchers if there is a lack of specific theory or an existing theory fall short or are lacking altogether (Merriam & Tisdell, 2015, pp. 16-17). Some of the points that I would like to take forward which played as decisive factors for me to choose qualitative measures are:

Understanding Experiences: The aim is to delve into the perspectives and experiences of portfolio managers and other stakeholders regarding AI integration. Qualitative methods enable a thorough exploration of their thoughts, feelings, and experiences, providing nuanced/tacit insights that quantitative methods may overlook. Unlike positivist research, where hypotheses are tested deductively, qualitative research follows an inductive approach. This involves piecing together information from various sources for instance- interviews, observations, documents, inquiries, etc. Through this process, researchers gradually develop broader themes and categories from specific details (Merriam & Tisdell, 2015).

Flexibility: Qualitative methods offer adaptability in data collection and analysis. Adjustments can be made, allowing for a more organic exploration of the research context. This flexibility is particularly valuable in a dynamic environment like a prototype team where practices and attitudes may evolve over time.

Contextual Insight: With a focus on a specific organizational context, the prototype team within a financial institution – qualitative methods are well-suited to capture the contextual intricacies. Through interviews, interactions, ethnography, or workshops researchers can uncover the unique challenges, opportunities, and impacts of AI integration in UX enhancement/consideration within this setting. For example, through interviews, interaction, observation, or use-case study we can delve into the details of how AI tools like Chat GPT 3.5/4 are used/planned in daily/future tasks and see how it affects the experience for the stakeholders.

Rich Data Collection: Qualitative research facilitates the collection of rich, detailed data that offers valuable insights into the complexities of AI integration. By capturing participants' perspectives, researchers can uncover underlying motivations, barriers, and success factors that quantitative measures alone may not capture.

In this study, the main goal is to dig into how organization like Simcorp is actually using AI in their day-to-day work or is planning to use in their relevant context, especially when it comes to making their UX better. It is kind of like exploring new territory because there is not a lot of dedicated research on how AI is really being put to work in these kinds of financial settings. That is where this research plan to provide a bridge and attempt to fill up the gap. To bridge this gap, I have embraced the qualitative approach, utilizing combination of methods/techniques such as interviews and observations, to understand stakeholders' perspectives on the integration of AI into UX enhancement.

4 METHODOLOGY

Grounded theory is a research methodology used in information science and sociology. It is all about developing a broad, general theory based on what people actually say and do (Eisenhardt, 2021). This means collecting lots of different kinds of information and organizing it into categories that help us understand how things work (Charmaz, 2006; Corbin & Strauss, 2007, 2015; Creswell & Creswell, 2018; Eisenhardt, 2021). It is an inductive approach where instead of starting with specific hypotheses or theory and testing it with data, researchers begin with collecting and analysing data without any preconceived ideas. Researchers look for patterns and themes in the data and then develop theories or explanations based on what they observe. While grounded theory offers a valuable methodology for exploring the integration of AI technologies into daily work practices, I ultimately opted to employ a different approach for my research. Grounded theory requires extensive time (cyclical in nature) and data collection, which violates the time constraints of my research project and the need for timely deliverables. Additionally, there was not enough sample (hindering depth and breadth) to adequately conduct grounded theory analysis within the given timeframe.

Moreover, while grounded theory allows for the exploration of diverse perspectives and the generation of new theoretical insights, I prioritized a more focus and pragmatic approach for my research. Since my primary goal was to practically/verbally test and observe or interview relevant stakeholders about AI integration to address specific research questions, grounded theory, with its emphasis on theory generation, was not the most suitable methodology for my study, despite its high potential.

After careful consideration of different research approaches, I have chosen to adopt a qualitative approach combined with pragmatism for my study. While the interpretivist approach combined with pragmatism could have also been an alternative, it may not align well with the nature of my research. The interpretivist approach primarily emphasizes understanding subjective experiences and perspectives, as explained in the prior section, drawing from insights provided by Mackenzie & Knipe (2006). Although valuable for exploring individual's thoughts and feelings about integrating AI, it might not fully capture the practical implications and outcomes of AI integration in my context. Therefore, I believe that a qualitative approach combined with pragmatism is more suitable for my research context. This approach allows me to delve into stakeholders' perspectives while also considering the practical consequences (user-tested insights) of AI integration within the real-world context of financial institutions.

According to Alghamdi and Li (2013), pragmatism offers researchers a lot of flexibility. It is not tied to any specific philosophical system or reality. Instead, researchers have the freedom to choose the methods, techniques, and procedures that best suit their needs and research goals. Pragmatism do not believe in one absolute truth; instead, they see truth as something that is based on what works in practice. In other words, the truth is whatever is currently being put into action, rather than something that is fixed or dependent on someone's thoughts or ideas.

As derived from Leighton (2017, pp, 14-15), Patton (2015) outlines various types of qualitative approaches, each serving a specific purpose. These include journalism interviews, celebrity TV talk shows, personnel evaluations, clinical diagnoses, motivational discussions, compliance checks, interrogations, cognitive enhancement interviews for eyewitnesses, and religion-based interviews. Each type is tailored to address particular questions or objectives. For instance, journalism interviews aim to gather stories that captive readers or viewers, while think-aloud and cognitive laboratory interviews focus on uncovering underlying cognitive processes involved in problem-solving and comprehension. Unlike journalism interviews, data from think-aloud and cognitive laboratory interviews are often used to understand unseen psychological phenomena, such as how people think and understand information. In the following sections, I will provide a detailed explanation of the research approach and strategies that I have chosen to do the research and how I navigated through it.

4.1 RESEARCH DESIGN AND STRATEGY

Research involves thorough exploration, careful investigation, and sometimes experimentation to uncover new information and insights. It can also refer to the study of various topics, involving gathering information, analysing facts, and updating existing theories or laws based on new evidence. More intricate research may be necessary for deeper investigation (Adams et al., 2007). According to the authors, there are various types of research study that allows us to gain different knowledge outcomes:

- Descriptive Research: The aim is to describe phenomena without delving into why they occur. It is valuable for establishing basic understandings or *"templates"* of how things are in the world. This kind of research is often a starting point, especially when exploring topics with limited prior knowledge.
- Explanatory Research: Explanatory research goes deeper not only describing phenomena but also aiming to uncover why they occur. It helps us grasp the essence of what we are studying. This type of research seeks to shed light on social relations or events, enhance our understanding of their structure and processes, identify connections between factors, and develop, test, or refine theories.
- Predictive Research: Predictive research goes beyond explaining behaviour; it aims to forecast future behaviour based on changes in relevant variables. Understanding natural or human phenomena helps us anticipate their future trajectories and potentially influence them. This type of research is crucial for government when developing and implementing policies.

The research strategy will encompass a combination or say varieties of qualitative approach to delve into the intricacies of product development, planning, and strategy concerning AI implementation and modern web UI/UX design. Researchers can choose to use either a single research design or a combination of two designs (Adams et al., 2007). It is up to the researcher to determine which types and combinations of research methods will be most effective in achieving the study's goals.

According to Bryman (2016), research design provides the structure for collecting and analysing data, while research strategy guides the overall directions of the study. The literature outlines three main approaches to research: *qualitative, quantitative, and mixed methods*. Qualitative research focuses on exploring the meanings individuals or groups attribute to social or human problems, aiming to gain deeper insights into subjective experiences (Creswell & Creswell, 2018). On the other hand, quantitative research is characterized by its emphasis on testing theoretical hypotheses through the analysis of numerical data and the relationship between variables.

In Contrast, mixed methods research involves the collection and integration of both quantitative and qualitative data, offering a more holistic understanding of the research problem (Creswell & Creswell, 2018). This combined approach provides complementary insights, enriching the analysis and leading to a more comprehensive understanding of the topic at hand (Bryman, 2016; Cresswell & Plano Clark, 2018a). By integrating multiple research methods, researchers can effectively explore various facets of a particular issue, enhancing the overall quality and depth of their study. Creswell (2008, p.2) defines Mixed Methods Research (MMR) as a versatile approach that spans various aspects of the research process. He defines MMR as "*a broad umbrella term encompassing perspectives that see it as a research method of data collection and analysis, a methodology that spans the process of research from philosophical assumptions to interpretations, a philosophy of research, and set of procedures used within existing research designs such as case studies, experiments, and narrative projects. (p.2)."*

In essence, MMR is about being flexible and creative in how we approach research, using a combination of methods to get a richer understanding of the topic we are studying. MMR allows researchers to complement qualitative insights with quantitative data or vice versa, providing a more comprehensive understanding of the research topic and produce robustness in the nature/quality of insights gained.

Different research designs are utilized for collecting and analysing qualitative data, such as verbal reports. It is essential to recognize that the type of data collected does not dictate the research design used. For instance, there are various qualitative research designs like grounded theory, ethnography, and narrative research, each serving different purposes. Grounded theory explores common thematic experiences, ethnography delves into shared cultural aspects, and narrative research focuses on personal stories. These designs are labelled as qualitative because they aim to explore phenomena. Textual stories and images are often used in qualitative research, and text analysis is employed to extract data, identify themes, and develop a comprehensive understanding of those themes. This process enhances researchers' understanding of the subject matter (Leighton, 2017; Cresswell, 2005, 2013).

However, in my case, the emphasis is less on actively contributing to the development of the prototype and more on evaluating/studying its impact or challenges on user experience compared to the existing product. The testing of the prototype is conducted within the organization's product development (PD) area, where it is accessible only to a limited group of internal stakeholders and not yet available to a wider client base. Given this focus, incorporating quantitative methods are deemed less relevant as they typically require a larger sample size and are better suited for assessing broader trends and patterns. Instead, qualitative methods combined with multiple variations of it is prioritized for conducting the research. These approaches allow for a detailed exploration of user experiences, feedback, and perceptions, providing valuable insights into the effectiveness and usability of the prototype in its current developmental stage.

Nevertheless, I acknowledge the potential benefits of quantitative and mixed methods, if the prototype were to be deployed to a wider audience or into production, adopting a mixed methods approach would be beneficial for gathering diverse insights and ensuring robust research findings. This would allow the opportunity of including the various measuring factors provided by Azure DevOps, such as performance bandwidth or team velocity, response time, application insights, logs from dedicated plugins for AI etc. Qualitative methods like interviews, ethnography, narrative analysis or focus group etc. would provide rich, contextual insights into user experiences, complementing the quantitative data. This mixed approach would offer a comprehensive understanding of the tool's impact and usability, guiding further refinements.

4.2 SAMPLING

Sampling is crucial in academic research because it helps researchers gather data/information efficiently and accurately. Instead of studying every single person or item in a population, researchers select a smaller group, called a sample, to represent the whole. This allows researchers to draw conclusions about the entire population without having to study every individual thus saving time and resources. Sampling methods in research can be classified into two main groups: probability and non-probability methods (Omair, 2014; Tyrer & Heyman, 2016). In probability sampling, cases are chosen randomly from the population, ensuring fairness in selection. This includes methods like random sampling, systematic sampling, stratified sampling, and cluster sampling (Shorten & Moorley, 2014). Conversely, non-probability sampling relies on the researcher's judgement rather than random selection. Examples include quota sampling, purposive sampling, self-selection sampling, and snowball sampling (Elfil & Negida, 2017). The researcher needs to make sure that the information gathered is suitable for addressing the problem at hand. This requires the researcher to have a good understanding of where the information is coming from (Adams et al., 2007).

In my thesis research in Simcorp, I am delving into how the prototype team utilizes AI, e.g. Azure OpenAI, to enhance user experience, for instance in tasks like viewing positions or equities, analysing the data, visualizing the data, and creating simulations among other various financial tasks. However, before diving in, I needed to choose participants carefully. Due to the specialized nature of financial operations and on top of that due to the compliance policies and regulations, I decided to interview only the individuals who have a good understanding of the company's existing legacy software and has right to access to this prototype being built as well. This approach fits well with the definition of purposive sampling highlighted by Saunders et al. (2012), which identifies that I am gathering insights from those directly involved and knowledgeable about the system, rather than randomly selecting participants who may not have the necessary expertise. As per Saunders et al. (2012), purposive sampling is employed for small populations when researchers aim to identify and choose the most informative sources, a method that aligns well with my case and seems to be a good fit.

4.3 QUALITATIVE ANALYSIS APPROACH

Various methods exist for gathering qualitative research data, including interviews, focus groups, ethnography, contextual inquiry, observations, case study and so on. If we look at the qualitative interviews itself, these can be structured, semi-structured, or unstructured. In a semi-structured interview, the researcher asks open-ended questions to encourage detailed responses (Bryman, 2016b). Structured interviews are more common in quantitative studies, aiming for reliability and validity through precise questions (Bryman, 2016b). On the other hand, semi-structured and unstructured interviews are preferred in qualitative research for their flexibility and openness to participants' perspectives (Bryman, 2016).

Focus groups involve similar individuals discussing topics guided by a facilitator to explore attitudes, opinions, and experiences (Bryman, 2016b; Adams et al., 2007). In these kinds of group discussions, members can share their thoughts and either agree, disagree, or adjust each other's ideas as they see fit. If the conversation steers off the relevant track, the facilitator/researcher may step in to guide it back on track. This ethnographic approach allows participants to express tacit knowledge through their unconscious behaviours. It helps uncover the hidden or say instinctual insights by observing people's behaviour and actions in their natural settings, giving us even deeper understanding of their experiences and perspectives.

Ethnography is one another qualitative research method where researchers immerse themselves in a particular culture or social group to understand their way of life, beliefs, and behaviours (Merriam & Tisdell, 2015). Ethnography aims to offer comprehensive understanding of people's thoughts and actions, along with the environment they live in, by gathering detailed observations and interviews (Reeves, Kuper, & Hodges, 2008). Ethnography usually engages in participant observations, which involves directly interacting with the community researchers are studying. Alongside these observations, researchers often conduct informal interviews in a casual style, enabling them to explore emerging topics or inquire about unique occurrences in a natural and relaxed manner.

Case study is one of the complex qualitative research methods where researchers investigate specific instances or phenomena in depth, especially in context-dependent situations. Case study can include both the qualitative and quantitative methods. Although its range is wide, the term "*case study"* is often used interchangeably with *"qualitative research"* (Merriam & Tisdell, 2015, p. 37). Generally, case studies are preferred method when researchers want to understand *'how'* or *'why'* things happen. It is useful when researchers cannot control what is happening and when they are looking at something happening right now in the real world (Yin, 2009). Researchers gather various information by observing, asking questions through surveys, and conducting interviews. These studies can delve deep into specific issues, examining how they impact organizations, groups, departments, or individuals. Case studies help generate ideas and hypotheses rather than proving them right or wrong, and other researchers can later test these hypotheses (Adams et al., 2007).

Similarly, Contextual Inquiry (CI) is a way to learn about users and how they work. It involves watching and chatting with people while they do their jobs in their natural working environment (Raven & Flanders, 1996; Holtzblatt & Beyer, 2016). It is good at discovering tacit knowledge because it is less affected by memory problems compared to surveys and interviews, as mentioned by Holtzblatt & Jones (1993). Raven & Flanders (1996) categorize contextual inquiries into three types: work-based interviews, where the research occurs during the activity; post-observation inquiries, where the researcher interviews the participant after observing them; and artefact walk-through, which involves investigating items created during work, especially if the work happens sporadically or even an extended period.

In my *case study*, I am focusing on examining the integration of AI and its associated challenges and opportunities from Simcorp's perspective. Given that the prototype has not been widely distributed for testing or is still in the early stages of development, it remains somewhat of a black box to many stakeholders, which limits my ability to conduct CI. Therefore, I have opted for a methodological approach (case study) that is well-suited for exploring the *'how'* and *'why'* of phenomena in situations where control is limited. This method allows for the observation and analysis of real-world events as they unfold, facilitating a deeper understanding of the integration process (Yin, 2009).

Fig:2, Types of Qualitative Research. Taken from Merriam & Tisdell (2015, p. 42).

Qualitative researchers take a hands-on approach to understanding a phenomenon by diving deep into the experience and perspective of participants in their natural settings (Spiers et al., 2018). The main distinction between qualitative and quantitative research lies in their underlying philosophies, the types of questions they ask, the methods they use, how they analyse the data, and how they present findings (Yin, 2017). When choosing a research method, it is crucial to consider the research question and the study's purpose. In this study, which aims to explore/assess strategies for enhancing user experience in product innovation and address any potential challenges it carries, the qualitative method is preferred over quantitative approaches. I opted for qualitative research approach because in addition to the previously mentioned reasonings, it allows for open conversations with participants, enabling me to delve deep into the nuances of their experiences and gather detailed textual data (sometimes tacit knowledge) for analysis.

Echoing Yin's (2017) insights, qualitative research is well-suited for diving deep into different aspects of the research context. This approach helps uncover and understand various parts of the phenomenon I am studying/investigating. Yin (2017) emphasizes how qualitative research is a good fit for collecting and analysing data in situations that resonate closely with mine. Researchers often employ qualitative methods to investigate *how* and *why* certain phenomena occur and allows for an in-depth exploration of complex scenarios where it is challenging to measure experiences, emotions, or knowledge using numerical methods.

So, in my research strategy I decided to embrace combinations of research approaches and strategies to provide my case-study the proper direction. Initially, desk research will be conducted, focusing on gathering internal/exclusive research papers and knowledge sharing slides or presentations/huddle/recordings from archives. This comprehensive collection of information will serve as a foundation for the subsequent phases of the research. The gathered information will then be meticulously dissected into manageable sections, facilitating dedicated analysis of each component.

Furthermore, the research strategy will include interviews and observation techniques. Interviews will offer insights from key stakeholders, while observations will provide in-depth exploration of specific instances. Observation, in the form of field notes and/or reflexivity, will supplement these methods, offering nuanced perspectives and enriching the overall understanding of the research context. Through this multifaceted approach, the research aims to uncover the valuable insights into the dynamics of AI implementation and UX design/enhancement strategy applicable in Simcorp.

4.3.1 ETHICS

In this study, ethical guidelines outlined in the Danish Code of Conduct Research Integrity (Ministry of Higher Education and Science, Denmark, 2014) and the Belmont report (Sims, 2010) were strictly followed. These guidelines emphasize principles such as honesty, transparency, accountability, respect for persons, beneficence, and justice. Prior to their participation, all individuals involved in the investigation were provided with comprehensive information regarding the purpose and procedures of the investigation, and their consent was obtained before any recording was done. They voluntarily agreed to take part and were assured that their participation was entirely voluntary. Participants' privacy was carefully safeguarded, with data shared securely through private Google Drive and OneDrive folders accessible only to strictly relevant personnels. They were informed that their data would be deleted after the completion of the thesis examination by the end of June 2024, ensuring confidentiality and adherence to ethical standards.

