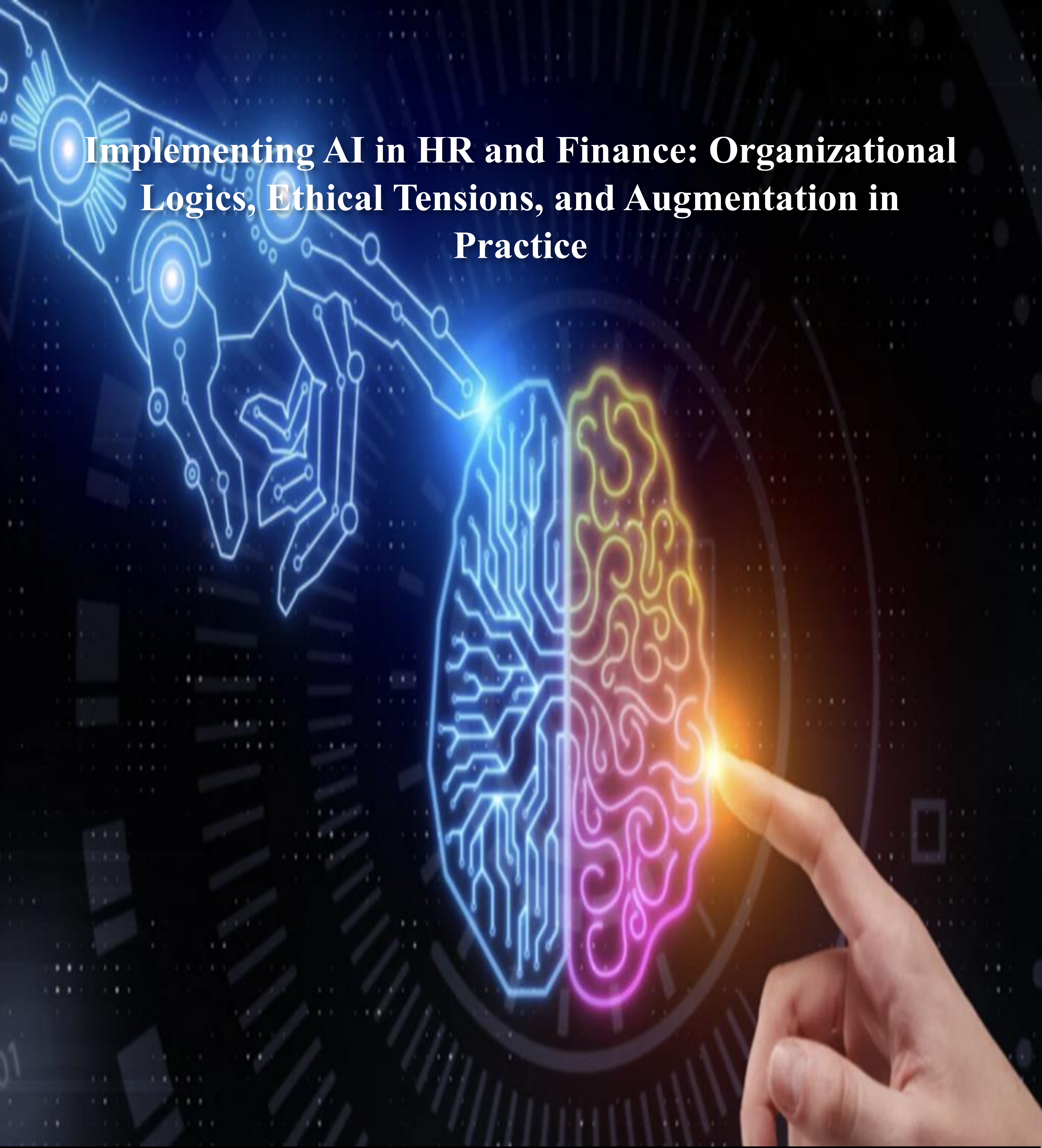
Implementing AI in HR and Finance: Organizational Logics, Ethical Tensions, and Augmentation in Practice



Aalborg Universitet

Politik & administration – Ledelse & Forvaltning

Specialeprojekt: 28/05-2025

Alex Jadon: 20202845

Number of characters: 176.793 ≈ 74 pages

Table of content

Abstract

Denne opgave undersøger, hvordan kunstig intelligens (AI) anvendes og implementeres i HR- og finansfunktioner gennem to cases: IBM og OP Financial Group. Gennem dokumentbaseret analyse og med udgangspunkt i Implementeringsteori og Socio-Teoretiske Systemer (STS) belyses både de tekniske, organisatoriske og kulturelle faktorer, der former AI-implementering i praksis.

Begge virksomheder anvender en gradvis og ledelsesstyret tilgang, hvor AI indføres gennem pilotprojekter og understøtter snarere end erstatter medarbejdere. Hos OP ses tegn på implementeringstræthed og forskelle i organisatorisk parathed. IBM udviser teknisk modenhed, men vægter målstyring og afkast, hvilket kan svække etiske og medarbejdercentrerede hensyn.