4.3.2 ON-SITE ENGAGEMENT AND OBSERVATIONAL RESEARCH

In this section of my report, I detail my immersive approach to studying the integration of AI within the company's prototype team. Through daily involvement in scrum meetings and various other activities such as team huddles, planning meetings, and review meetings, I gained firsthand insights into how AI tools like Azure OpenAI are utilized to enhance user experiences, particularly in tasks related to portfolio management. By actively participating in these meetings and closely observing the team's actions, I could monitor the evolution of AI concepts within the company and the strategies for further integration. Observation may seem simple and straightforward method where you just watch, participate, or record the interactions (Stanton & Young, 2003). However, the effectiveness of observation depends heavily on how we record and analyse the data. Echoing Stanton & Young (2003), there are concerns about how intrusive observation might be, the amount of effort required for data analysis, and whether the observational method covers all aspects of information comprehensively.

To address the challenge posed by the comprehensiveness and to deepen/strengthen my understanding, I have decided to complement observation with interviews in the later phase of my research. I conducted interviews with the relevant stakeholders to gather their perspectives on how AI might impact their workflow and what are the opportunities and challenges associated with it, which I will discuss in more detail in the subsequent sections. This on-site engagement and observational research provided invaluable context and real-world insights into the company's AI initiatives, enriching the depth of my perspective and study to drive this research.

According to Baker (2006), observation research can be quite complex because it involves the researcher taking on various roles and using different techniques, including relying on their senses, to gather data. Moreover, regardless of how involved the researcher becomes with the group being studied, it is crucial for them to remember their main role as a researcher. They must stay detached enough to collect and analyse data that is relevant to the issue being studied. In the review by Brotherton (2022), they discussed different ways to observe people. Sometimes, researchers directly interact with the group being observed. Other times, they quietly watch without group knowing. Building upon Baker's (2006) insights and drawing from Gold's (1958) foundational work, it becomes clear that the roles of researchers in observational studies entails a broad spectrum of responsibilities. Yet, fundamentally, these roles can be simplified into three main tasks:

Participant Observer: In this role, the researcher actively participates in the group or setting being observed while also observing and taking notes. They are part of the group's activities and interactions, but they maintain their role as an observer. For example, a researcher may join a community group as a member and participate in their meetings while also observing and recording their interactions for research purposes.

Observers as Participant: Here, the researcher primarily observes the group or setting but may occasionally engage or interact with participants. They maintain a more passive role compared to the participant observer. For instance, a researcher might attend a session as an observer but occasionally ask clarifying questions to better understanding the dynamics of the session in context.

Non-Participant Observer: In this role, the researcher remains outside of the group or setting being observed and does not actively engage with participants. They observe from a distance, often using tools like video cameras or one-way mirrors. An example could be a researcher observing behaviour in a public park without interacting directly with the people there.

In my research study for my thesis, I primarily assumed the role of an *Observer as Participant*. This decision stemmed from my lack of active involvement in the core team and my limited influence over the direction of prototype development. Additionally, I lacked prior knowledge or experience regarding the evolution of AI within the organization. Therefore, my focus was on observing the core team and stakeholders to gain valuable insights into their interactions and experiences and occasionally step into for doubt clearance (if any). For example, I attended team brainstorming sessions as an observer, and occasionally asking probing questions to gain deeper insights into their decision-making processes.

4.3.3 INTERVIEW STRATEGY

In qualitative interviews, there are different approaches: structured, semi-structured, and unstructured. A semi-structured interview is a flexible method where the researcher asks open-ended questions to encourage participants to share detailed personal insights and experiences (Brinkmann & Tanggaard, 2010; Bryman, 2016). Semi-structured and structured interviews are often preferred in qualitative research. They allow for open-ended exploration, adapting to participants' perspectives and viewpoints. Planning interview is crucial because they can be time-consuming, as highlighted by Adams et al. (2007). Therefore, it is essential to allocate sufficient time and effort to ensure they are well-prepared and conducted effectively.

During my research, I addressed various errors and biases that can affect the quality of interview data. I ensured that the interview transcripts were not altered as much as possible, to make them 'nice'. While I corrected spelling errors or words that were inaccurately captured by the auto-transcription feature of Microsoft Teams, the transcripts remained otherwise untouched and in their pure form. This approach was taken to preserve the actual meaning of the participants' words and to avoid any possible misinterpretation. Additionally, maintaining the integrity of the transcripts helps ensure the authenticity of the data and allows for more accurate analysis and interpretation of the participants' perspectives.

One of the common issues during the interview is misunderstanding either the questions asked, or the answers provided. To minimize this, I included related questions to cross-check responses. Secondly, I also took measures to mitigate interviewer bias, ensuring that my own perspective or prejudices did not influence the interview process (Adams et a., 2007). Similarly, I was also aware of the potential respondent bias, where participants might consciously or unconsciously provide inaccurate or misleading responses just so they think it will please the interviewer, potentially skewing the data. To counter this, I created an atmosphere where respondents felt respected, valued, and understood, which encouraged openness and honesty in their responses.

A common semi-structured interview technique used to grasp how people solve problems or think through things is called *think-aloud*. Jacqeline Leighton (2017) explains how think-aloud interviews provide a clear method for understanding participants' problem-solving or comprehension strategies or cognitive directions. By using this technique, researchers can uncover insights into participants' cognitive processes, which can be especially useful in understanding how they engage with complex tasks, could be based on the prototypes, like the one in my study context. In my research, I would utilize the think-aloud technique in semi-structured task-focused interview with the portfolio manager, to gain insight into how portfolio manager engages with the prototype integrated with Azure OpenAI. By asking participants to verbalize their thoughts as they interact with the prototype, I can understand participant's decision-making process, uncover any challenges they encounter, and try to identify areas where the AI integration enhances or hinders their experience. This approach allows for a detailed explanation of participants' cognitive processes and provides valuable qualitative data to assess the effectiveness of the AI solution in improving user experience and productivity or say simplicity.

4.3.3.1 INTERVIEW QUESTION FORMULATION

In this section, I will describe how I planned the structure/direction of the interviews with the stakeholders. This involved carefully evaluating what I already knew and considering if I needed more information from research. My previous knowledge set the foundation for how the interviews would be conducted (Barriball & While, 1994; Turner, 2010). It was crucial to prepare thoroughly before the interviews and have a sound understanding of the research topic (Turner, 2010). Reviewing existing literature helped me assess what was already known and what gaps needed to be filled (Barriball & While, 1994). Additionally, my set of predefined research questions played important role in drawing boundaries so that questions revolve around the area of interest and research-context as much as possible. This sort of provided me with the idea and direction to start conceptualizing the beginning phase. However, due to limited research published in my area of interest, it seemed difficult and not so rational to solely rely on existing literature and journals.

When existing literature lacks sufficient information, researchers can turn to empirical knowledge to augment their understanding of the topic. Consulting experts in the field is one approach, as these individuals possess practical experience and specialized insights that may not be found in academic literature (Krauss et al., 2009; Rabionet, 2011). I approached the lead product owner of the prototype team to establish further conversation regarding the evolution and goals of the product (prototype) under development. This conversation aimed to gain insight into the company's progression regarding AI and modern web UI. Drawing on the product owner's prior experience with similar interviews with the relevant stakeholders, I sought guidance on formulating and reviewing questions, resulting in an iterative process to shape the interview questions effectively.

The questions were designed to explore the current scenario with the legacy software solution and any challenges or inefficiencies encountered. More importantly, the interview aimed to assess the usability and effectiveness of the prototype under development compared to the existing system i.e., Simcorp Dimension, which will be referred to as SCD in the upcoming sections.

To begin, questions were designed to understand the portfolio manager's familiarity with the legacy software and their typical workflow. This could involve inquiries about common tasks performed, any pain points experienced, and areas where improvement was desired. For example, questions may include:

1. Can you describe your typical workflow when using the current Simcorp Dimension (SCD, current prevalent system in use) to view positions or equities?
2. What are some challenges or difficulties you encounter when performing tasks in the SCD?
3. Are there any specific features or functionalities you find lacking in the current SCD solution?

Following this exploration of the current state, the interview questions transitioned to evaluating the prototype under development. The aim was to assess whether the AI-driven enhancements addressed the identified challenges and improved the user experience. Tasks were designed to simulate real-world scenarios and gauge the usability and efficiency of the prototype. Sample questions for this phase that were thought of include:

1. Please walk through your experience using the prototype to performs tasks such as viewing positions or asking for currency exposures or charts etc.
2. How does the user experience with the prototype compare to your experience with the legacy software?
3. Were there any particular tasks where you found the prototype to be especially helpful or intuitive? Conversely, were there any tasks that were more challenging or confusing?

The interview questions were designed/thought to make sure participant could share abundance of details, helping us understand how well the AI prototype was working to make their experience better. Additionally, the iterative nature of the interview process allowed for adjustments and refinements to the questions based on feedback and emerging themes from earlier interviews, the final set of interview questions/guides can be viewed in the appendix section of this report or in the *Miro,* linked down in the appendix section.

According to Kraus et al., (2009), semi-structured interview guide typically consists of two factors of questions: *main themes* and *follow-up* questions. The main themes address the core topics related to the researcher subject, providing participants with the opportunity to share their thoughts and experience openly within these areas. The sequence of main themes could follow a logical progression (Kraus et al., 2009), providing a structured framework for the interview. Additionally, these themes could serve as an icebreaker, helping to establish a comfortable and relaxed atmosphere for the discussion (Kraus et al., 2009; Rabionet, 2011).

Follow-up questions were employed to help participants grasp the main themes more easily (Turner, 2010) and steer the conversation towards the research topic. The goal was to ensure a smooth flow of dialogue (Whiting, 2008) and gather accurate (Barriball & While, 1994; Whiting, 2008; Rabionet, 2011) and comprehensive information (Turner, 2010). These questions could be either pre-planned (Whiting, 2008; Rabionet, 2011) or spontaneous, depending on the participant's response (Whiting, 2008; Turner, 2010). Pre-planned follow-up questions might enhance consistency across interviews conducted by different interviews (Krauss et al., 2009). Alternatively, spontaneous follow-up questions would allow interviewers to delve deeper into specific points raised during the interview, prompting participants to provide further details (Whiting, 2008) or examples related to the topic. We aimed to adhere to the pre-planned questions or the topics as much as possible, turning to the spontaneous ones only when necessary.

4.3.3.2 INTERVIEW GUIDE

The interview guide was developed with a chosen semi-structured approach, comprising of two types of questions, also discussed in the above section i.e., *main themes* and *follow-up inquiries*. The interview guide was evaluated to ensure its comprehensiveness and relevance to the research objectives. This assessment helped us make informed changes to the interview questions/guide in iterative manner, thereby enhancing the quality of data collection (Barriball & While, 1994; Chenail, 2011). Moreover, pilot test or the assessment of the interview guide gave us insights into research ethics and context which helped us assess the integrity of the research, thereby improving the ability to conduct data collection (Chenail, 2011). The pilot test of the interview guide basically involves three techniques: *internal testing, expert assessment, and field-testing.* Given the lead product owner's sound knowledge of the SCD and prior experience in conducting similar interviews and close involvement with the prototype development, we chose expert assessment as our preferred method, where our expert was the lead product owner herself.

Sharing the preliminary interview guide to expert in the field yielded valuable results. Her expertise allowed for a thorough evaluation of the questions' relevance and coverage of essential study topics/context. This expert assessment facilitated discussions regarding the appropriateness of the questions, as well as provided guidance on effective wording and arrangement of the questions (Barriball & While, 1994).

4.3.3.3 HOW INTERVIEWS WERE CONDUCTED

The interviews as noted by Adams et al. (2007, p.146), generally span from 20 minutes to an hour. In my approach, I aimed to maintain participants engaged for approximately 20 to 45 minutes to cover comprehensive knowledge and possibly meet the saturation point, while also taking into consideration their busy schedules. Despite a predefined set of questions guiding the discussion, additional follow-up questions were asked to delve deeper into participants' responses and seek clarity. The interview with the portfolio manager was conducted using the think-aloud approach while performing some given tasks, followed by open-ended questions and response session. During the interview session we aimed to create a natural environment to the best of our ability. The interview was conducted via a remote video call where participants was in his own natural environment (workstation). Similarly, the other two semi-structured interviews with the product manager and software engineer were also conducted in their own selected natural environment via remote video calls. The video calls were recorded with the consent of participants. To ensure the participants' comfort, focus and, to minimize distractions we made the decision for all members except the participant and interviewer to turn off their cameras.

This approach proved beneficial, as semi-structured interviews offer a good balance between structure and flexibility. They allow for thorough exploration of research topics while also giving participants the opportunity to share their unique viewpoints and experiences. Both the verbal and non-verbal probing methods serve as effective follow-up questions in interviews. Verbal probes include restating the participant's points, showing interest verbally, or demonstrating familiarity with specific information (Whiting, 2008; Turner, 2010). Non-verbal probing involves remaining silent or to node in sync to encourage participants to let the participants think aloud (Whiting, 2008).

In interviews, it is crucial to let the subject speak the most, ideally around 80% of the time (Adams et al., 2007). We should be aware to not guide the participants too much, but make sure they stay on topic. After they answer important questions, repeating what they have stated as a summary help us check our interpretation of the understanding. Ability to listen, asking good questions and reflecting on the answers or statements produced by the participants/subject during the interview is denoted as the best skill that any researcher could possibly attain. These things were taken into consideration for the interviews, we focused on actively listening, and carefully considering the responses provided by the participants. Occasionally, we made an effort to briefly summarise the critical response provided by the participants to make sure we understood it correctly.

During the interviews, we planned to let participant think aloud by staying quiet at times. But we didn't always stick to being silent. Sometimes, we felt it was important to speak up or be verbal. This decision stemmed from the need to maintain the flow of the conversation and ensure that participants felt supported and engaged throughout the interview process. Additionally, becoming verbal allowed us to provide subtle prompts or redirections when participants seemed to require clarification or are too quiet, thus helping to steer the conversation back to the intended research objectives. Overall, while non-verbal probing techniques are valuable tools in semi-structured interviews, the occasional use of verbal cues can enhance rapport, comprehension, and the overall quality of data collected.

Microsoft Teams was used to conduct all the interviews, which offered the advantage of generating a transcript directly from the video itself. This saved me from the hassle of writing down the note during the conversation in real-time and also saved me from the worry about repeatedly going back and forth in the video for transcription later. However, before considering the transcript as collected valuable data and proceeding with thematic analysis, I made sure to thoroughly check its accuracy and validity by reviewing the videos and auto-generated transcripts carefully.

User Profile Table			
Participant	**Experience in field**	**Job Title**	**Age**
P1	10+ Years	Portfolio Manager	30 - 40
P2	20+ Years	Product Manager	40 - 50
P3	3+ Years	Software Engineer	30 - 40

Fig:3, User profile table of the participants involved in the research.

5 RESULTS AND FINDINGS

An essential tool/process in transforming raw qualitative data into a coherent and reliable narrative is coding. Coding involves analysing chunks of the collected data, whether it is a single word, a paragraph, or even an entire page or whole conversation. Rather than limiting myself to short labels, I used clear and easily understandable sentences as codes. This approach provided greater clarity and facilitated subsequent processes such as axial coding and selective coding. Each code captures the essence of different categories of themes or sub-themes. Essentially, coding serves as an initial form of analysis, paving the way for drawing and validating conclusions (Miles & Huberman, 1994, p.11). According to Vaughn & Turner (2016), analysing qualitative data comes with its challenges. Efforts have been made to extract measurable meaning from qualitative text, but the results have often been informal, inconsistent, or not easily compared with other data (Knapp, 2004; Neurohr et al., 2013).

As highlighted by Vaughn & Turner (2016), because of the challenges related to the complexity of the software solution and due to having manageable amount of qualitative data collected for coding in my case, I chose to manually code and organize or identifying the theme out of the qualitative data during the study. In my research, I gathered a variety of data and materials to reach my conclusion and develop insights. This included insights from interviews itself, internal documents from the organization - produced during the internal research, and digital materials internally produced by the organization (audio-visuals), all these kinds of materials contributed to the final findings of the study. I will talk about the results and findings that I derived from the study in the subsequent sections but before that let’s discuss a bit about the *reliability* and *validity* of the data to begin with.

5.1 RELIABILITY AND VALIDITY

For the research, I utilized scientific/academic literatures, books, and peer-reviewed articles to gain the existing knowledge about theories and methodologies to drive my research. Reliability assesses the extent to which research findings can be consistently replicated. It measures the consistency of results across different individuals and studies conducted at various times. It is important to note that reliability focuses on the reproducibility of findings, ensuring that the same results can be obtained under similar conditions. However, reliability alone does not guarantee the accuracy or quality of the results. Validity, on the other hand, evaluates whether a research study or thesis accurately measures what it intends to measure and if its findings align with existing knowledge in the field (Stanton & Young, 2003). Validity determines the extent to which the research accurately represents the phenomenon under investigation and whether its conclusions are consistent with the other established findings (Middleton, 2019).

The documents and digital materials I studied were pre-existing, and participants in my research were professionals with considerable experience in their fields, reducing the chance of any potential biases in the data. We conducted three different interviews: one task-focused interview with portfolio manager using the think-aloud technique followed by open-ended questions, and the two normal semi-structured interviews with an engineer and a product manager. For the task-focused interview with the portfolio manager, we aimed to make the participant comfortable and encouraged participant to express thoughts in real-time. This approach was intended to avoid filtered responses and maintain a balance between reliability and the participant's cognitive processes. In the other two normal semi-structured interviews with the software engineer and product manager, we ensured the questions to be open-ended and neutral to the best of our knowledge, to avoid leading the participants. By doing this, we aimed to get genuine responses and keep a balance between reliability and the participants' cognitive processes.

Now let us move to the results and findings section, starting with the data analysis process in the below section.

5.2 QUALITATIVE DATA ANALYSIS

Qualitative data consist of direct quotations from people about their experiences, opinions, feelings, and knowledge. It is typically not about numbers or a clear structure. Instead, it is mostly made up of text, like answers to open-ended survey questions or transcripts of interviews. Sometimes, it can also include audio, photos, or videos or artifacts. Analysing qualitative data involves organizing and interpreting it to figure out what it means. Put simply, data analysis is how we find the answers to our research question(s). In qualitative research, data analysis should happen at the same time as data collection. The collection and analysis of data in qualitative research are iterative and dynamic. Completing data collection does not mean analysis is done. In fact, analysis intensifies as the study goes on and all data are gathered (Merriam & Tisdell, 2015; Eisenhardt, 2021). In my case, the interviews were done in a gap of few days, which naturally allowed me to immediately begin organizing and analysing the data. During this process, I ensured the confidentiality of the participants by assigning them anonymous labels like Participant-1, Participant-2 and so on.