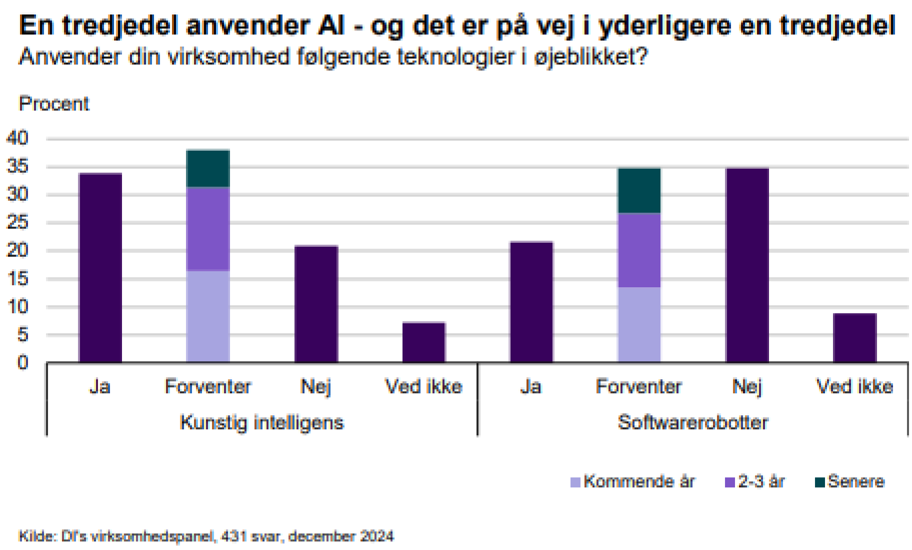
Diskussionen rejser spørgsmål om, hvorvidt AI reelt bruges til samspil mellem menneske og teknologi, eller primært som effektiviseringsværktøj. Fælles for begge cases er, at AI fungerer som beslutningsstøtte frem for fuld automatisering. Opgaven peger afslutningsvis på behovet for at forstå AI som en bredere organisatorisk forandring, hvor tekniske løsninger og menneskelige værdier må tænkes sammen.

Keywords: Artificial Intelligence (AI), Decision-making, Automation & Augmentation, Organizational frameworks, implementation, HR, Finance

1.0 Introduction

1.1 Problem area

In recent times, artificial intelligence, or AI and modern IT-systems have increasingly gained popularity, both on an individual level and an organizational level. Particularly through the use of the new and innovative AI systems, that use concepts such as deep learning and machine learning, to drastically enhance AI capabilities. This has been seen on the widely available AI programs, such as ChatGPT and DeepSeek, which gave the public access to new tools that can handle vast amounts of data and knowledge generating. These tools not only give them free access to image generation, video generation, or text writing, but also revolutionize the way data can be handled, stored, observed and analyzed, which has the tools to even change the way data-based decision-making is done. For private and public firms, these provide new ways to elevate their service deliveries. [1] Throughout the last few years, the use of AI-based tools has seen a noticable rise on the Danish market. In 2021, research showed that 24 pct. of Danish firms used AI[2] and by the end of 2025, Dansk Industri (DI) estimate an increase to approximately 50 pct. They also note a milder increase in the subsequent years from 2026 to 2028 which highlights the trajectory that AI is expecting to go.[3]



[1] Davenport, Thomas H. & Mittal, Nitin
[2] Danmarks Statistik, 03/09/2021
[3] DI (2025), s. 1-2

Figure 1.1 AI and Software usage in Danish firms [DI, 2025].

Modern AI has been described as a revolutionizing piece of technology, that is set to transform various fields within business and organizational workflows. Many point to AI as a transformative tool that will play a key role in their business endeavors and competitive strategies by enhancing workflows and optimizing key organizational processes. This even includes core functions such as management, as well as more specific business processes[4]. AI is set to become increasingly popular as a flexible tool, that can be used within different departments in the same organization or business, to joint-optimize and augment certain processes. A recent study by Danmarks Statistik, investigated the different uses of AI in businesses:

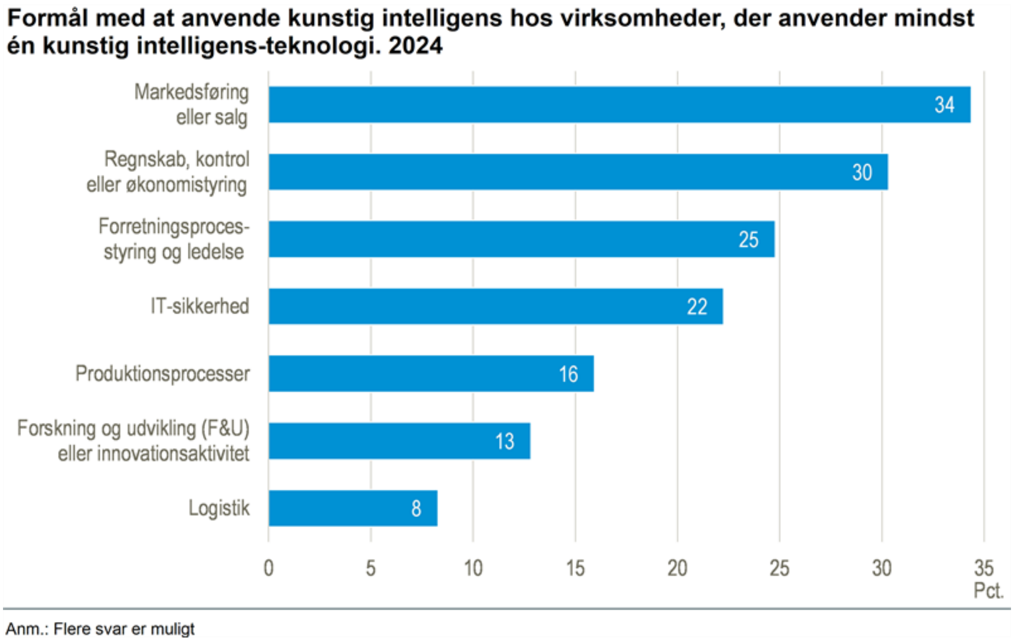


Figure 1.2 Purpose of AI-use [Danmarks statistik, 2025].