There are several types of qualitative data analysis methods, each with their own approach and focus. Some of the common types of methods that are widely used in the information science fields are:

- Thematic Analysis: It is about identifying, analysing, and interpreting patterns or themes within qualitative data. It can be used to explore common themes or sub-themes that emerge from the interview transcripts or other qualitative data sources that I have acquired.
- Content Analysis: It is about systematically analysing textual data to identify pattern, trends, frequency or categories. It can be used to quantify and categorize the content of text-based data sources, such as documents, reports, or media articles.
- Narrative Analysis: It is about examining the structure and content of narratives or stories to understand meaning and interpretation. It can be used to explore how individuals construct narratives about their lived experiences and out of that uncover underlying beliefs, values, cultural norms or any perception about anything.
- Phenomenological Analysis: It is about exploring and describing the lived experiences of individuals to understand their subjective perspectives. It can be used to delve into the subjective experiences of

employees or stakeholders to obtain a rich understanding of the human dimensions of technological change within any organization.

- Discourse Analysis: It is about examining language use and social practices to understand power dynamics, social structures, and cultural meanings. It can be used to shed light on how language shapes perceptions and discourses surrounding AI integration. It can help to uncover underlying ideologies, power relations, and discursive constructions that influence organizational attitudes and practices regarding any innovative technologies.

Among the various types of qualitative data analysis methods discussed above, I find thematic analysis and content analysis to be more suitable for my research context given the nature and the intention of my collected data. The implementation of AI technology within the organization is still in its early stages and not yet fully functional. Currently, it exists as a prototype of the potential copilot-solution intended to streamline daily tasks and serve as an assisting tool, rather than deeply impacting organizational culture or social norms. As a result, the likelihood of leveraging *narrative analysis, phenomenological analysis and discourse analysis* is out of the context as these methods usually delve deeper into aspects such as storytelling, individual lived experiences, and language use (Merriam & Tisdell, 2015). Content analysis is more suitable because it focuses on systematically analysing textual, audio, or visual content to identify pattern, themes, or trends (Braun & Clarke, 2021; Qualtrics, 2024). However, in my case, I am not attempting to identify trends or frequencies of specific words or quantify data into categories. My primary focus is to identify themes or sub-themes within the collected qualitative data to understand the underlying patterns and implications of integrating AI technology within the organization. So, due to these specific reasons, I have decided to approach thematic analysis for analysing my qualitative data.

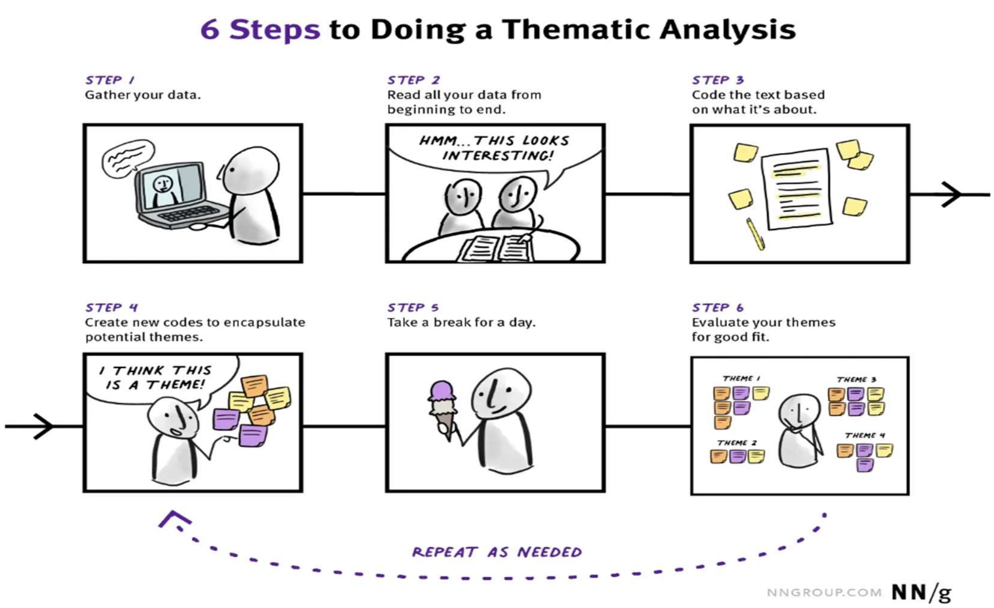

Fig:4, Steps in thematic analysis, taken from NN/g (https://www.nngroup.com/articles/thematic-analysis/).

Thematic analysis (TA) is a way of discovering, examining, and understanding patterns of meaning within a qualitative data (Clarke & Braun, 2017). So, by applying TA method, it allows me to explore and uncover recurring themes and patterns within the data, which aligns well with my goal of understanding how AI technology is perceived and utilized within the organization. By identifying key themes, I can gain insights into the challenges, opportunities, and implications of integrating AI technology within the organization. Additionally, it is worth noting that TA provides flexibility in adapting to the evolving nature of the data and allows for a nuanced understanding of the complex issues surrounding AI adoption.

5.3 CODING AND THEMATIC FINDINGS

A key step in making sense of raw qualitative data and creating a clear and reliable narrative is through coding (Linneberg & Korsgaard, 2019; Williams & Moser, 2019; Elliot, 2018). Coding involves using shorthand labels to identify and organize different parts of the data, making it easier to find specific information when needed. Most often a code is "a word or short phrase that symbolically assigns a summative, salient, essence-capturing, and/or evocative attribute for a portion of language-based or visual data" (Saldaña, 2013, p.3). In my research, I have taken inductive (data-driven) approach rather than deductive (theory-driven) approach because it allows me to derive insights directly from the data-context without any preconceived theories or assumptions or any objectives guiding the analysis.

In inductive coding, the codes are developed from the phrases or words used by the participants in the study. This approach keeps the codes closely linked to the data, reflecting what is actually said by the participants rather than the researchers' own ideas or prior knowledge (Linneberg & Korsgaard, 2019). It allows researchers to keep an open mind and accurately represent the viewpoints of the participants. It is crucial to establish clear and consistent coding procedures to maintain validity and reliability in qualitative research. The *open, axial,* and *selective* coding process in thematic analysis allows for a dynamic and iterative approach to analysing data (Williams & Moser, 2019). As I continuously create the initial coding and generate themes, I get closer to uncover the important and more clear themes/categories that I can connect to my research questions/context. In the process depicted in the given figure below, I would focus on *theme development* instead of *theory development* and in the last step would try to connect them to my research questions in order to find the answers related to my research context.

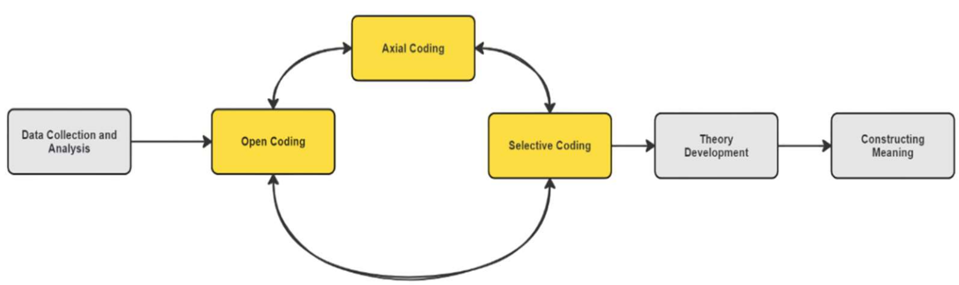

Fig.5: Non-Linear Process: Qualitative Research. Inspired from Williams & Moser (2019, p.48)

Open Coding:

Open coding or initial coding is the first level of coding where researchers identify key concepts and themes for categorization (William & Moser, 2019). This process can involve various methods, like reviewing transcripts or notes, examining each line carefully, looking at individual sentences and words (line by line reading), or analysing short sections of data to spot important themes and patterns (Birks & Mills, 2015). As mentioned earlier rather than using any dedicated software, I employed Microsoft Word to conduct this process manually, reading through the data carefully and using color-coding and comments to convert them into the codes.

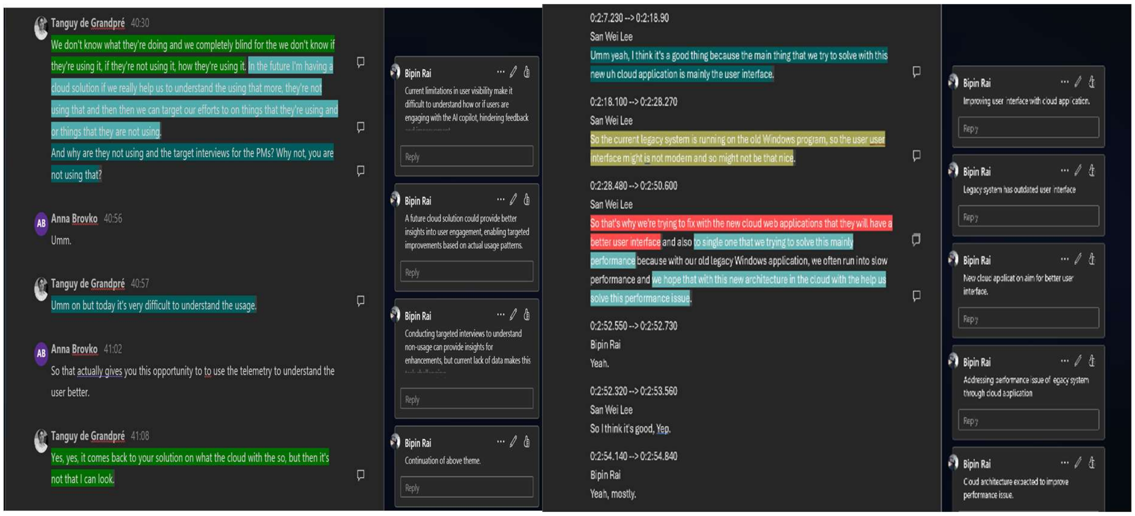

Fig.6: Open/Initial Coding. [*Full source can be found in miro board*]

Axial Coding:

Axial coding is the second level of coding which happens after the initial phase of coding. After identifying emergent themes during the open coding, axial coding then refines, aligns, and organizes these themes (William & Moser, 2019). This step involves analysing through the data to create clear thematic categories in preparation for selective coding. So, in axial coding the researchers work to connect the relationships between open codes to develop core codes placed into a specific category.

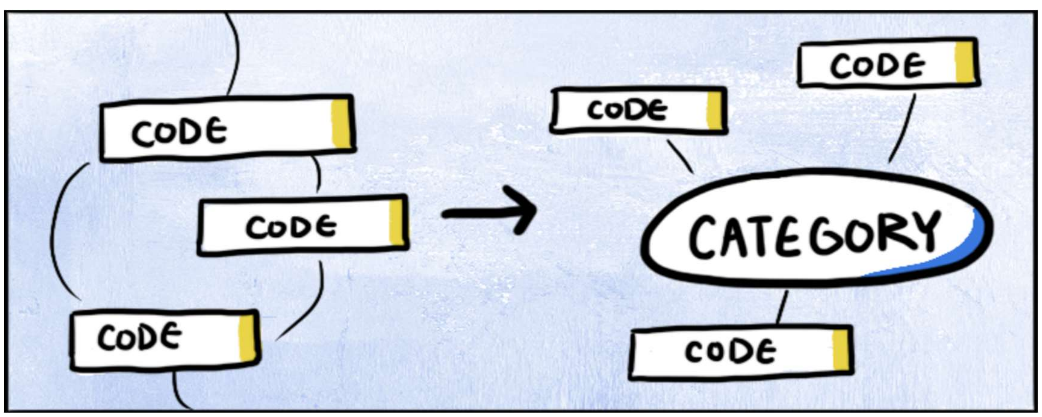

Fig.7: Axial Coding, Retrieved from Delve (https://delvetool.com/blog/openaxialselective)

I utilized Miro to store and visualize the themes and categories which could later on potentially address my research questions or interest of contexts. I used sticky-notes to convert the initial codes into manageable chunks. According to William & Moser (2019), thematic comparison and analysis are central to axial coding, as they help organize themes into clear categories. I iteratively compared and categorized these chunks on the Miro board until I identified the final themes to conduct the selective coding.

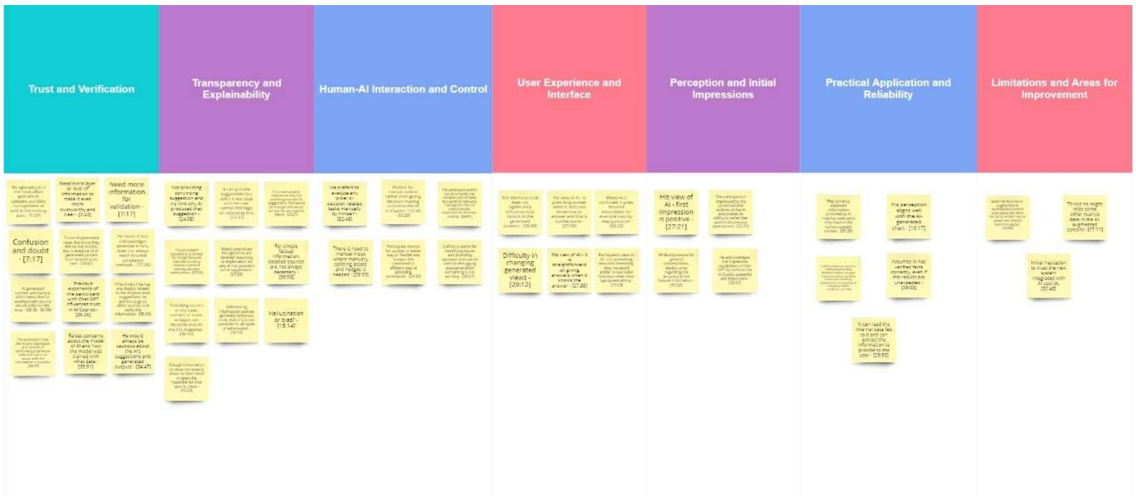

Fig.8: Axial Coding, can be found in Miro, link attached in the appendix section.

Selective Coding:

Selective coding is the third level of coding in qualitative analysis. It involves selecting and integrating categories from axial coding into cohesive and meaningful expressions. This process refines the data further, identifies the main thematic category, and systematically aligns it with other categories. The goal is to create a clear '*story*' or '*case*' from the data (William & Moser, 2019), which helps in developing theory and **constructing meaning**. Selective coding allows researchers to see patterns and predict how certain circumstances lead to specific responses or make a meaning out of it. In short, open coding involves identifying initial patterns, axial coding organizes these patterns into categories, and selective coding identifies the most significant themes or concepts within the data. In this stage, I focused on addressing my research questions by categorizing and organizing the qualitative data into distinct themes. With the data sorted into clear categories, it was easier to address the research questions and analyse the data systematically, making the process more straightforward and facilitating the extraction of meanings/insights.

In the following sections, I will delve into each research questions and discuss them based on the selective codes identified during the selective coding process.

5.3.1 ADDRESSING RQ.1

In my first research question, my aim is to address how financial institutions, particularly Simcorp, foresee the benefits and obstacles of integrating AI into their software solution. This involves exploring anticipated improvements in functionality and user experience, as well as identifying potential issues such as implementation difficulties or any other challenges associated to it. By understanding these perspectives, the study seeks to provide insights into the future of AI in financial software. Ultimately, this will help guide the successful integration of AI in fintech solutions. To address the research question, I further refined the codes under axial coding into two main categories: *Effectiveness* and *Challenges.* Subsequently, I thoroughly reviewed each category and identified specific codes relevant to answering the research question.

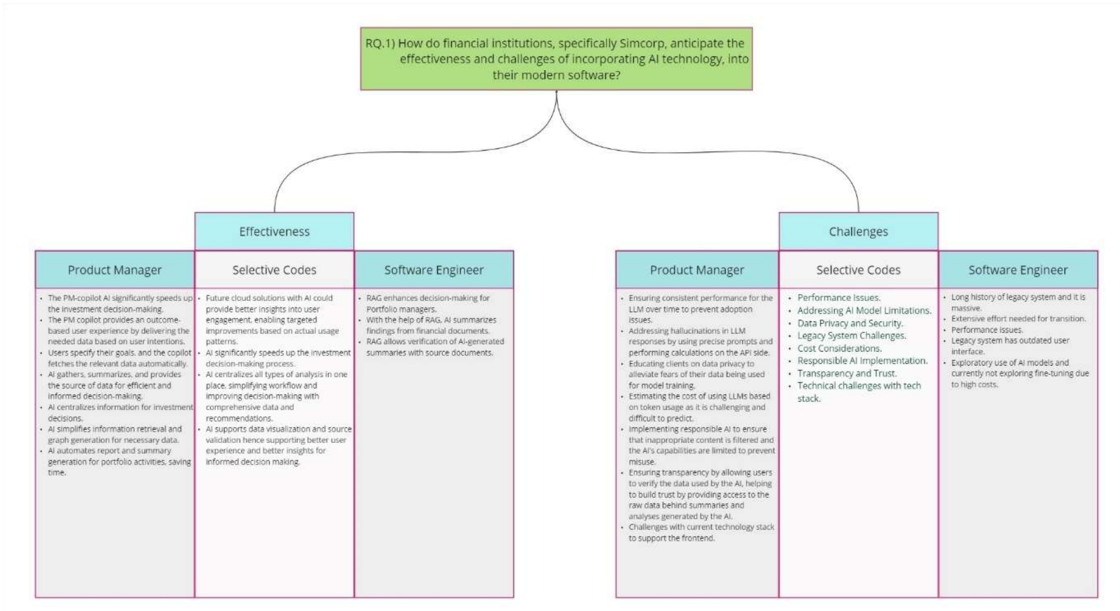

Fig.9: Selective Coding. Both the effectiveness and challenges contain codes from product manager and software engineer, which then is processed into one combined selective code to draw the meaning, to provide answer to the research question. Can be found in Miro.

Let us divide the findings into two parts for better presenting the answer and start with the effectiveness first:

Note – The timeframe inside the brackets at the end of every quotation represents the timepoint in the videorecording.

Effectiveness:

In relation to the effectiveness of AI several codes emerged out. First, it was understood that future cloud solutions integrated with AI have the potential to offer deep insights into user engagement, particularly speaking to portfolio managers and asset managers. This could lead to targeted enhancements based on real usage patterns, ultimately improving the user experience. During the open coding process, product manager mentioned the copilot is expected to help the users with outcome-based user experience by delivering the needed data based on user intentions, *"It's a completely different user experience in the sense that we are moving to outcome solution, that user can tell what he wants, and not how he wants to do it. He says, I want to do something and then the copilot will get all the data that is needed and presented to the end users. [11:55 – 12:50]".* Second, AI plays a crucial role in accelerating the investment decision-making process, to quote the product manager *"And also with the PM copilot, it's also something that really making the investment decision much faster… [11:50 – 11:55]".* By automating tasks and processing vast amounts of data swiftly, AI enables quicker and more informed decisions.

Additionally, AI serves to centralize various analyses into a single platform or central hub, streamlining workflows and enhancing decision-making by providing comprehensive data and recommendations. In the current application, there seems to be a difficulty as the portfolio managers have to switch between different platforms to access various documents while reviewing their investment positions, *"… they rely on external documents and that they use for the investment decision and the difficulty for them was, they could see the positions but then they had to go somewhere else to view the documents. [13:40 – 13-50]."* In counter to this problem, AI is expected to solve this problem, as it will act as a centralize point for viewing/fetching different internal and external documents or news relevant for the tasks, *"Today, we didn't have the solution without AI to address that. So, it's really like improving the efficiency for the investment decisions by giving the ability to gather the data, do a summary of the data… [14:40 – 14:55]".*

Lastly, on top of regular automating support, AI facilitates data visualization and validation, contributing to a better user experience and empowering decision-makers with valuable insights, which again boosts up the informed-decision making capacity of the decision-makers. So, with the help of solution like RAG, the users can view the actual source of the information (documents) and be informed while creating the orders. Also, the power to accumulate the historical data and calling different function calls to generate the meaningful charts or data visualizations capability is viewed as one of the most effective features that the AI can provide to the new solution, *"… it's intriguingness, and the simplicity when we do the graph generation in the use cases. I think here it shows that it can be very simple to get the information that they need in very fast way, in very simple way, today and especially for the past dates… [15:10 – 15:30]".*

Challenges:

Let us first start with the challenge that was seen during the task-focused interview with the portfolio manager. During the interview, participant expressed concern about the clarity of information provided by the AI-integrated solution. When asked whether the copilot offered sufficient information about a particular visualization, the participant responded that while it seemed to show the current currency exposure, there was more complexity involved to it. The participant noted confusion regarding the error message, which indicated that the chart displayed both assets and hedges, but it did not clearly convey this information. To borrow PM's words, *"I think I'm not sure if I understand this error because it says that the chart shows the assets and then the chart shows the hedges, but it doesn't really [5:40 – 7:18]"*. This highlights a significant challenge: the AI's inability to provide clear, comprehensive explanations, which can lead to misunderstandings and reduced trust in the system.

As highlighted by the Product Manager also, one of the challenges is ensuring the reliability of the Large Language Model (LLM) over time, particularly as it transitions into production. There is a concern regarding consistency, as the LLM's performance may vary, yielding both positive and negative results intermittently. This inconsistency poses a risk of adoption issues, where users may struggle to trust the LLM due to its unpredictable performance, taking reference from the product manager - *"… that we are going into production… making sure that there is no evolution in the LLM over time on the answers is given. I mean, we know that over time it's not consistent. So, the risk for us is that at some point we have good results and at some other points, we have bad results from the LLM, and the risk is that there is an adoption problem… [22:55 – 23:35]".* There is also a challenge of managing the occurrence of hallucinations, which are inaccurate or illogical responses generated by the LLM, *"The other challenge there, it's also one of the big questions we have from clients, like how do you mange the hallucinations? And I think everybody is really scared for that… [23:40 – 23:45]".*

Additionally, there is also a challenge of educating clients on how LLM and Azure OpenAI works and that they do not store users' critical information. There is a need for educating clients on data privacy to alleviate fears of their data being used for model training, *"Everybody is really scared of…, Uh, but then it's going to be used for* *training the model and it's like in the next day, it's going to be there and then everybody will be able to see my data… [24:20 – 24:40]".* Actually, this aligns well with what the portfolio manager said in the interview. During the interview, it is seen that PM has expressed his trust and reliability issues with the AI solution.

Also, there is an ongoing debate regarding whether AI/LLM, is always the best solution for various tasks. This challenge involves assessing the suitability of AI against traditional development methods, considering factors such as efficiency and effectiveness in different scenarios. And lastly, estimating the cost of utilizing the LLM poses a considerable challenge due to uncertainties surrounding end-user token usage once the system is deployed. Taking the reference form product manager – *"… the other challenge is, addressing and trying to address the price or the cost. … but how much the user will use it and how many tokens will be used when we go live by the end user, so much impossible to estimate [25:55 – 26:35]".*

5.3.2 ADDRESSING RQ.2

In my second research question, my aim is to address how AI, particularly LLMs can serve as a valuable tool in supporting portfolio managers within the domain of portfolio management and analysis. This inquiry delves into the potential applications of LLMs in aiding portfolio managers with their tasks, encompassing activities such as data analysis and informed decision making. By exploring the capabilities of LLMs and examining their integration into the portfolio management workflow, this research question seeks to uncover novel approaches and insights that can enhance efficiency, accuracy, and effectiveness in portfolio management practices.

If we are to visualize the selective coding process targeted for this research question, we get:

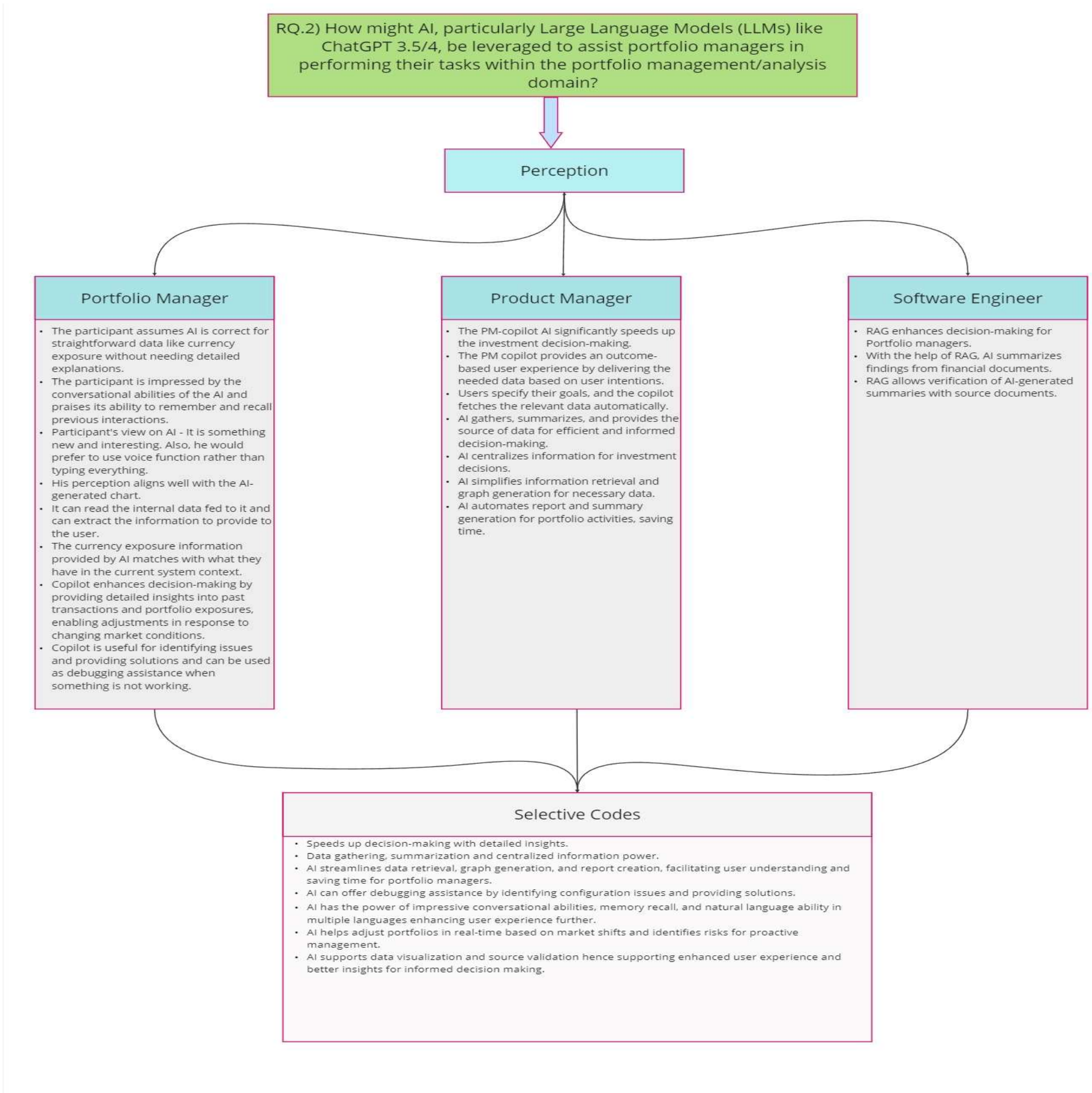

Fig.10: Selective Coding. The combined perception of product manager, portfolio manager and software engineer were considered to extract the insight well enough to address the research question no. 2. Can be found in Miro.

As discussed previously in addressing the first research question, AI enhances decision-making capabilities. One of the key advantages of AI which can be used to help the portfolio managers in their daily tasks is its ability to gather data both internally and from authorized external documents. By combining this data-gathering capability with its impressive summarizing features, it is seen that it can be leveraged to provide the portfolio managers with detailed insights very quickly. To quote the product manager, *"...we didn't have the solution without AI to address that. So, it's really like improving the efficiency for the investment decisions by giving the ability to gather data, do a summary of the data, but still give the end users the possibility to view where the data is coming from and what the actual data is. [14:40 – 15:00]"*. This power of being a centralized informational hub with capability of summarizing the documents and also allowing the decision-makers to view the actual source of data, can significantly speed up the decision-making process and increase efficiency. It eliminates the need for portfolio managers to switch between different platforms to gather relevant information to make the decision. This information is something that we can also reflect to study conducted by the McKinsey Global Institute in 2012. They found knowledge workers spent around 20% of their workweek, which equals to about one day each week, on searching for and gathering information (Chui, et al., 2023, p.13). Chui et al. (2023) suggests that generative AI could remarkably enhance worker efficiency by rapidly processing vast amounts of corporate data and improving the results with human help.

In addition to regular automation jobs, AI can be leveraged to debug by identifying configuration issues or any faults in personalization settings and providing solutions. This feature or ability of AI helps to ensure that systems run smoothly and efficiently. It also eliminates the need for portfolio managers to handle low-level tasks, allowing them to be concentrated at the higher-level responsibilities and save the time. AI at the current point of time, for sure bears the impressive conversational abilities, which allow it to engage in natural and intuitive interactions (multiple languages) with users. This capability ensures smooth and efficient communication, making AI and effective assistant for various tasks. The portfolio manager says, *"I think it's extremely impressive in the way it can, I'd say, generate a conversation and speak with you. Remember what you have said like ten time before, like the previous ten questions and drawing that... [35:37 – 35:55]"*. Lastly, AI supports data visualization or say it understands or triggers different function calls, all thanks to prompt engineering. It gathers the data and feeds them into the dedicated APIs to generate visual charts. These capabilities of AI lead to better insights and assist in making the informed decision, enhancing overall investment strategies and outcomes compared to what they have in the current solution.

5.3.3 ADDRESSING RQ.3

Coming to my third research question, my main aim is to explore and investigate how portfolio managers perceive the recommendations generated by AI, and also evaluate the usability of the AI-integrated prototype for viewing portfolios. This enquiry seeks to understand their level of trust in AI recommendations, how effectively they can use the AI-integrated solution even if it is just a prototype. Along with these motives, my aim is also to investigate if there are any challenges they encounter while using the AI-integrated system/prototype. By addressing these aspects, the research aims to identify areas for improvement and assess the overall impact of AI integration on portfolio management practices.

If we are to visualize the selective coding process targeted for this research question, we get:

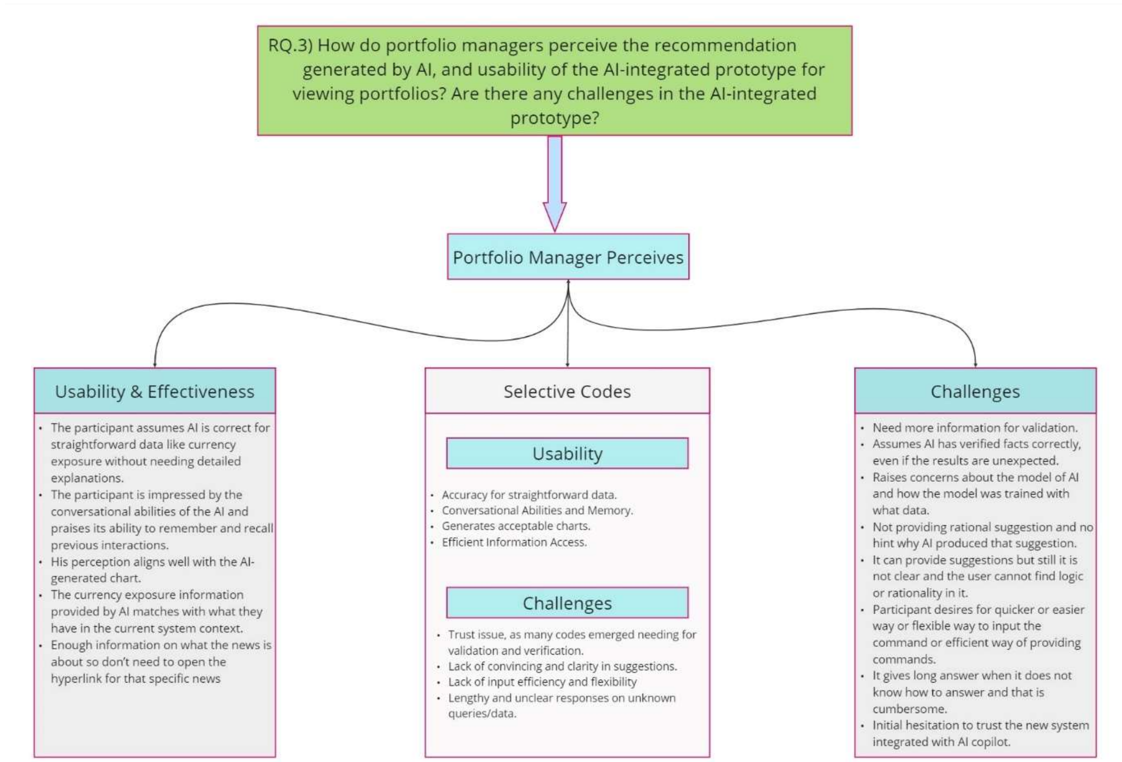

Fig.11: Selective Coding. Portfolio manager's perception on usability and AI-generated recommendations to address the research question no. 3. Can be found in Miro.

Let me address the research question into two sections here, and let's start with Usability.

Usability of AI-integrated solution:

The portfolio manager finds it easy and straightforward to get the answers or the recommendations the AI has to offer when the AI is well trained or engineered with effective prompts in that context. As noted, down in the previous sections, the ability to engage in natural interactions or the conversation in multiple languages is also one of the useful features that is considered to enhance the usability of the solution in the view of portfolio manager. He also stresses upon the ability of AI to figure out some configuration or setting issue, as per him – *"… if it can understand how the system is configured then it can understand why I can or cannot do certain things. That to me from a precious perspective, that would be very useful [30:59 – 31:18]"*. He also acknowledges the information that the AI has provided in the form of charts look good and fits well with what he currently has in the system. He states, *"I'm trying to look at obviously, like it's highlighting a lot in the UK, US, and Switzerland as well. Which matches what we have in the currency exposure and yeah, it makes sense to me. [10:00 – 10:19]"*. The charts are in general helpful and easy to understand, which makes it simple for the users to make decisions based on the information AI provides. And lastly, the AI integrated in the solution can be very useful on saving time and making efficient information access with its ability to provide news or information on any documents right away on demand. The portfolio manager says, *"If I see that I have 10% exposure to an issuer and I can ask the copilot, why is my exposure 10% and then it can tell you, well because at this point in time you bought this much… and so on. Or as we did with the news, and I can look at what my top ten exposures are and check for the news around… [31:40 – 32:10]"*.

Challenges in AI-integrated solution:

In discussing the challenges identified during the interviews regarding the AI-integrated solution, several key issues were mentioned. There seems to be a need for more information for validation. Portfolio manager expressed a need for more detailed information to validate AI's recommendations. They are concerned about how AI models were trained, and the data used to train them. During the interview, the portfolio manager expresses his thoughts, *"Also, it makes me wonder like what the biases are. Since, I asked for news of Novo Nordisk and it shows me news from Microsoft AI which have nothing to do… Yeah, that's a question mark, what exactly is this Copilot trying to do… we just don't know or at least I don't know how it's been trained and what has been introduced there. So, that would be, uh, I'd always wary of whatever it comes up with the certain degree. [34:00 – 34:50]."* This lack of transparency is seemingly making it hard for portfolio manager to trust the outputs provided by AI.

One of the other challenges in the prototype solution is that portfolio manager finds AI's suggestions/recommendations often lack clarity and are not convincing. He was apparently struggling to understand the logic and reasoning behind the AI' recommendations. During the interview or the test session, he said – *"… but then I don't know why it has suggested to buy a TRS. It would seem strange that I would just instead of buying it directly. Well, depends on type to type portfolio, but I was a little surprised to see the suggestion below [23:20 – 24:00]".* This makes it difficult for him to fully rely on AI for decision-making, as he cannot see the rationale behind the suggestions, which he expresses by saying – *"I think it would be comfortable if it just wrote the reason… [26:27 – 26:31]".* It appears that enhancing the AI's ability to explain its recommendations in a clear and logical or in comprehensive manner would help users understand and trust the AI's advice. This same phenomenon was also observed by Lu, Zhang, Zhang, and Li (2022) in their research, where participants raised trustworthiness issue of AI while generating the result.

It was also seen that the prototype solution is vulnerable to hallucination issue. The portfolio manager encountered cumbersome long answers at one point during the testing session. He came to an understanding that when the AI does not know how to respond, it tends to provide long, drawn-out answers. He also felt that drawn-out and cumbersome answers can make the system feel less efficient and harder to navigate. This was one of the problem or issue that was raised during the interview with product manager also, where he acknowledged addressing the hallucination in LLM responses by using precise prompts and performing calculations on the API side is one of the main challenges in the new web solution.

And lastly, the final challenge that is seen is hesitancy to trust the AI-integrated solution. I will talk about this in dedicated section down below. But to mention the trust issue expressed by portfolio manager, it was the unfamiliarity with the new technology and concerns about its reliability. To borrow his words, *"I mean until I get used to it, it would be a bit scary of saying like, yeah, I'm 2% into these names and order through that. I would have to go and do it myself to make sure that this is actually the amount that the cash matches and that we are not going overdrawn and so on [32:48 – 33:10]."*

5.3.4 ADDRESSING RQ.4

Coming to my fourth research question, my main is to explore how stakeholders perceive the trustworthiness of AI-generated content in their financial software solution and to understand how this perception influences their decision-making process. This investigation seeks to uncover the level of confidence stakeholders have in AI outputs, the factors that contribute to their trust or scepticism, and how their trust in AI impacts their financial decisions.