While the majority did use AI for marketing and sales purposes, it is likewise interesting to note its use in accounting, control and financial management at 30 pct., as well as business procedure management and general management at 25 pct., which shows AI's relevance in more integral administrative and other central functions as well. This shows that AI not only becomes a tool to enhance surface-level functions, like sales or perhaps production, but it also plays an important role as an administrative tool that plays an increasingly central role within organizations[5]. The study also dives in into the topic of AI's positive effects in firms, where a majority of respondents answered,

[4] Gartner 05/07/2023
[5] Danmarks Statistik 12/03/2025

that AI "streamlines workflows" at 70 pct. And a further 33 pct. said that it provided a better basis for making company decisions.[6]

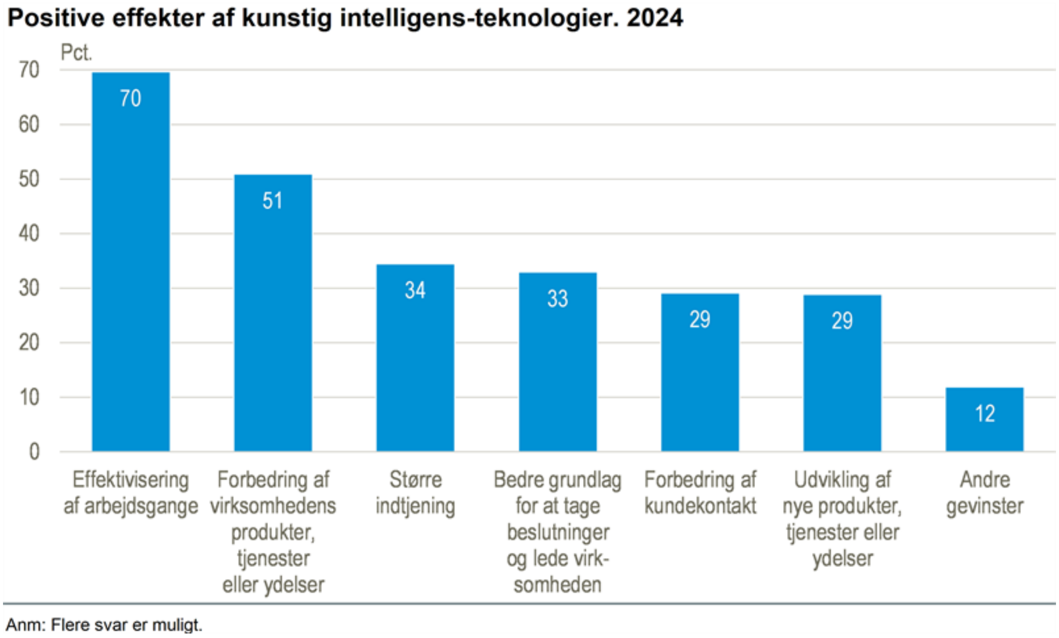
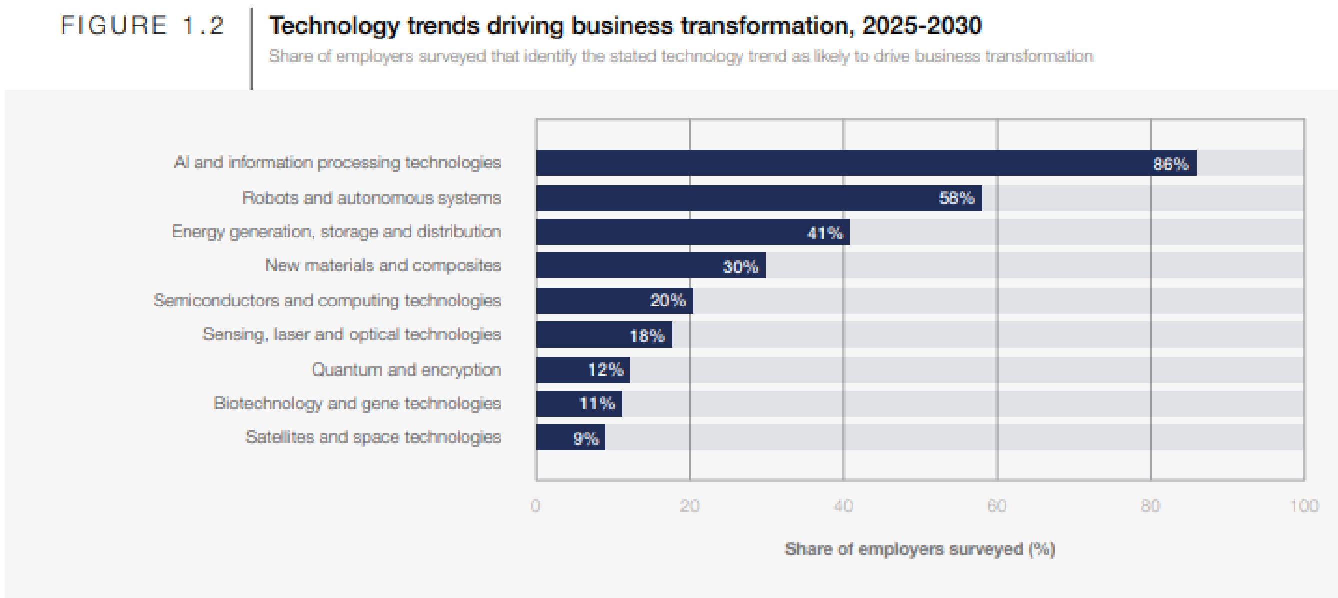


Figure 1.3 Positive effects of AI-use [Danmarks statistik, 2025].

The World Economic Forum, or WEF, also conducted a study on the modern technological trends that drive business transformation. In the study, it shows that 86 pct. of participants said that AI and information processing technologies were the main factors that will transform businesses in the upcoming five years. A significant proportion of employers see AI as an essential factor to their business trajectory, dictating the framework of the organization. It also shows that 58 pct. of employers see robots and autonomous systems as a technological trend to transform their business.[7]

[6] Ibid
[7] WEF Future of job reports (2025), figure 1.2, s. 10



Figur 1.4 [WEF, 2025]

1.2 Rationale and intuition

The subject of AI or IT-integration within public and private spheres raises debate of rationale versus intuition in work processes and decision-making, as AI may provide an alternative to complex human processing in the matter of decision-making. Modern AI and IT-systems have the capacity to act, at least semi-autonomously, from human interference. AI-cognitive software, that incorporates deep learning, has exponentially increased AI's functionality, making them on par with humans in certain actions, like making rational decisions. Through intricate data-recognizing patterns, AI has developed complicated systems of deriving "rational" decisions based on their data input. This creates a rigorous and algorithmic approach, which has its advantages, by also allowing it to derive results with vast amounts of data, at high speeds. The human, while also rational, can act on the sense of intuition that extends past logic. It involves making decisions based on fantasy, creativity and occasionally "a gut feeling." Carl Jung, a prominent psychologist from the early 20th century, coined the term "intuitive intelligence" as something that is not necessarily bound by anything deliberate. It can be understood as an amalgamation of the human subconscious, that can either supersede the rationale, be used alongside it, or be completely sidelined by it. This raises the question of whether decision-making can be done entirely on data-driven results, or whether human intuition should be a key part of work, business and decision-making, by joint-optimizing the human-AI workflow.[8]

1.3 Ethical Considerations

Despite AI's rapid rise in popularity, several concerns can be raised surrounding AI as a work tool and as an integrated part of public and private organizations. AI and technology usage can potentially give rise to ethical dilemmas since it has the capacity to make human-like decisions that may alter an individual's or even an organization's trajectory. But what does this mean?

A study by Danmarksstatistik shows that 33. Pct. of firms have not implemented AI yet, due to ethical concerns. This highlights the level of awareness firms have about AI- technologies, a majority of these can be described by the term "black box". This term denotes the low degree of transparency that occurs in AI decision-making. This is prominent in data-based AI algorithms as AI operates based on data, which can be subject to bias, this can lead to discriminatory and preferential patterns. This is since users of AI do not have insight into the complete process behind how AI reaches a decision. One example of AI's discriminatory risks could be in HR-related decisions. In a scenario where numerous studies and data sets conclude that men appear more competent for a particular position, this presents a statistical bias that AI may consider. If AI is used as a screening or recruitment tool, it will likely analyze such data without considering possible social or contextual factors. Here, we see risks of bias and preferential treatment toward men, based on statistics alone.

[8] Jarrahi, M. h. (2018) s. 3-5

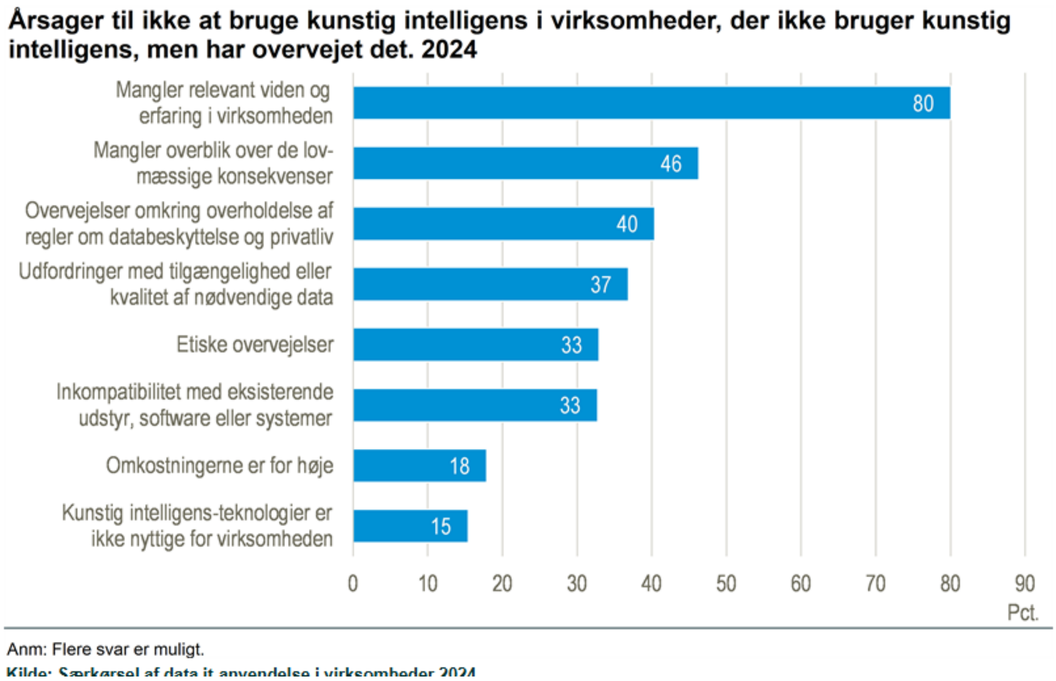


Figure 1.5 [Danmarksstatistik 2025]