If we are to visualize the selective coding process targeted for this research question, we get:

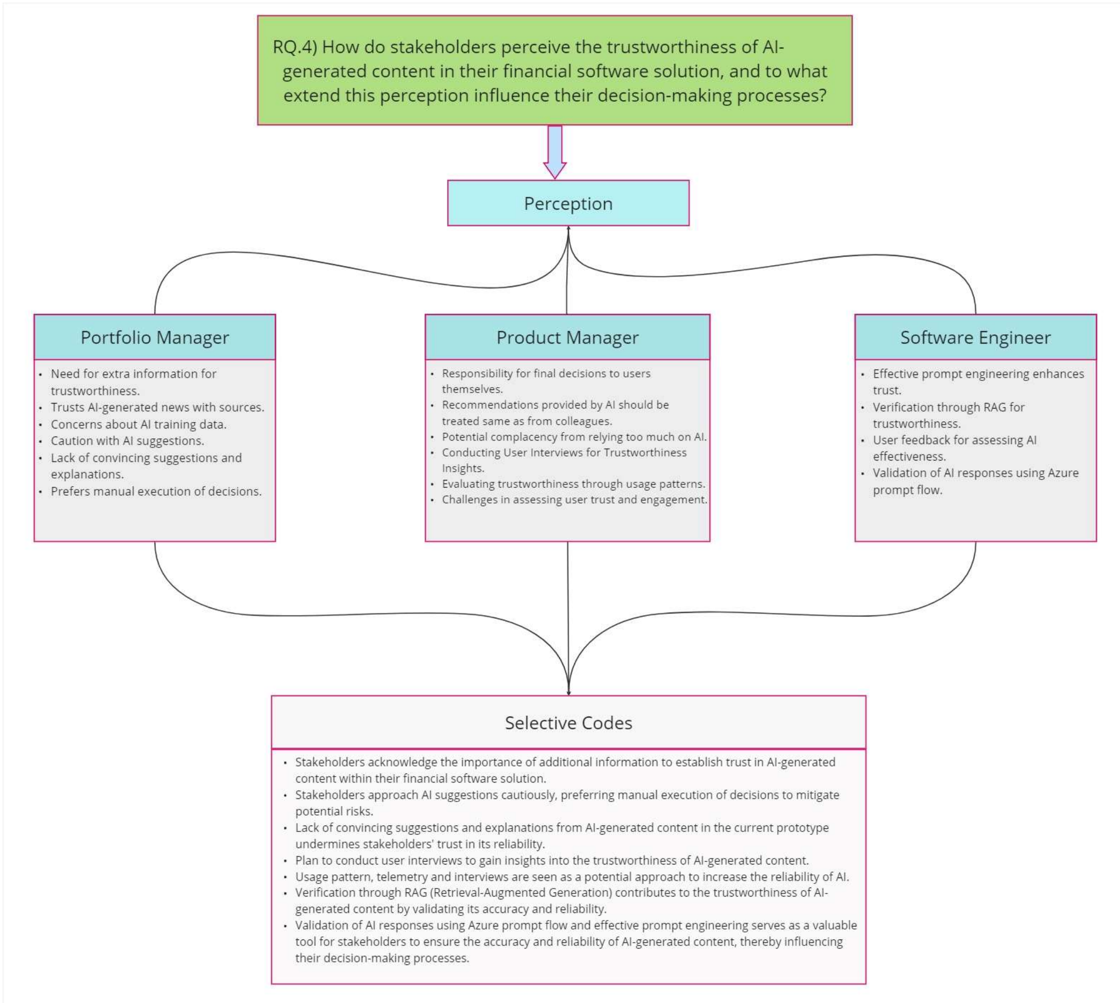

Fig.12: Selective Coding. Stakeholders' perception on trustworthiness of AI-generated content to address the research question no. 4. Can be found in Miro.

Portfolio manager:

Talking about the portfolio manager, he needs more detailed information to fully trust the AI. In the interview, on asking what would make him accept the suggestion provided by AI, he says, *"So, I think I would be comfortable if it just wrote the reason, it wouldn't need to go into the very specific details… [26:27 – 26:35]."* He feels it as a need to view basic reasoning behind the suggestion it provides but would not need to go into the very specific details. It appears that he wants to understand the source and logic behind AI recommendations to feel confident in using them. In the case of fetching the news, he was confident on that because he could see the source of the news and he responds that being able to view the source of the information, like where it is coming from enhances the trust. But he moves on to say he would not prefer the AI-augmented or summarised content in the news intro inside the news widget, to borrow his words, *"I would personally prefer to have the actual text from the article instead of written summary by the AI [16:48 – 17:00]."* He thinks the AI-augmented news intro might lose the actual wordings and nuances of data, so he personally would like to see the actual summary from the original content or source [17:22].

As discussed in the previous sections, the portfolio manager has difficulty understanding the suggestions and recommendations provided by the AI-integrated solution. The lack of clear explanations or reasonings makes it hard for the portfolio manager to trust these recommendations. Because of this, despite AI's capabilities, the portfolio manager still prefers to execute decisions manually. He says, *"So for the actual decision of the implementation of the decision, I think I would go and do it myself. ...But I would not let the copilot release any orders [32:50 – 33:20]"*.

Product manager:

It is understood that the product manager believes the AI-integrated solution significantly speeds up the investment decision-making. It can enhance the user experience and make the process quick and efficient by approaching outcome-based solution, where users specify their goals, and the copilot fetches the relevant data automatically. He also emphasizes the importance of AI on bridging the gap between past and present data. AI can help users see/visualize how their positions have changed over time, including sector exposure and performance against benchmark, *"...what happened six months ago and how position has changed over six months then it opens up new possibilities that we don't have in the current solution. Today in the current solution, we can see what was my position three months ago, what is my position today. But you cannot see any relationship between the positions three months ago and today. You cannot see how the position has changed or how exposure to a sector has changed, what has changed against benchmark... [15:15 – 16:15]"*. He strongly believes that the new AI-integrated solution will enhance the decision-making ability of the users and provides all kinds of information readily available needed to make the decision.

However, he recognizes the challenge of managing hallucinations, making it difficult for the product manager to fully trust AI in making important decisions. He strongly states that the recommendation or suggestions provided by the AI should be viewed as that of provided by their colleague and should never be fully relied or dependent on it and though the AI can generate simulations, the real order can only be generated by the portfolio managers and no one else. He says, *"The first we uh in the limit, we've set that the AI can generate a recommendation to generate the simulations but will never be able to generate an order. The order can only be generated by the portfolio managers. So, it will always be the responsibility of the portfolio managers to release an order for execution [30:45 – 30:57]"*.

Software engineer:

The software engineer believes that implementing Retrieval-Augmented Generation (RAG) is crucial for building trust between users and the Large Language Model (LLM). To make the AI-integrated solution reliable in users' eyes, he thinks RAG is necessary because it allows users to see the actual sources of the data or documents from the AI generates its recommendations or suggestions. He suggests using Azure Prompt Flow to assess the accuracy of AI responses, which can enhance the trustworthiness and reliability of the AI-integrated solution.

He acknowledges the issue of AI hallucinations, where the AI might generate incorrect or misleading information or the information that does not make any sense to the users. However, he is confided that this problem can be addressed through better prompt engineering. He believes that user testing – observing how different users interact with the AI and collecting their feedback, can help the development team to create better prompts. In his view, improved prompt engineering leads to better AI performance and a more reliable AI-integrated solution.

5.4 INSIGHTS GAINDED FROM THE OBSERVATIONAL RESEARCH

Qualitative observation involves watching how things happen naturally without specific behaviours in mind, then describing what was seen afterward. During my time conducting observations for my thesis research, I found that my observations not only led me to generate valuable notes and insights regarding the working culture, learning practices among staffs, but also enabled me to locate secondary data by examining archived files and videos that was deemed relevant to me (through communications). Additionally, I had the opportunity to delve into the evolution of wireframes and prototypes from their initial stages, allowing me to gain a deeper understanding of the development process. Moreover, I was able to participate in discussions and brainstorming sessions held in the past via Miro board, providing me with valuable insights for my analysis. Furthermore, I was invited to attend team meetings providing me with firsthand experience and insights that enriched my study. Overall, these observation experiences have been instrumental in helping me gain a thorough understanding of the complexities of the current system and the challenges it poses, as well as understand the necessity of integrating AI into fintech through Simcorp's lense.

The understandability and usability of the product or system matters greatly than how attractive it appears. Still, having an appealing appearance or aesthetics is crucial for success of the product (Norman, 2013; Moran, 2017). Norman (2013) suggests that these two aspects of design should complement each other seamlessly. In my observations I also witnessed the aesthetics of the application were a significant point of discussion during interviews and team meetings. For instance, comments were made about the appearance of the current system or application, with some referring it to something from the 60s-70s. This suggests that the design aspect for better user experience may not have been adequately addressed in the past. There may be a need to improve the visual design to make it more modern and appealing to users. This issue aligns with concerns raised by Cordeiro & Weevers (2016), highlighting the significance of addressing visual design to meet modern user expectations. In the financial software solutions, the usability, integrity, performance, security, and scalability of the software comes in the top priorities. However, there is now a growing recognition of the importance of modernizing legacy systems. Users tend to be more forgiving of usability issues when the interface is visually appealing, as highlighted by Moran (2017), emphasizing the importance of aesthetics in enhancing user satisfaction and product success.

During my observations, significant concerns surfaced regarding potential biases and hallucinations that are reportedly found in AI models. Stakeholders expressed apprehensions about the trustworthiness of AI-generated data, as well as concerns regarding data security and privacy of sensitive resources that the company might expose to AI. This underscores the existing gap in trust towards artificial intelligence, with many hesitant to wholly depend on or view its generated content as reliable asset. Despite acknowledging the potential of AI when combined with human intelligence, there remains a reluctance to solely rely on AI-generated content for decision-making purposes. People rather seem comfortable and prefer to use AI as an assisting tool. To address these issues related to biases and hallucinations or privacy and security, the strategic area has come out with the idea of utilizing RAG (Retrieval Augmented Generation) with the acquired AI-models. Retrieval Augmented Generation is an architecture that enhances the abilities of Large Language Model (LLM) such as ChatGPT by integrating an information retrieval system. This system supplies grounding data, offering control over the information used by the LLM to generate responses (Steen & Wahlin, 2024).

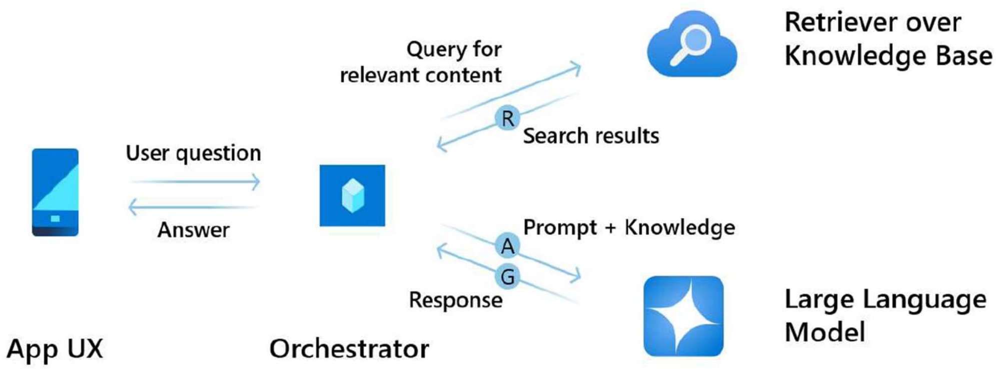

Fig.13, RAG architecture, retrieved from internal source in Simcorp.

In this implementation, RAG works by first retrieving relevant information from a vast knowledge bases, such as internal databases or enterprise data sources. This ensures that the generated content is grounded in a factual and accurate data without exposing its reach to external premises. Then, using generative models, RAG augments this retrieved information with additional context or insights, resulting in content that prioritizes accuracy and aims to minimize biases and hallucinations.

Based on the "Images of Organizations" (Morgan, 2006), as retrieved from Digha (2014), the organizational culture also exhibits characteristics of a 'Learning Organization'. There is a strong emphasis on continuous learning and innovation, supported by organizational leaders who actively promote technological advancements. This is evident through the establishment of a dedicated learning platform, *Workday,* where employees have access to AI-related learning materials and resources among other learning materials related to upgraded tools. Learning opportunities are shared widely throughout the organization via email notifications, reflecting a culture of inclusivity and accessibility, fostering a learning environment for all individuals within the organization. Additionally, the *'knowledge sharing sessions'* with Microsoft's employees, who are experts in Azure OpenAI, signify a collaborative culture where external expertise is valued and integrated into internal processes. This aligns with Schein's model of organizational culture (Schein & Schein, 2016), particularly the notion of 'Artifacts', which represent the visible aspects of culture such as structures, processes, and behaviours. The active engagement of leaders in promoting learning knowledge sharing demonstrate their commitment to shaping organizational culture and driving change.

Now, at this point of the study, I had the idea of initial motivations behind the company's initiative to modernize their product while also incorporating AI technology. As mentioned earlier, my observations led me to uncover additional information or say secondary data in terms of files and videos. In one of these video archives, the discussion related to necessity of integrating AI into the ongoing modernization efforts was found. One of the main statements used in there was 'technological and data tsunami' where the offer manager states *"... data tsunami with the emergence of the more digital world, I think we have never seen so much data on the market. The market is flooded with vast amounts of data, including information for PMs, as well as data generated through various interactions and responses".* The other important and noticeable statement the offer manager uses is *'We never thought we would be in this position today with AI one year ago'*. He moves on to saying *"... so, it's building a cloud-based PMs supporting all asset class listed OTC and alternatives coupled from the start with the best-in-class optimizer and generative AI is actually a game changer..."*. The reason he provides for the need to integrate AI in the ongoing modernization of the product is *"...So, nobody on the market is doing that today and that we will be reshaping the way PMs will approach the problem solving and decision making with* *user centric design approach".* The offer manager provides a scenario on the planning as *"... to utilize AI insights for improved decision-making. By aggregating incoming data with AI and generating summaries, we assist PMs in enhancing their capabilities through AI-enabled informed decision-making".*

So, to conclude what we can gather from the offer managers' insight, integrating AI into their cloud-based portfolio management system is revolutionary, as it supports various asset classes and optimizes performance using generative AI. This approach is unique in the market and aims to reshape problem-solving and decision-making for portfolio managers. By leveraging AI to aggregate and summarize data, the system enhances portfolio managers' capabilities, enabling them to make more informed and efficient decisions.

6 DISCUSSIONS

AI is already deeply integrated into user experiences with widely used products like Netflix, Amazon, Microsoft, Google, Facebook, Instagram and so on (Lee, Suh, Roy, & Baucus, 2019). Many users may not realize that the recommendations they receive on these platforms are generated by AI algorithms that learn from their preferences. For instance, Netflix's recommendation engine, valued at approximately a billion dollars, demonstrates the immense value of AI technology in enhancing user experiences. Similarly, devices like Alexa continuously learn and update their skills, seamlessly integrating into users' daily lives. Users enthusiastically embrace these AI-driven assistants, incorporating them into their homes, cars, and offices. Despite concerns about privacy, people readily interact with AI assistants like Siri and Google, underscoring the widespread acceptance of AI technology in our daily lives (Meritt, 2017).

We are edging closer to a world where computing is everywhere, known as ubiquitous computing or the Internet of Things (IoT). With virtual assistants, AIs, and chatbots becoming increasingly common in our daily routines, the distinction between humans and machines is becoming less clear. As AI systems learn and adapt, they accumulate vast amounts of data about us (Lee, Suh, Roy, & Baucus, 2019). This data collection can reach tremendous levels, with multinational companies amassing up to 2.5 terabytes of data per hour. As we continue to feed more data into these systems and interact with them, they become better at recognizing patterns and making sense of the information available (Shankar, 2018; Zhang et al., 2021; Ernst et al., 2019).

The current approach to UX design can often be complex and time-consuming. However, AI, particularly through deep learning techniques, has the potential to significantly reduce the time required for this process. While human oversight may still be necessary, AI is advancing rapidly and becoming increasingly adept at creating content that is virtually indistinguishable from human-created content. AI can also help personalize user experiences by learning individual patterns and preferences (Cao, 2022). By analysing user behaviour, AI can tailor user interfaces to better suit the needs of each individual user. Conversely, it can also identify highly skilled users who may have different preferences compared to the average user. However, in my research, I observed a notable gap in knowledge regarding the integration of AI into design teams and its utilization by UX professionals. While AI technologies are being increasingly utilized by the engineering team within the organization, there remains uncertainty surrounding its adoption by the design team. As of now, the design team has no immediate plans to incorporate AI tools into their workflow. This situation echoes concerns raised by Q.V. Lia et al. (2023) and Jiang et al. (2022), who highlight that current AI-based tools are primarily benefitted towards software developers rather than UX designers. Whether this uncertainty stems from the lack of AI-tools for UXPs or a knowledge gap remains unclear. This difference shows that more research is needed in this area, as Chatterjee & Kar (2017) have also pointed out.

Predicting what is ahead for a concept involves a bit of a guesswork, but by looking at the past and present we can with some certainty make rational predictions. In the coming years, areas like Artificial Customer Service and bots will likely become more prominent, assisting with various problems. GPT-4 has shown exceptional performance in various mock exams, which has increased trust in its capabilities. It scored in the top 10% on the

Uniform Bar Exam, top 7% on the SAT Reading & Writing, top 11% on SAT Math, and top 22% on GRE. Additionally, it ranked in the top 20-10% in university exams for subjects like English, economics, physics, and history. This level of achievement is absolutely remarkable and surpasses at least 80% of humans who have taken these standardized exams (Cao & Zhai, 2023). Moreover, it can be speculated that the UX design will expand beyond traditional devices like phones and computers to include everyday items like televisions. This could mean that in the future, when we interact with TV, the experience will be more user-friendly and intuitive. For example, we might have easier navigation through channels and streaming services, clearer menus, and perhaps even voice-controlled commands for adjusting settings or finding content.

In Austin's case (Austin, 2017), initial doubts about using new technology like the Amazon Echo, which includes Amazon's voice-based digital assistant Alexa, were replaced by a compelling desire to own the product after actually using it. This suggests that people's attitudes towards AI technology can change once they experience its benefits firsthand. As a result, it is plausible that the use of AI technology as a helpful tool may become more widespread in the very near future.

Similarly, PM and other stakeholders are excited about the capabilities of ChatGPT and see AI's potential as a valuable assistant in their own workspace as well. Over time, it is anticipated that the AI Co-pilot under development will further support PMs or other clients, making their tasks easier and aiding efficient decision-making. Technologies like prompt engineering and RAG can enhance the technical aspects of their work and address any technical issues they encounter. However, there is still a need to study the aesthetics and usability (affordance) of the user interface of the currently under development web solution in Simcorp. When asking if the interface plays any role in increasing trustworthiness of the solution or copilot, the portfolio manager responded it does not affect that much. But still collecting a broad spectrum of data with larger sample group or people would provide us confidence in that regard. This would ensure a balance between technical functionality and user experience for the organization's product and move to the correct path with more confidence backed up with empirical data.

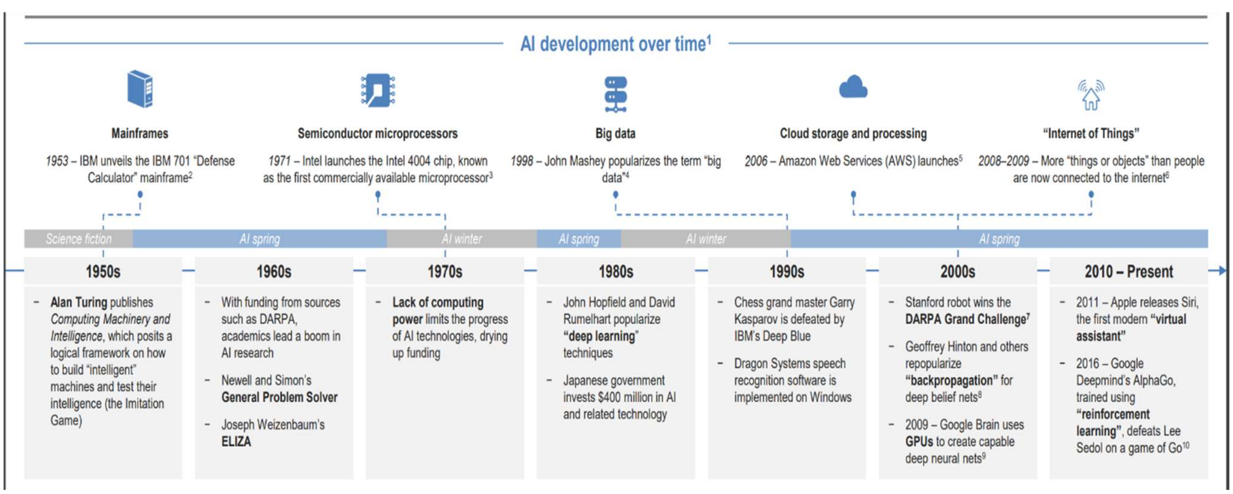

Fig: 14, AI development over time, derived from World Economic Forum (2018).

The attached image illustrates the significant milestones in AI development over time. Starting from the 1950s with Alan Turing's pioneering work, the timeline progresses through key innovations such as the creation of mainframes, the introduction of semiconductor microprocessors in the 1970s, and the emergence of big data in the late 1990s. The 200s saw the rise of cloud storage and processing, followed by the Internet of Things (IoT) in the late 2000s. Since the late 1990s, AI has been in a period of rapid growth, often referred to as an *'AI* *spring'* characterized by continuous breakthroughs and increasing integration into various aspects of technology and daily life.

Given the current trends and recent achievements in AI, it appears that this period of accelerated development will continue or at least stay for longer period. Embracing AI, therefore, seems not only smart decision but also inevitable. Integrating AI into our systems and processes can offer numerous benefits, enhancing efficiency and innovation. Running away from AI would mean missing out on these potential advancements and the competitive edge they provide. Thus, incorporating AI into our strategies and workflows is a forward-thinking approach that aligns with the ongoing and future trends in technology.

7 REFLECTIONS

In reflecting on my research journey, I acknowledge that grounded theory could have been a viable alternative if I had more time and had not already formulated prior research questions. Formulating these questions proved to be a challenging and esoteric task, as narrowing down the research scope was not straightforward, and there was limited context or literature available to guide the process. However, as I gradually accumulated information and insights, I refined the questions in iterative manner to be the best of my ability and knowledge which helped me in focusing on the research scope and provided more clarity for moving ahead.

In selecting my research methodology, I opted for a qualitative approach combined with pragmatism. This choice was informed by the presence of a coded prototype within the organization, allowing stakeholders to interact with AI through the user interface (UI). This prototype served as a foundational element for adopting the pragmatic approach and also facilitated the data collection. During usability testing session with PM, I utilized the think-aloud method to gain insights into their cognitive understanding of the prototype and their perceptions of the integrated AI technology. Despite the prototype being in its early stage, lacking dynamic real data flowing from middle-tier APIs, and not encompassing all features of a PM's daily tasks, it provided valuable insights into the PMs' perspectives on AI and the virtual assistant PM-Copilot.

I am immensely grateful to the company for granting me access to their premises and allowing me to immerse myself in their operations. This enabled me to conduct thorough observations and engage with the team members involved in the AI integration process. Through these observations and occasional interactions, I gained valuable insights into the technical aspects of the integration process and gained a deeper understanding of the company's culture. Most importantly, this firsthand experience also provided me with the necessary knowledge and insights to prepare effectively for the interview conducted as part of my research. The decision to include Portfolio Managers was crucial because they are key decision-makers and the primary users of the copilot being developed. Similarly, the Product Manager was interviewed for his deep understanding of the study context and strategy/decision-making authority. Engaging with engineer was essential to grasp the technical aspects and functioning process of AI. I believe this diverse participant selection in the interview process enriched the research by offering insights from various perspectives, enhancing my understanding of AI development and integration at SimCorp.

Creswell & Creswell (2018) highlight the importance of triangulating data to ensure its quality. In my research, I employed multiple methods to understand the context thoroughly and validate my findings. This involved conducting interviews, observing *discussions* and *meetings* within the organization, and analysing documents and audio-visuals materials simultaneously. By integrating these diverse sources of information data, I aimed to develop a comprehensive understanding of the case and this decision/process helped me a lot in accumulating the required knowledge and drive my research forward with a right mindset. I also considered internally produced documents as valuable data, aligning with Glaser & Strauss's (1967) perspective that such materials are as valuable as interviews or observations. They even move on to give a statement, which I totally agree with and is touched - *"When someone stands in the library stacks, he is, metaphorically, surrounded by voices* *begging to be heard. Every book, every magazine article, represents at least one person who is equivalent to the anthropologist's informant or the sociologist's interviewee. In those publications, people converse, announce positions, argue with a range of eloquence, and describe events or scenes in ways entirely comparable to what is seen and heard during fieldwork" (p.36).*

I initially considered using an abductive reasoning approach while analysing my qualitative data, *abductive approach* blends *deductive* and *inductive* reasoning, to explore the impact of AI in finance. However, I encountered several challenges that led me to reconsider. Firstly, the AI prototype I was studying was still in its early stages, making it difficult to draw upon existing theories or comparisons or assumptions. Additionally, the topic of AI in finance is relatively novel. This means participants had limited understanding or experience or practice with this innovative technology, especially in the context of it being studied in the form of a prototype. Without solid theoretical frameworks or established norms to guide my reasoning, I ultimately decided to rely on inductive coding. Opting for inductive coding over an abductive approach was a good move for a few reasons. It allowed me to remain open-minded and flexible, adapting to the evolving nature of the data as I collected and analysed it. It allowed me to let the themes and pattens emerge organically from the qualitative data, providing organic perception on the topic without imposing preconceived ideas. Ultimately, it helped me moving forward with the analysis and reach to my findings.

Talking about my personal experience, this research project has been a valuable learning experience for me. I have improved my research skills and used it practically in the real world. In the beginning, I struggled to figure out how to approach my study. Narrowing down the research questions was particularly challenging. But as I progressed, conducting investigations and interviews, things started getting clearer. With each step forward, my understanding improved, and I was able to refine my research questions a bit. After the first round of interview with portfolio manager, I identified gaps in my approach based on their feedback. This prompted me to adjust and fine-tune the interview guide for the next round of interviews. So, in this sense I believe I have improved or accrued the understanding and skill of using research methodology, data collection, and analysis.

Moreover, interacting with professionals in the field has broadened my understanding of the intersection between technology and finance and how organizations work. This project has also enhanced my ability to navigate complex organizational structures and adapt to dynamic work environments. Furthermore, conducting interviews and observations has improved my communication skill. Overall, this research journey has not only deepened my understanding of the subject matter, but I believe has also equipped me with valuable skills that will benefit me in my future endeavours.

8 CONCLUSION

As stated by Kore (2022), most of the AI systems publicly available today fall under the category of narrow AI. Simcorp's use of AI is no different. Simcorp uses AI based on natural language processing (NLP) to develop an AI copilot using ChatGPT-4. This AI copilot is a prime example of narrow AI, designed to perform specific tasks within the financial sector. It provides targeted solutions and helps portfolio managers optimize their processes. By focusing on these specialized functions, Simcorp effectively leverage narrow AI to boost productivity and improve decision-making within its domain.

The pragmatism approach was highly beneficial for my research. The task-focused interview with the portfolio manager provided real-time insights and allowed me to capture detailed information as it happened. Similarly, the two other interviews with the product manager and software engineer offered valuable insights into how the AI copilot would work in a real-world context. These interviews did not only help me address my research questions and come to the answers, but also helped me understand practical issues, technical challenges, and opportunities for improvements, giving me a comprehensive view of the AI Copilot's practical implications.

The process of analysing qualitative data can be tough, especially when we are new to qualitative research (Linneberg & Korsgaard, 2019). It is not just about reading through transcripts and documents and finding the answers. Instead, it involves carefully sorting through information to identify key points and then crafting them into a clear and convincing narrative. This narrative should address the research questions and offer insights that accurately reflect the data (Linneberg & Korsgaard, 2019; Miles et al.,2013). Initially, I found thematic analysis and generating codes more sophisticated than anticipated. However, as I progressed, the process began to open up in my mind, helping me manage and organize the qualitative data effectively. This approach enabled me to stay aligned with my findings and produce reliable insights to address my research questions.

In conclusion, the integration of AI technology, particularly LLMs like ChatGPT-4, holds great promise for enhancing effectiveness and efficiency in modern financial solutions, such as those used in portfolio management. AI has shown potential in accelerating decision-making processes, centralizing data analyses, and providing valuable insights through data visualization.

However, challenges exist in ensuring the trustworthiness and usability of AI-generated content. Stakeholders, including portfolio managers, product managers, and software engineers, have varying perceptions of AI's trustworthiness. Portfolio managers require clear explanations and detailed information to trust AI recommendations fully. They also express difficulties in understanding AI-generated content, preferring original sources over AI-augmented summaries. Product managers recognize AI benefits but highlights challenges in managing hallucinations and emphasize the responsibility of portfolio managers in decision-making. Software engineers propose technical solutions like RAG implementation and prompt engineering to address trust issues and improve AI reliability.

To maximize the potential of AI in financial software solutions, addressing these challenges is essential. Enhancing transparency, clarity of recommendations, and trustworthiness of AI-generated content are crucial steps. Technical solutions like RAG implementation and user testing can help improve AI performance and reliability. Balancing AI capabilities with stakeholder trust concerns is key to successful adoption and integration, ultimately leading to more informed decision-making and improved outcomes in portfolio management.

Additionally, there seems to be a need for a close interconnection and balance between AI and UX, with each benefiting from the other. AI to reach to its full potential, it needs to be supported by good UX design and concepts. While AI technology holds promises, it must be more than just a futuristic concept to gain widespread acceptance. Effective UX design ensures that the average internet user can easily interact with AI systems, allowing them to access its capabilities seamlessly. Ultimately, the importance of good UX design in AI lies in ensuring that users can effectively utilize the technology's features. Prioritizing functionality over complexity is key to creating successful AI products or any other products that are embraced by users (Lew & Schumacher, 2020). This similar issue was raised during the interview with the product manager. He mentioned that while the current asset manager software has many functionalities, it is difficult to configure and adjust settings. The complexity often required external help, and they were sometimes afraid to make changes themselves. Therefore, it is crucial for Simcorp to balance usability, affordance, and features in their new web solutions.

To sum up, as I conclude the exploration of Simcorp's new web solution, it is clear that ensuring the reliability and trustworthiness of its AI component is crucial. The concerns raised by the portfolio manager regarding trust issues with AI, as well as worries about privacy and security, highlights significant challenges that need to be addressed. Moving forward, building trust among users and ensuring robust privacy and security measures will be vital for the successful adoption and utilization of the system.

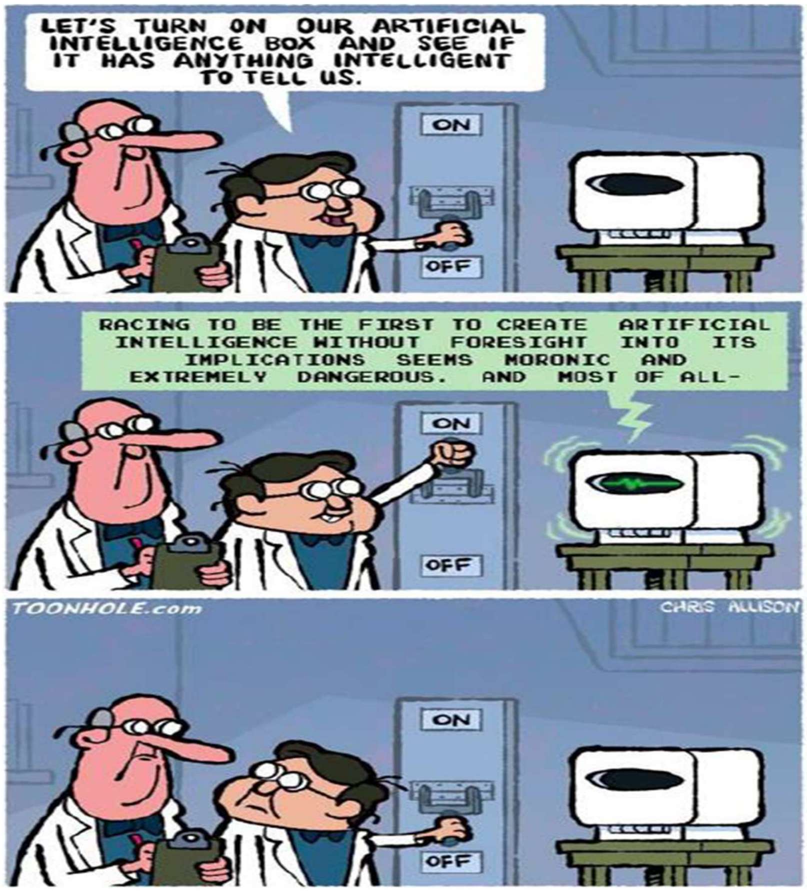

Fig.15: Toonhole Comic (*https://toonhole.com/2017/07/artificial-intelligence/*)

In wrapping up my thesis, I cannot help but think of this comic strip. It humorously highlights the need for caution. AI is amazing and, with its recent advancements (almost every now and then), it can truly boost human capabilities, productivity, and creativity. However, just like in the comic, we must also keep in mind the importance of ethics and security. We need to be careful and take steps to prevent any misuse of AI. So, while we embrace AI as a powerful tool, let us also remember to use it wisely and responsibly.

9 LIMITATIONS AND FUTURE RESEARCH

In this section, I will try to write about the limitations and future research possibilities and opportunities. First, I will write about the limitations that this research bores and then will end by writing or discussing about the future research.

Limitation:

In conducting this research, efforts were made to minimize bias. However, the limited number of participants may have introduced some degree of bias into the findings. It is important to acknowledge that the perspectives and experiences of a single participant, for whom the copilot is being developed, may not fully represent the diversity of viewpoints within the target population. Therefore, it is crucial to interpret the findings carefully, understanding that they may not apply to everyone and may not provide a comprehensive understanding.

Additionally, the prototype under investigation is still in its infancy and lacks full completion, limiting its ability to demonstrate the full range of intended functionalities. Consequently, the prototype only covers a portion of the envisioned solution, failing to delve deeply into the context. To improve the research process, additional rounds of data collection and analysis are required, as suggested by Cresswell & Creswell (2018). Being a lone researcher has certainly limited the validation of the research as I did not have any sparring partner. Lacking a sparring partner means that I had to rely solely on my own judgement, potentially leading to oversight or bias in the analysis. This approach may have hindered the thoroughness and robustness of the research, as external feedback and critique are essential for refining ideas, looking the data from different angle, and ensuring the validity of the findings.

Lastly, the study did not achieve saturation as I had expected in the beginning. The fact that I could not reach to the point where I could assure myself that the new information has stopped emerging, suggest there could be more insights to uncover. Without reaching the saturation point, there always remains a possibility of gaps in the understanding of the topic, limiting the depth of analysis and the ability to draw definitive conclusions.

Future research:

In the future, as the system continues to evolve and additional features are added, it is expected to expand its reach beyond its current state. Currently, the prototype has not been widely used, even within the organization. However, once it is equipped with more features and ready for broader testing, we could employ theories like sense-making theory, affordance theory or cognitive load theory etc., to better understand how users engage with the system and perceive its functionality and aesthetic. This understanding could inform future evaluations of the system's effectiveness in enhancing user experience.

In the discussion section, the close relationship between AI and UX has been highlighted, emphasizing the importance of good UX design for AI to realize its full potential. AI itself can enhance UX, like using deep neural networks to analyse user behaviour data and improve product development, although these capabilities are currently under used (Yang et al., 2019, p.9). Automation in AI can also enhance UX by simplifying tasks such as editing content based on user input or contextual factors like location. Future research could explore why AI-driven capabilities in UX design are underutilized, examining factors such as privacy concerns, lack of awareness about AI's benefits in UX, or resistance to change.

Moreover, AI can assist in the design process by utilizing user data and past designs to generate flowcharts, wireframes, and other design elements. It can also automate the creation and analysis of questionnaires, reducing the time required for designers. Despite these advancements, concerns about job displacement can be mitigated by recognizing the indispensable role of humans in creative decision-making processes (Donahole, 2021). Future research could explore the impact of AI-driven design assistance on the efficiency and creativity of designers. For example, studies could investigate how AI-generated flowcharts, wireframes, or any form of design elements can influence design processes, as well as the quality of the final products. So, echoing on this angle, future research could focus on understanding how designers perceive their roles in AI-driven design landscape and how organizations can effectively integrate AI tools while preserving the creative input of human designers.