Although AI can process and act on vast amounts of data, it still lacks the ability to act with human-like moral and contextual understanding. In this way, AI can make decisions that optimize certain processes, but may come at the expense of social and external circumstances - factors a human being would be more likely to consider. This also introduces challenges in terms of accountability, especially in cases of technical errors. This is particularly problematic when multiple stakeholders are involved. Is it the software or AI provider who should be held accountable? The IT department? Or the users themselves? Such questions reveal ambiguities in responsibility, which can overlap between the different parties. These implications can create organizational imbalances and erode trust due to technical failures or breaches of confidence.[9]

Additional concerns manifest in the form of job displacement, the loss of employment. As technologies and systems evolve, human labor, at least in certain roles, is being replaced by AI or other forms of automation. This means that individuals may lose their jobs to machines or software that now carry out tasks systematically and without interruption. This is already visible in retail, where traditional checkout counters are replaced by self-service systems. It also occurs in the finance sector, where AI is used for risk assessments and credit approvals. AI chat systems are increasingly used in modern customer service, replacing traditional human-based channels like

[9] Kitek.dk

phone or email, while other knowledge- and service-based functions are now handled by IT systems, something once deemed too complex for automation.

For many people, especially those with low or no formal qualifications, this trend poses the risk of unemployment. The previously mentioned study by the World Economic Forum (WEF) estimates that restructuring the labor market will eliminate up to 92 million jobs (8%). For individuals, this presents a range of socioeconomic consequences that may be hard to fully uncover. It also raises concerns about skills gaps, where much of the workforce lacks the necessary competencies. Re-skilling and professional development may be time-consuming and costly. By 2030, the sectors expected to be hit hardest by job displacement include postal workers, bank assistants, office support staff and data entry clerks, with an estimated decline of over 20 pct.[10]

However, it is important to point out that job displacement, as a result of technological innovation, is not a new phenomenon. A similar trend was seen in the 1950s and 60s, when the manufacturing sector underwent drastic changes. Manual labor was no longer the only relevant function. Cigarette packaging became automated and car parts were incorporated into automated production lines. Another example was the mining industry, where new technologies shifted the demographics. Several thousands of coal miners in Appalachia, USA, lost their jobs due to new mining technologies that made extraction faster and more efficient. This too was met with significant resistance at the time and certain regions, such as Appalachia, still feel the consequences of job displacement. These include worsening economic conditions and social challenges, especially for local communities whose livelihoods were tied to the mining industry. To this day, job displacement continues to have localized impacts. This still raises concerns of mistrust and displacement, as a consequence of AI's growing use.[11]

These points highlight the importance of understanding AI as a tool that can drive both positive and negative changes. Therefore, it must be recognized not only as a technical tool, but also as an instrument embedded within organizational structures and dynamics, that affect broader societal structures.

[10] WEF Future of job reports (2025), figure 2.2, s. 19
[11] Garcio-Murillo, Martha; MacInnes, Ian (2019) s.12 & 18-19

1.4 Problem Statement

"How is Artificial Intelligence (AI) implemented in HR and finance functions and what organizational and strategic factors drive firms to adopt AI systems?"

Research Questions

- *How is AI used and implemented within the organizations*
- *What organizational and technical factors affect the successful integration of AI?*
- *How do feedback mechanisms and user participation influence the refinement and acceptance of AI tools?*
- *How does AI influence task-distribution, workflows and decision-making?*
- *What are the positive and negative effects on work and organizational processes AI has?*

The purpose of this research statement is to understand AI as a technical tool and as an organizational transformative tool. The focus is set to HR and finance processes, to analyze and understand how it shifts work processes, decision-making and organizational structures. At the same time, seeking to understand how organizational contexts may shape the use of AI. This will be done based on existing literature and data on the subject, to better expand upon existing knowledge and contribute to AI research in an organizational context.

1.5 Limitations

This thesis investigates how artificial intelligence (AI) is implemented in core organizational functions, specifically within HR and finance, with a focus on implementation logics, organizational factors and the interaction between technological and human systems. The study is limited to analyzing existing empirical data from four company cases and two supplementary studies, which cover various degrees of AI maturity and application contexts. The cases were selected to create variation in function, maturity and industry structure, which enables a comparative and theoretically informed analysis, while also narrowing the scope within an empirically broad field to sectors where ethical responsibility is greater. This is justified by the fact that HR and finance have a significant impact on individuals' lives and well-being. This carries a higher ethical responsibility for those sectors in particular, which raises concerns about AI implementation.

The thesis focuses on AI technologies such as machine learning and generative AI, where the systems are used to support or transform processes such as recruitment, decision-making, document analysis and risk management. Traditional automation technologies are only included to the extent that they overlap with AI functions, or are integrated into hybrid systems.

The analysis is limited to functional and organizational perspectives, rather than exclusively technical modeling and is based on a document-based method, in which both case studies, report and other supplementary study sources are analyzed through a theoretical framework consisting of Socio-Technical Systems (STS) Theory and the Implementation Model. The aim of the thesis is to explore the field of AI and seeks, through abductive analysis, to develop a context-relevant understanding of how AI is embedded in existing workflows and which factors support or hinder implementation. Furthermore, to address what consequences it has for organizational practice and design. Tech does not operate in a vacuum. Successful implementation happens when social and technical subsystems are jointly optimized. This thesis investigates how that manifests itself, based on a multiple-case approach.

1.6 Defining AI

To better understand the subject of this thesis, it’s essential to first define the term AI, as it does not necessarily have one agreed-upon definition. This broader definition of AI may limit one’s understanding and make it difficult to accurately assess AI in any meaningful way. This paragraph aims to define the relevant terminology of AI, because the term AI can be quite arbitrary. And also because modern discourse around it may vary and, at times, can be unprecise.

The term Artificial Intelligence (AI) covers technologies and systems that can solve tasks that normally need human input or intelligence. This includes the skills to learn, problem-solving, decision-making and so on. AI has undergone a noticeable transition from more linear systems that react to input A and respond with B. These are the rule-based AI systems, where modern learning-based algorithms have become a thing in recent years, capable of learning and responding to vast amounts of data. The most prominent of the modern breakthroughs came in the form of machine learning (ML) and deep learning (DL). According to LeCun, Bengio and Hinton (2015), prominent computer scientists who specialize in AI, this is described as a deep form of machine learning, where computer systems learn to recognize patterns in data to a degree that matches human thinking. This is done via neural networking, algorithmic structures that mimic the human brain's way of handling information and deriving decisions or results. Deep learning is achieved through hierarchical neural networking, that takes AI to the next step. Using DL algorithms, AI can process complex and incoherent data patterns and make sense of it. This allows AI to create images, imitate voices and recognize intricate patterns.

The core of modern AI is in the data processing ability, that no longer binds it to pre-determined results or actions. For one, this makes technology more flexible and precise in the output one may derive and creates a dynamic tool to handle many more tasks – tasks which may previously have necessitated human work. Secondly, AI is no longer bound by routine tasks, but has unlocked a high degree of autonomy, supported by training and continual learning to increase its scope of work.[12]

This definition by LeCun, Bengio and Hinton (2015) was chosen because of the authors' role and experience in the relevant field. It was also chosen due to its place in the general understanding and narrative of modern AI, where it matches many other prominent authors' definitions. Authors like Stuart J. Russell and Peter Norvig (2020), who authored many modern books on artificial intelligence, describe AI more broadly as something that mimics intelligence and action artificially, hence the word artificial intelligence. This definition is slightly broader but fits the definition of LeCun as something that perceives, resonates and acts in complex environments. Although, it remains as something that can augment or automate certain functions and processes.[13]

By specifying the definition of AI, the analytical framework can maintain a more coherent and modern structure to understand the concepts in the analysis and discussion sections. This paves the way for analyzing and understanding AI in these modern contexts, but also to understand the technological constraints and how these tools may affect organization, culture and social contexts. This section describes the functional 'what' of AI and the structural 'how' of AI. It also highlights the technical distinctions between classical, linear systems and the modern dynamic AI tools.

1.7 Literature Review

The purpose of this literature review is to understand the current scientific knowledge and trends on the subject of AI, to gain a fundamental understanding of the subject. And, to familiarize the reader

[12] LeCun, Y., Bengio, Y., & Hinton, G. (2015) p. 436-444
[13] Russell, S. J., & Norvig, P. (2020)

with AI-systems and create a more structured approach to this thesis, so that it better builds upon and contributes to relevant scientific AI-research. The following literature review is based upon several peer-reviewed studies and articles about AI, with the relevant thematic and theoretical frames. The methodology section will explain more in-depth on the strategy and approach to the selection process. The integration of AI into the private and public spheres has had an impact on the way decisions are made, as well as the structure of organizations. This has been done across multiple sectors across the world, but this literature review, in line with the thesis, will be narrowed down to the HR-department and the finance sector. The reason for this will be explained further in the methodology section.

A relevant study by Xin, Wider and Ling (2022) in the field of human-resource management investigated organizational performance using quantitative studies. The empirical data was based on a study from 352 Malaysian HR employees, using statistical methods to find the quantifiable correlation between AI and performance. These methods are used to analyze the relationship between variables, like AI-implementation in HR and its relations to the general organizational performance, by mapping cause-and-effect. The field of study was how AI integration in talent acquisition, human capital development and performance management affected the overall organizational performance. The method provides a strong and coherent empirical framework, using online surveying and gathering a significant amount of data amongst relevant functions within HR. The study is built upon the 5P's model (purpose, principles, processes and People & Performance)[14]. The theory adds a well-rounded framework to investigate AI as a systemic part of organizational behavior and not exclusively as a technological tool. This ties into the themes of STS and implementation model, that also look at AI from a more holistic perspective, which will be discussed more in-depth further down. This study is wholly interesting for two reasons: 1) it dives into AI's effect on HR and the organization, but 2) it does so by quantifying the magnitude of its effect on a holistic basis. It is based on cross-sectional data of several different people, in different organizations. The study concluded that AI could explain 39 pct. of the change in organizational performance (based on the authors' three process-level variables). The most significant HR function was Talent Acquisition, which had the most noticeable effect through streamlining of screening processes, reducing risks related to mismatch, while also increasing the speed of recruitment. The

[14] Xin, O. K., Wider, W., & Ling, L. K. (2022), p. 30

second most significant area was Performance Management Process, with the least effect on Human Capital Development, which the authors attribute to technological barriers[15].

This study provides an important quantitative contribution to understanding AI in the HR department. By giving empirical insight into AI as a tool, it lays the foundation for an in-depth discussion point and the framework for others to contribute to the field. Due to its quantifiable approach and structure, it does not provide a more in-depth understanding through qualitative insight. It does not provide the “why” or “how” of the successes described, nor insight into relevant resistance, adaptation, or negotiation. This leaves a gap for further contribution and research, based on these theoretical and empirical approaches.[16]

A Jordanian study in the field of HR, that sought to understand which factors helped determine whether employees are willing to accept and use AI in HR functions, was conducted by Basheer Hmoud (2021). He explores private and public organizations to see which factors were positively affecting the desire to use AI at work. The study is, like the previous study by Xin (2022), based on a quantitative research method, surveying 224 HR workers. The methodological framework is based on the quantitative research method, using Structural Equation Modeling, that is used to analyze the complex nature between several variables. By compiling the relevant factors, a result is derived by seeing its effect on the behavioral intention of the employee.