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APPENDICES

The appendix of this report is divided into two parts. The first part contains the literature approval section, where I will provide screenshots and images of the approved literature list and relevant content. The second part includes research-related images, such as screenshots of the interview guides. However, the actual recordings of the interview sessions, transcripts, and coded transcripts are stored on personal Google Drive. Additionally, the coding procedure conducted during the research can be viewed on Miro. The link to both the resources are:

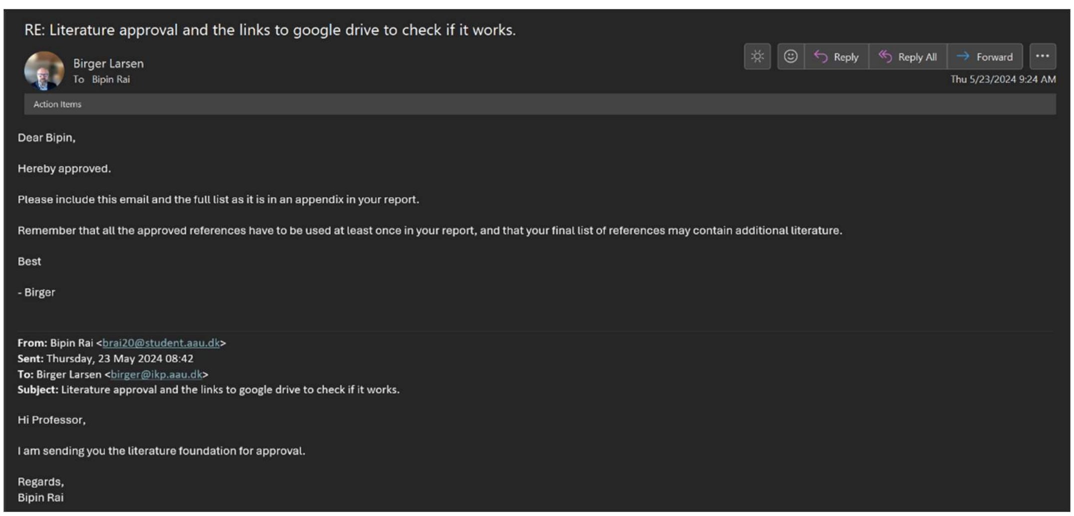
Google Drive: https://drive.google.com/drive/u/1/folders/16zUih5hZVCWeZIPa8H5OPOlntFLlS2uj

Miro: https://miro.com/app/board/uXjVKHlWF9k=/

It is important to note that a Non-Disclosure Agreement (NDA) was signed between me (researcher) and the host organisation (Simcorp). Due to its confidential nature, this very document is uploaded separately in the digital exam submission.

LITERATURE LIST APPROVAL

The below is the approval email from the designated supervisor.



RE: Literature approval and the links to google drive to check if it works.

Birger Larsen
To Bipin Rai

Reply | Reply All | Forward

Thu 5/23/2024 9:24 AM

Action Items

Dear Bipin,

Hereby approved.

Please include this email and the full list as it is in an appendix in your report.

Remember that all the approved references have to be used at least once in your report, and that your final list of references may contain additional literature.

Best

- Birger

From: Bipin Rai <brai20@student.aau.dk>
Sent: Thursday, 23 May 2024 08:42
To: Birger Larsen <birger@ikp.aau.dk>
Subject: Literature approval and the links to google drive to check if it works.

Hi Professor,

I am sending you the literature foundation for approval.

Regards,
Bipin Rai

The final list of literature, also separately included in the digital exam:

Page count	Reference (preferably in APA format)	Academic?	Supervisor note	Year
14	Abbas, A. M. H., Ghauth, K.I., & Ting, C.-Y. (2022). User Experience Design Using Machine Learning: A sys-tematic review. IEEE Access, 10, 51501-51514. https://doi.org/10.1109/access.2022.3173289.			2022
11	Acemoglu, D., & Restrepo, P. (2020). The wrong kind of AI? Artificial intelligence and the future of labour demand. Cambridge Journal of Regions, Economy and Society, 13(1), 25-35			2020
77	Adams, J., Khan, H.T.A., Raeside, R., & White, D.I. (2007). Research Methods for Graduate Business and Social Science Students (1st ed.). SAGE Publications India Pvt. Ltd. (Chapters 1, 2, 6, 9, 10, pp. 48-61, pp. 82-87). https://doi.org/10.4135/9788132108498			2007
7	Agarwal, A., Gans, J.S., & Goldfarb, A. (2019). Exploring the impact of artificial intelligence: Prediction versus judgement. Information Economics and Policy, 47, 1-6			2019
15	Agner L., Necyk, B., & Renzi, A. (2020). Recommendation systems and machine learning: Mapping the user experience. In A. Marcus & E. Rosenzweig (Eds.), Design, User Experience, and Usability. Design for Con-temporary Interactive Environments (pp. 3-17). Springer International Publishing. https://doi.org/10.1007/978-3-030-49760-6_1.			2020
12	Alghamdi, A.H., & Li, L. (2013). Adapting design-based research as a research methodology in educational settings. International Journal of Education and Research, 1(10), 1-12.			2013
19	Baker, L. (2006). Observation: A Complex Research Method. Library Trends, 55(1), 171–189. https://doi.org/10.1353/lib.2006.0045			2006
137	Baker. (2017). Agile UX Storytelling: Crafting Stories for Better Software Development (pp. 1-35, pp. 65-116). Apress L. P. https://doi.org/10.1007/978-1-4842-2997-2			2017
4	Barry, E.S., Merkebu, J., & Varpio, L. (2022). Understanding State-of-the-Art Literature Reviews. Journal of Graduate Medical Education, 14(6), 659-662. https://doi.org/10.4300/JGME-D-22-00705.1			2022
8	Barriball, K.L., & While, A. (1994). Collecting data using a semi-structured interview: A discussion paper. Journal of Advanced Nursing, 19(2), 328-335. doi:10.1111/j.1365-2648-1994.tb01088.x			1994
100	Bartram, S.M., Branke, J., & Motahari, M. (2020). Artificial Intelligence in Asset Management. CFA Institute. Retrieved from https://www.cfainstitute.org/-/media/documents/book/rf-lit-review/2020/rflr-artificial-intelligence-in-asset-management.pdf.			2020
13	Bawden, D., & Robinson, L. (2022). Introduction to information science (Second edition.). Facet. (chapter 4, pp. 63-75)			2022
11	BELKIN, N. J., ODDY, R. N., & BROOKS, H. M. (1982). ASK FOR INFORMATION RETRIEVAL: PART I. BACKGROUND AND THEORY. Journal of Documentation, 38(2), 61–71. https://doi.org/10.1108/eb026722			1982
11	Braun, V., & Clarke, V. (2021). Can I use TA? Should I use TA? Should I not use TA? Comparing reflexive thematic analysis and other pattern-based qualitative analytic approaches. Counselling and Psychotherapy Research, 21(1), 37–47. https://doi.org/10.1002/capr.12360			2021
25	Brock, J.K.U., & Von Wangenheim, F. (2019). Demystifying AI: What digital transformation leaders can teach you.			2019
34	Brotherton, J.J. (2022). Book review of Lloyd, A. (2021). The qualitative landscape of information literacy research [Review of Book review of Lloyd, A.2021. The qualitative landscape of information literacy research]. Journal of Information Literacy, 16(2), pp.55-88. https://doi.org/10.11645/16.2.3282			2021
14	Bryman, A. (2016). Chapter 10: Self-completion questionnaires. In Social research methods (Fifth Edition, pp. 231-244). Oxford University Press.			2016
35	Bryman, A. (2016). Chapter 20: Interviewing in qualitative research. In Social research methods (Fifth Edition, pp. 465-499). Oxford University Press.			2016
22	Bryman, A. (2016). Asking Questions (chapter 11). In Social Research Methods (5th ed.). New York, NY: Oxford University Press.			2016
64	Bughin, J., Seong, J., Manyika, J., Chui, M., & Joshi, R. (2018). Notes from the AI frontier: Modelling the impact of AI on the world economy. McKinsey. Retrieved from https://www.mckinsey.com/featuredinsights/artificial-intelligence/notes-from-the-ai-frontier-modelling-the-impact-of-ai-on-the-world-economy.			2018
15	Cao, Y., & Zhai, J. (2023). Bridging the gap – the impact of ChatGPT on financial research. Journal of Chinese Economic and Business Studies, 21(2), 177-191. https://doi.org/10.1080/14765284.2023.2212434			2023
38	Cao, L. (2022). AI in Finance: Challenges, Techniques, and Opportunities. ACM Computing Surveys, 55(3), 1-38. https://doi.org/10.1145/3502289			2022
4	Cao, L., Yuan, G., Leung, T., & Zhang, W. (2020). Special Issue on AI and FinTech: The Challenge Ahead. IEEE Intelligent Systems, 35(3), 3-6. https://doi.org/10.1109/MIS.2020.2983636			2020
21	Chatterjee, S., & Kar, A. K. (2018). Effects of successful adoption of information technology enabled services in proposed smart cities of India: From user experience perspective. Journal of Science and Technology Policy Management, 9(2), 189–209. https://doi.org/10.1108/JSTPM-03-2017-0008			2018

13	Chen, L., et al. (2019). An artificial intelligence-based data-driven approach for design ideation. Journal of Visual Communication and Image Representation, 61. 10-22. https://doi.org/10.1016/j.jvcir.2019.02.009.			2019
7	Chen, S., & Ge, L. (2021). A learning-based strategy for portfolio selection. International Review of Economics and Finance, 71, 936-942. https://doi.org/10.1016/j.iref.2020.07.010			2021
8	Chenail, R.J. (2011). Interviewing the investigator: Strategies for addressing instrumentation and researcher bias concerns in qualitative research. The Qualitative Report, 16(1), 255-262			2011
68	Chui, M., Hazan, E., Roberts, R., Singla, A., & Smaje, K. (2023). The economic potential of generative AI.			2023
1	Clarke, V., & Braun, V. (2017). Thematic analysis. The Journal of Positive Psychology, 12(3), 297-298. https://doi.org/10.1080/17439760.2016.1262613			2017
4	Cordeiro, T., & Weevers, I. (2016). Design is No Longer an Option-User Experience (UX) in FinTech. The FinTech Book: The Financial Technology Handbook for Investors, Entrepreneurs and Visionaries. 34-37. https://doi.org/10.1002/9781119218906.ch9			2016
34	Creswell, J. W., & Plano Clark, V.L. (2018). Chapter 2: The foundation of mixed methods research. In Designing and Conducting Mixed Methods Research (3rd ed., pp. 19-52). SAGE Publications Inc.			2018
24	Creswell, J.W., & Creswell, J.D. (2018). Chapter 1: The Selection of a Research Approach. In J.W. Creswell & D. Creswell, Research design: Qualitative, quantitative, and mixed methods approaches (pp. 40-63). SAGE Publications Inc.			2018
4	Creswell, J.W. (2008). Mixed methods research. In L.M. Given (Ed.), The SAGE encyclopedia of qualitative research methods (pp. 527-530). https://doi.org/10.4135/9781412963909.n269			2008
24	Cucculelli, M., & Recanatini, M. (2022). Distributed Ledger technology systems in securities post-trading services. Evidence from European Global Systems Banks. European Journal of Finance, 28(2), 195-218. https://doi.org/10.1080/1351847X.2021.1921002			2022
36	Deloitte. (2023). 2023 Investment Management Outlook. Deloitte Insights. Retrieved from https://www2.deloitte.com/content/dam/insights/articles/us175546_cfs_fsi-outlook-investment-mgmt/DI_US175546_CFS_FSI-Outlook-Investment-mgmt.pdf			2023
6	Digha, M.N. (2014). Morgan's Images of Organizations Analysis. International Journal of Innovative Research & Development (IJIRD), 3(3). pp. 201-205.			2014
11	Dixon, M., Klabjan, D., & Bang, J.H. (2017). Classification-based financial markets prediction using deep neural networks. Algorithmic Finance, 6(3-4), 67-77. https://doi.org/10.3233/af-170176			2017
4	Duarte, E., & Baranauskas, M. (2016). Revisiting the Three HCI Waves: A Preliminary Discussion on Philosophy of Science and Research Paradigms. ACM International Conference Proceeding Series, 128046, 1–4. https://doi.org/10.1145/3033701.3033740			2016
14	Eisenhardt, K. M. (2021). What is the Eisenhardt Method, really? Strategic Organization, 19(1), 147–160. https://doi.org/10.1177/1476127020982866			2021
4	Elfil, M., & Negida, A. (2017). Sampling methods in clinical research: An educational review. Emergency, 5(1). e52. https://doi.org/10.4172/2165-7548.1000e52			2017
13	Elliott, V. (2018). Thinking about the coding process in qualitative data analysis. Qualitative Report, 23(11), 2850–2861. https://doi.org/10.46743/2160-3715/2018.3560			2018
26	Enholm, I.M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. Information Systems Frontiers, 24(5), 1709-1734.			2022
35	Ernst, E., Merola, R., & Samaan, D. (2019). Economics of artificial intelligence: Implications for the future of work. IZA Journal of Labor Policy, 9(1), 1-35. https://doi.org/10.2478/izajolp-2019-0004			2019
14	Fahad, & Shahid, M. (2022). Exploring the determinants of adoption of Unified Payment Interface (UPI) in India: A study based on diffusion of innovation theory. Digital Business (Amsterdam), 2(2), 100040-. https://doi.org/10.1016/j.digbus.2022.100040			2022
5	Fink, A. (2019). Conducting research literature reviews: From the internet to paper. SAGE Publications. (Chapter 1)			2019
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19	Hashim, N. H., & Jones, M. L. (2007). Activity theory: A framework for qualitative analysis.			2007
17	Heston, S.L., & Sinha, N.R. (2017). News vs sentiment: Predicting stock returns from news stories. Financial Analysts Journal, 73(3), 67-83. https://doi.org/10.2469/faj.v73.n3.3			2017
6	Holmquist, L.E. (2017). Intelligence on tap. Interactions, 24(4), 28-33. https://doi.org/10.1145/3085571			2017
68	Holtzblatt, K., & Beyer, H. R. (2016). Contextual Design: Design for Life (2nd ed., pp. 3-70). Elsevier Science.			2016
4	Johnston, V., Black, M., Wallace, J., Mulvenna, M., & Bond, R. (2019). A framework for the development of a dynamic adaptive intelligent user interface to enhance the user experience. In Proceedings of the 31st Europe-an Conference on Cognitive Ergonomics (pp. 32-35). https://doi.org/10.1145/3335082.3335126			2019
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7	Jiang, Y., et al. (2022). Computational Approaches for Understanding, Generating, and Adapting User Inter-faces. In CHI Conference on Human Factors in Computing Systems Abstracts. https://doi.org/10.1145/3491101.3504030.			2022
10	Kirschner, P. A. (2002). Cognitive load theory: implications of cognitive load theory on the design of learning. Learning and Instruction, 12(1), 1–10. https://doi.org/10.1016/S0959-4752(01)00014-7			2002
24	Kore, A. (2022). On Intelligence. In A. Kore (Ed.), Designing Human-Centric AI Experiences: Applied UX Design for Artificial Intelligence (pp. 3-26). Apress. https://doi.org/10.1007/978-1-4842-8088-1_1.			2022
51	Karwowski, W., Soares, M.M., & Stanton, N.A. (2011). Human factors and ergonomics in consumer product design: Uses and applications (Chapters 25-29). CRC Press			2011
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INTERVIEW GUIDE

This section contains the images from Miro. The images are the interview guides that were developed during the research. They contain the whole thought process of the interview question formation.

Goals:

What are the pain points in the current solution?
How were they identified? - user satisfaction?

Introduction:
Who are we - what the thesis are about

- What is you role in SimCorp and how are you involved in the development of the new UI for portfolio managers?

Understanding the Need for a New Web UI:

1. What were the primary motivations behind developing a new web UI for portfolio managers at SimCorp?
2. Can you describe some of the specific pain points or limitations of the current SimCorp Dimension that the new web UI aims to address?

Role and Impact of the AI Copilot:
As part of the new web UI, there will be implemented an AI Copilot.

Is there a specific reason for incorporation of the AI the new solution? Which problem do you try to solve with this implementation?

1. Can you name specific functionalities that the AI Copilot will bring to the new web UI?
2. Which workflows that exist within the current solution will be enhanced in the new web UI with the implementation of the copilot?
3. Can you discuss how the AI Copilot is expected to improve decision-making for portfolio managers?
4. Were there particular challenges or concerns that emerged during the AI Copilot's development?

Trustworthiness and Strategic Perspectives
One of the use cases within the AI Copilot is providing recommendations to the portfolio managers.

1. What is the main goal you aim to achieve with this feature?
   a. Save time of the portfolio manager or to provide them with a holistic analysis?
2. What measures have been/plan to be implemented to ensure the AI Copilot's recommendations are reliable and transparent?
3. How do you foresee the AI Copilot influencing the trust portfolio managers have in automated recommendations?
4. Can you discuss how the user's trust in the recommendations may impact the experience with the AI Copilot? And how will it affect the development process of the AI Copilot?
5. Have you considered measuring the user's trust in these recommendations?
6. What feedback mechanisms are planned to be or implemented to gather user experiences with the AI Copilot, especially regarding trust and reliability?

Future Directions and Strategic Importance

1. How does the AI Copilot align with SimCorp's broader strategic goals?
2. Are there any plans to expand the AI Copilot's capabilities in future design iterations?
3. What role do you see AI playing in the future of financial management platforms, particularly in relation to trust and decision-making?
4. How does SimCorp plan to address potential ethical concerns that might arise with further AI integration into financial decision processes?

Introduction

- Could you describe your role at SimCorp and your involvement in the development of the new web UI for portfolio managers?

Understanding the Need for the New Web UI

- "What were the key drivers behind the decision to develop a new web UI for portfolio managers at SimCorp?"
- "Could you detail some specific pain points or limitations of the current SimCorp Dimension that this new UI aims to resolve?"
- "What specific challenges or needs led to the decision to incorporate an AI Copilot into the new solution?"
- "Can you outline the decision-making process that led to the implementation of the AI Copilot? How were the priorities set for this feature?"

Role and Impact of the AI Copilot

- "What are the key functionalities that the AI Copilot will introduce in the new web UI?"
- "Which existing workflows will be enhanced by the AI Copilot in the new UI, and how?"
- "How do you anticipate the AI Copilot will transform decision-making for portfolio managers?"
- "Were there any significant challenges or concerns that emerged during the development of the AI Copilot, and how were they addressed?"

Trustworthiness and Strategic Perspectives

- "What are the main benefits that the AI Copilot is expected to deliver to portfolio managers? Is the focus more on saving time, providing holistic analyses, or other aspects?"
- "How have you tailored the AI Copilot to maximize its value to portfolio managers?"
- "How might the trust portfolio managers place in the AI Copilot's recommendations affect its strategic integration into the new web UI?"
- "During the design and development phases, how was the trustworthiness of the AI Copilot ensured?"
- "What specific design decisions or mechanisms have been implemented to enhance the trustworthiness of the AI Copilot's recommendations?"

Future Directions and Strategic Importance

- "How does the implementation of the AI Copilot align with SimCorp's broader strategic objectives?"
- "What role do you foresee for AI in the future of financial management platforms, especially concerning trust and decision-making?"
- "How does SimCorp plan to address potential ethical concerns that may arise with further AI integration into financial decision-making processes?"