The study was built around hypotheses testing:

H1: Competitive Pressure

H2: Top Management Support

H3: Performance Expectancy

H4: Employee Champion

H5: Change Agent

H6: Administrative Expert

H7: Strategic Partner

[15] Ibid, p. 28
[16] Ibid

The purpose of this literature review is to explain the methods and findings of the relevant studies. It is not to present a comprehensive insight into the entire methodology and theoretical aspects within. Therefore, only the hypotheses which had statistical significance will be explained, as they provide the context to understand AI's effect on organization.

The study found four statistically significant factors that drive AI engagement amongst employers. Those being: H1, Competitive Pressure, which entails the amount of pressure an organization perceives from external competitors, is a relatively significant factor; H3, Performance Expectancy, which is defined as the degree an individual feels that using AI will help enhance job performance, was statistically significant; H4, Employee Champion, which denotes the feeling of HRM involvement in maintaining employee engagement and commitment, was significant in explaining the positive effect of AI; and H5, Change Agent, which denotes the role as a promoter of change and adaptability, was also a significant factor. The significance factor explains the correlation between AI and increased or positive effects on the area (H1 to H7).[17]

The behavior of HR workers and their interest in adopting AI can be explained by these factors. What is seen is that performance and competition seem to be very important drivers behind AI transformation, but it also highlights AI's perceived role as an enhancer of well-being and job satisfaction. This creates a dual perspective, one which heavily builds upon AI as a technical tool and one that tilts towards the socio-organizational benefits of AI. The study is built on conceptual frameworks like the Unified Theory of Acceptance and Use of Technology to operationalize a question framework. It explores relevant factors such as "why" AI has seen exponentially high use in recent years. Although it has gaps in design-use misalignment, seeing AI as a finished and usable product, it does not consider several organizational dynamics or how these affect AI leveraging.[18]

The previous studies looked at AI from a strict performance and purpose angle, while another study from India sought to see AI's implementation in effect using a different approach, qualitative research methods. The study by Mukherjee (2022) found that AI had an increasing role in HR functions across several industries, which also includes HR. The study found that AI contributes positively to the workflow by enhancing recruitment, screening processes and employee engagement, which matches the findings of the previous studies. This study was done using semi-structured interviews with several HR managers and more across energy, detail, health and

[17] Hmoud (2021), p. 107
[18] Ibid, p 112-114

construction sectors. The author triangulated this with several secondary data points and sources, which adds to the nuance of the empirical field. The author does highlight the degree at which AI affects organizations, but looks at it from a societal perspective. Here, Mukherjee sees it as a societal dilemma that the government should help monitor. The study also found that highly educated and resourceful employees benefited more from AI, where people who were less resourceful and less educated failed to keep up. The study does not include a strong theoretical framework and does not draw from any systematic approaches to explain the technical and societal aspects of the article.[19]

In the United Kingdom, an interesting study was done in public healthcare institutions to observe and understand AI. The study was conducted using quantitative methods, employing semi-structured interviews with three different NHS hospitals, using their theory as a questionnaire framework and handling their findings by coding their interviews. It was found that AI is important within the UK healthcare sector through several automation tools. AI is a highly beneficial tool in straightforward and routine tasks that can lift the burden of the public health sector. An example given was Dora software, a tool that could handle 1,000 call-ups, whereas healthcare staff would only be able to call a fraction of that. The task of diagnosing had seen increased rates of success and reduced times through AI screening programs, where a radiologist would approximately use 14 minutes and AI reduced that time to 30 seconds, adding to the positive impact of AI. Although, the study also concluded that more intricate and specialized tasks, like surgery, could not be implemented due to technological constraints. Another limit was AI's inability to empathize with patients, which can be quite detrimental to the perceived effect of treatments. From an administrative aspect, AI helps alleviate many mundane tasks that take up limited resources. From the healthcare aspect, it has the power to enhance treatment and speed of treatment. While the effects of AI are seen visibly within the interviewed hospitals, technological constraints and barriers, like regulations, price of entry and red tape, hinder the potential of AI to fully manifest. Although AI was recognized for its capabilities, it was also recognized for its risks on patient empathy and even job displacement, which remained a conceptual thought. The study saw AI not as a replacement, but rather a tool to enhance existing practices and workflows. Through their secondary data, they conclude that AI will develop further and that the upcoming years will see a noticeable increase in AI throughout the healthcare sector, which may alter the way AI is

[19] Mukherjee (2022), p. 155 & 160-161

implemented, potentially increasing its autonomy. The study was conducted through a theoretical lens, using Socio-Technical Systems theory to operationalize certain themes and elements of the organization. The STS lens sought to explain organizational change through the intricacy of the work system, where AI technologies are tied to the greater network of what constitutes the organization.[20]