Introduction:
Who are we - university, thesis, transition from on-premise to the cloud solution and focus on trustworthiness as a value in design

- Could you describe your role at SimCorp and your involvement in the development of the new web UI for portfolio managers?

Understanding the need of the new web UI:

- Could you detail some specific pain points or limitations of the current SimCorp Dimension that this new UI aims to resolve?
- Which challenges in the current solution would you like to solve with the implementation of AI?
- Have there been encountered challenges in implementing the AI into the new web UI?
- Can you outline the decision-making process that led to the implementation of the AI Copilot?
- What are the core values that have influenced the decision-making and development processes for the AI Copilot?
- How have these values shaped the features and functionalities that have been prioritized?

Role and impact of the AI Copilot:

- What are the key functionalities that the AI Copilot will introduce in the new web UI?
- Which existing workflows will be enhanced by the AI Copilot in the new UI, and how?
- Can you discuss how the AI Copilot is expected to improve decision-making for portfolio managers?

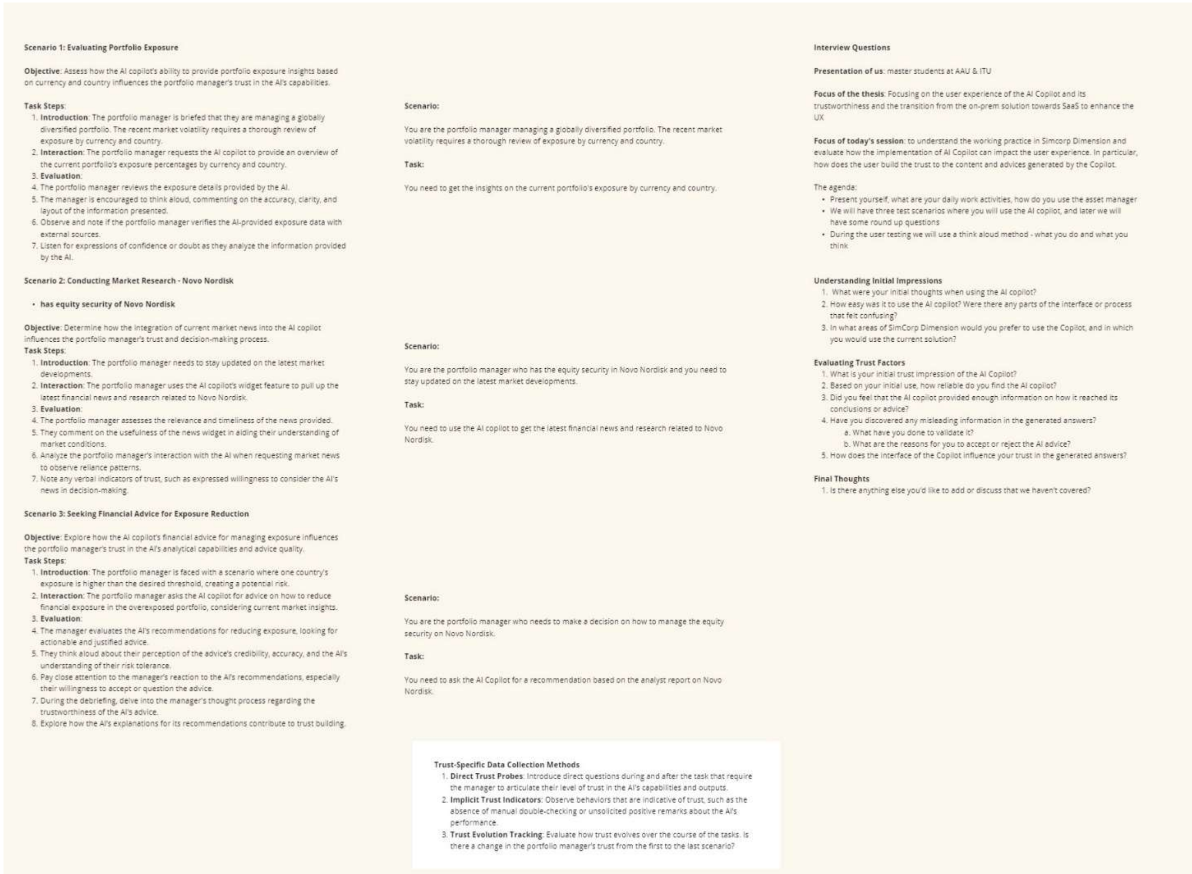
Trustworthiness and strategic perspectives:
One of the use cases within the AI Copilot is providing recommendations to the portfolio managers.

- What is the main value that the AI Copilot is expected to deliver to portfolio managers?
  NOTE: Save time of the portfolio manager or to provide them with a holistic analysis?
- How might the portfolio managers' trust in the AI Copilot's recommendations affect its strategic integration into the new web UI?
- During the design and development phases, how was the trustworthiness of the AI Copilot ensured?
- What specific design decisions or mechanisms have been implemented to enhance the trustworthiness of the AI Copilot's recommendations?

Future directions and Strategic importance:

- How does the implementation of the AI Copilot align with SimCorp's broader strategic goals?
- What role do you see AI playing in the future of financial management platforms, particularly in relation to trust and decision-making?
- How does SimCorp plan to address potential ethical concerns that might arise with further AI integration into financial decision processes?

Fig: Interview Guide – Product Manager. Can be found in Miro.



Scenario 1: Evaluating Portfolio Exposure

Objective: Assess how the AI copilot's ability to provide portfolio exposure insights based on currency and country influences the portfolio manager's trust in the AI's capabilities.

Task Steps:

1. **Introduction**: The portfolio manager is briefed that they are managing a globally diversified portfolio. The recent market volatility requires a thorough review of exposure by currency and country.
2. **Interaction**: The portfolio manager requests the AI copilot to provide an overview of the current portfolio's exposure percentages by currency and country.
3. **Evaluation**:
4. The portfolio manager reviews the exposure details provided by the AI.
5. The manager is encouraged to think aloud, commenting on the accuracy, clarity, and layout of the information presented.
6. Observe and note if the portfolio manager verifies the AI-provided exposure data with external sources.
7. Listen for expressions of confidence or doubt as they analyze the information provided by the AI.

Scenario 2: Conducting Market Research - Novo Nordisk

- **has equity security of Novo Nordisk**

Objective: Determine how the integration of current market news into the AI copilot influences the portfolio manager's trust and decision-making process.
Task Steps:

1. **Introduction**: The portfolio manager needs to stay updated on the latest market developments.
2. **Interaction**: The portfolio manager uses the AI copilot's widget feature to pull up the latest financial news and research related to Novo Nordisk.
3. **Evaluation**:
4. The portfolio manager assesses the relevance and timeliness of the news provided.
5. They comment on the usefulness of the news widget in aiding their understanding of market conditions.
6. Analyze the portfolio manager's interaction with the AI when requesting market news to observe reliance patterns.
7. Note any verbal indicators of trust, such as expressed willingness to consider the AI's news in decision-making.

Scenario 3: Seeking Financial Advice for Exposure Reduction

Objective: Explore how the AI copilot's financial advice for managing exposure influences the portfolio manager's trust in the AI's analytical capabilities and advice quality.
Task Steps:

1. **Introduction**: The portfolio manager is faced with a scenario where one country's exposure is higher than the desired threshold, creating a potential risk.
2. **Interaction**: The portfolio manager asks the AI copilot for advice on how to reduce financial exposure in the overexposed portfolio, considering current market insights.
3. **Evaluation**:
4. The manager evaluates the AI's recommendations for reducing exposure, looking for actionable and justified advice.
5. They think aloud about their perception of the advice's credibility, accuracy, and the AI's understanding of their risk tolerance.
6. Pay close attention to the manager's reaction to the AI's recommendations, especially their willingness to accept or question the advice.
7. During the debriefing, delve into the manager's thought process regarding the trustworthiness of the AI's advice.
8. Explore how the AI's explanations for its recommendations contribute to trust building.

Scenario:

You are the portfolio manager managing a globally diversified portfolio. The recent market volatility requires a thorough review of exposure by currency and country.

Task:

You need to get the insights on the current portfolio's exposure by currency and country.

Scenario:

You are the portfolio manager who has the equity security in Novo Nordisk and you need to stay updated on the latest market developments.

Task:

You need to use the AI copilot to get the latest financial news and research related to Novo Nordisk.

Scenario:

You are the portfolio manager who needs to make a decision on how to manage the equity security on Novo Nordisk.

Task:

You need to ask the AI Copilot for a recommendation based on the analyst report on Novo Nordisk.

Trust-Specific Data Collection Methods

1. **Direct Trust Probes**: Introduce direct questions during and after the task that require the manager to articulate their level of trust in the AI's capabilities and outputs.
2. **Implicit Trust Indicators**: Observe behaviors that are indicative of trust, such as the absence of manual double-checking or unsolicited positive remarks about the AI's performance.
3. **Trust Evolution Tracking**: Evaluate how trust evolves over the course of the tasks. Is there a change in the portfolio manager's trust from the first to the last scenario?

Interview Questions

Presentation of us: master students at AAU & ITU

Focus of the thesis: Focusing on the user experience of the AI Copilot and its trustworthiness and the transition from the on-prem solution towards SaaS to enhance the UX

Focus of today's session: to understand the working practice in Simcorp Dimension and evaluate how the implementation of AI Copilot can impact the user experience. In particular, how does the user build the trust to the content and advices generated by the Copilot.

The agenda:

- Present yourself, what are your daily work activities, how do you use the asset manager
- We will have three test scenarios where you will use the AI copilot, and later we will have some round up questions
- During the user testing we will use a think aloud method - what you do and what you think

Understanding Initial Impressions

1. What were your initial thoughts when using the AI copilot?
2. How easy was it to use the AI copilot? Were there any parts of the interface or process that felt confusing?
3. In what areas of SimCorp Dimension would you prefer to use the Copilot, and in which you would use the current solution?

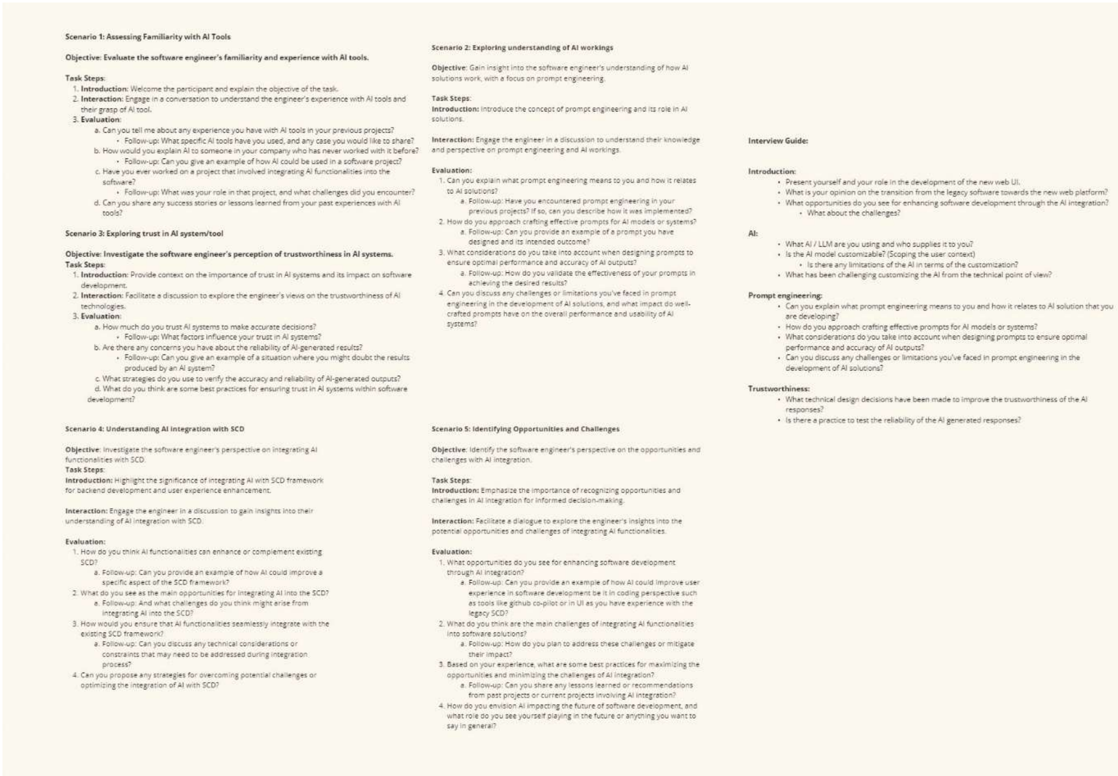
Evaluating Trust Factors

1. What is your initial trust impression of the AI Copilot?
2. Based on your initial use, how reliable do you find the AI copilot?
3. Did you feel that the AI copilot provided enough information on how it reached its conclusions or advice?
4. Have you discovered any misleading information in the generated answers?
    a. What have you done to validate it?
    b. What are the reasons for you to accept or reject the AI advice?
5. How does the interface of the Copilot influence your trust in the generated answers?

Final Thoughts

1. Is there anything else you'd like to add or discuss that we haven't covered?

Fig: Interview Guide – Portfolio Manager. Can be found in Miro.



Scenario 1: Assessing Familiarity with AI Tools

Objective: Evaluate the software engineer's familiarity and experience with AI tools.

Task Steps:
1. **Introduction**: Welcome the participant and explain the objective of the task.
2. **Interaction**: Engage in a conversation to understand the engineer's experience with AI tools and their grasp of AI tool.
3. **Evaluation**:
    a. Can you tell me about any experience you have with AI tools in your previous projects?
        - Follow-up: What specific AI tools have you used, and any case you would like to share?
    b. How would you explain AI to someone in your company who has never worked with it before?
        - Follow-up: Can you give an example of how AI could be used in a software project?
    c. Have you ever worked on a project that involved integrating AI functionalities into the software?
        - Follow-up: What was your role in that project, and what challenges did you encounter?
    d. Can you share any success stories or lessons learned from your past experiences with AI tools?

Scenario 2: Exploring understanding of AI workings

Objective: Gain insight into the software engineer's understanding of how AI solutions work, with a focus on prompt engineering.

Task Steps:
Introduction: Introduce the concept of prompt engineering and its role in AI solutions.

Interaction: Engage the engineer in a discussion to understand their knowledge and perspective on prompt engineering and AI workings.

Evaluation:
1. Can you explain what prompt engineering means to you and how it relates to AI solutions?
    a. Follow-up: Have you encountered prompt engineering in your previous projects? If so, can you describe how it was implemented?
2. How do you approach crafting effective prompts for AI models or systems?
    a. Follow-up: Can you provide an example of a prompt you have designed and its intended outcome?
3. What considerations do you take into account when designing prompts to ensure optimal performance and accuracy of AI outputs?
    a. Follow-up: How do you validate the effectiveness of your prompts in achieving the desired results?
4. Can you discuss any challenges or limitations you've faced in prompt engineering in the development of AI solutions, and what impact do well-crafted prompts have on the overall performance and usability of AI systems?

Scenario 3: Exploring trust in AI system/tool

Objective: Investigate the software engineer's perception of trustworthiness in AI systems.
Task Steps:
1. **Introduction**: Provide context on the importance of trust in AI systems and its impact on software development.
2. **Interaction**: Facilitate a discussion to explore the engineer's views on the trustworthiness of AI technologies.
3. **Evaluation**:
    a. How much do you trust AI systems to make accurate decisions?
        - Follow-up: What factors influence your trust in AI systems?
    b. Are there any concerns you have about the reliability of AI-generated results?
        - Follow-up: Can you give an example of a situation where you might doubt the results produced by an AI system?
    c. What strategies do you use to verify the accuracy and reliability of AI-generated outputs?
    d. What do you think are some best practices for ensuring trust in AI systems within software development?

Scenario 4: Understanding AI integration with SCD

Objective: Investigate the software engineer's perspective on integrating AI functionalities with SCD.
Task Steps:
Introduction: Highlight the significance of integrating AI with SCD framework for backend development and user experience enhancement.

Interaction: Engage the engineer in a discussion to gain insights into their understanding of AI integration with SCD.

Evaluation:
1. How do you think AI functionalities can enhance or complement existing SCD?
    a. Follow-up: Can you provide an example of how AI could improve a specific aspect of the SCD framework?
2. What do you see as the main opportunities for integrating AI into the SCD?
    a. Follow-up: And what challenges do you think might arise from integrating AI into the SCD?
3. How would you ensure that AI functionalities seamlessly integrate with the existing SCD framework?
    a. Follow-up: Can you discuss any technical considerations or constraints that may need to be addressed during integration process?
4. Can you propose any strategies for overcoming potential challenges or optimizing the integration of AI with SCD?

Scenario 5: Identifying Opportunities and Challenges

Objective: Identify the software engineer's perspective on the opportunities and challenges with AI integration.

Task Steps:
Introduction: Emphasize the importance of recognizing opportunities and challenges in AI integration for informed decision-making.

Interaction: Facilitate a dialogue to explore the engineer's insights into the potential opportunities and challenges of integrating AI functionalities.

Evaluation:
1. What opportunities do you see for enhancing software development through AI integration?
    a. Follow-up: Can you provide an example of how AI could improve user experience in software development be it in coding perspective such as tools like github co-pilot or in UI as you have experience with the legacy SCD?
2. What do you think are the main challenges of integrating AI functionalities into software solutions?
    a. Follow-up: How do you plan to address these challenges or mitigate their impact?
3. Based on your experience, what are some best practices for maximizing the opportunities and minimizing the challenges of AI integration?
    a. Follow-up: Can you share any lessons learned or recommendations from past projects or current projects involving AI integration?
4. How do you envision AI impacting the future of software development, and what role do you see yourself playing in the future or anything you want to say in general?

Interview Guide:

Introduction:
- Present yourself and your role in the development of the new web UI.
- What is your opinion on the transition from the legacy software towards the new web platform?
- What opportunities do you see for enhancing software development through the AI integration?
    - What about the challenges?

AI:
- What AI / LLM are you using and who supplies it to you?
- Is the AI model customizable? (Scoping the user context)
    - Is there any limitations of the AI in terms of the customization?
- What has been challenging customizing the AI from the technical point of view?

Prompt engineering:
- Can you explain what prompt engineering means to you and how it relates to AI solution that you are developing?
- How do you approach crafting effective prompts for AI models or systems?
- What considerations do you take into account when designing prompts to ensure optimal performance and accuracy of AI outputs?
- Can you discuss any challenges or limitations you've faced in prompt engineering in the development of AI solutions?

Trustworthiness:
- What technical design decisions have been made to improve the trustworthiness of the AI responses?
- Is there a practice to test the reliability of the AI generated responses?

Fig: Interview Guide – Software Engineer. Can be found in Miro.