Where Holdsworth & Zaghloul (2022) shed light on AI's implications for public healthcare, a different study was conducted by several authors, including Samuel Fosso Wamba. Wamba is a prominent researcher and author on digital transformation and artificial intelligence from Toulouse Business School, who has written several works on the subject primarily from a business perspective. This paper investigates (Wamba-Taguimedje et al., 2020) how AI-capabilities contribute to organizations overall performance particularly through AI transformation projects. The study is based on 500 organizational case studies, to highlight tangible impact on firms' process-level performance using secondary data. The study looked at AI from Theory of IT capabilities, operationalizing their analysis and discussion around three capabilities namely AI management capabilities, AI Personal Expertise and AI Infrastructure Flexibility which each has a positive effect on the improvement of processes and performance. They found that AI-technologies have a massive potential to enhance organizational performance across several industries. This includes automation, augmentation, efficiency while saving costs. They found that AI is not necessarily limited to one department but can be efficiently leveraged across the firm's value-chain. Things like customer experience, sales, administrative functions and more[21]. They note that commerce, trade, distribution and communication benefited the most. Wamba-Taguimedje likewise notes that AI is also a disruptive technology that needs organizational re-structuring and changing that way a firm may operate internally if they wish to implement AI more extensively. Particularly through automatization and transformation and information-related effects that alter decision-making processes from an internal perspective and shape the way firms operate. The authors argue that this is not without challenges and proper AI leveraging needs managerial action, change and adaptation. To this they point out the need to account for job-displacement issues and ethical concerns related to data. Although it is vaguely mentioned, it highlights the consistent issues with AI despite its potential. [22]

---

[20] Holdsworth & Zaghloul (2022), p. 54-59
[21] Wamba et al., (2020)
[22] Ibid

A different study by Arakelyan (2024) focuses on the financial sector by looking at AI implementation in banking systems by similarly employing a mixed method approach. The study integrates qualitative and quantitative data based on secondary sources to systematically understand AI in banking systems. The purpose of this study is to see which factors drive and engage AI-implementation. The conclusion found that technological maturity was a key component of sufficiently being able to leverage AI, which entails infrastructure, cyber security and IT-experience. Arakelyan argues that many organizations are missing key elements like these to properly employ AI. Arakelyan also argues that organizational culture and openness to change are important factors that succeed the best with AI-implementation. The study goes to pinpoint challenges and risks related to AI on the surface as an important point. Nonetheless AI is seen as an innovative and transformative tool that through proper initiatives can enhance the banking systems[23]. This aligns with points made by Wamba-Taguimedje that AI implementation needs proper leveraging.

Furthermore, AI within the logistics sector has also seen increasing relevance in the academic and practical fields, to understand how AI more efficiently can be integrated in global logistics and trade. A study conducted by Merli et al. (2024), that uses the Business Process Re-engineering model (BPR), a conceptual model for redesigning and optimizing organizational processes to improve efficiency, in the usage of Non-autoregressive Transformer Recognizer (NRTR) and Self-Attention-based Text Knowledge Mining (STKM). These are specific algorithms used within the logistics sector, that read and analyze waybills, identify mistakes, propose corrections and categorize document types automatically. Based on these systems, the study found increased performance. The fail rate of inputting data fell from 10 pct. to less than one pct., while the necessary processing time for a document block was reduced from approximately five minutes to 10–15 minutes for the entire block. This saved the cost and time of one full-time employee on day-to-day operations. This was nonetheless done by implementing a human-in-the-middle system, where, in cases where AI has difficulty in reading sections of documents, a human is available to address the issues. The study describes the process of implementation as occurring over four months, through technological adaptation, change in workflows, as well as communication with suppliers. While AI's positive effects are clear, they were not without issues. The entire process of successful implementation is not successful without surrounding systems and processes being readjusted. Even then, AI would initially make mistakes, which needed fine-tuning through a

[23] Arakelyan (2024), p. 90-93

feedback loop, allowing AI to improve over time. This study differs from the previous, as it approaches the subject of AI from a more technical and practical implementation, by focusing on very specific algorithms and models. This highlights the varied academic field that can be categorized as "AI," and furthermore shows the interdisciplinary essence of AI implementation.[24]

Munnisunker et al. (2022) conducted a different study that explores AI within EU agricultural practices. The study was conducted by Hungarian researchers, and it examines how modern agriculture is shaped by AI through waves of transitional technologies. The algorithm wave brought precision agriculture via data collection and tracking, the augmentation wave brought semi-autonomous tractors, drones and the autonomy wave is said to be on its way by almost entirely automating agriculture. Munnisunker et al., based on previous and ongoing trends, make conceptual predictions. They see agriculture almost completely shifting into AI. This is seen as a response to the labor shortage, as the EU population from now to the year 2044 is expected to fall by 4 pct., or 20 million. AI is not set to completely replace farmers but make up for the lack of workforce and capacities. In this study, the authors do not argue for AI as an operation-enhancing tool, but rather a functional necessity to the ongoing job market and population changes. Munnisunker's study is noticeably less empirical and conclusive, but still gives valuable insight into the future of EU agriculture and presents AI as the "solution." The conceptual approach is important, as it allows academics and readers to discover or understand the potential risks and possibilities of given issues like these.[25]

Author	Title	Purpose	Findings	Relation to STS-theory	Academic Journal & database
Xin et al. (2022)	Human Resource Artificial Intelligence Implementation and Organizational Performance in Malaysia	To explore the relation between AI implementation in HR and internal performance	AI had a strong correlation with performance, particularly in recruitment and screening	Implicit by addressing HR and technological effect on performance	Asia Pacific Social Science Review Research Gate

[24] Merli et al. (2024), p. 3-11
[25] Munnisunker et al. (2022), p.

Hmoud (2021)	The adoption of artificial intelligence in human resource management	To explore factors that influence HR-employees' intention to use AI	Competition, performance and employee-retention were determining factors of AI-use	Organizational & technological-social interaction	Forum Scientiae Oeconomia Research Gate
Mukherjee (2022)	Application of artificial intelligence: benefits and limitations for human potential and labor-intensive economy – an empirical investigation into pandemic ridden Indian industry	Assessment of AI effect on labor and HR-functions	AI enhances performance but does so disproportionately favor certain high capital individuals. Raises questions of fairness	Addresses Socio-technical implications although on a wider societal scope	Management Matters (Emerald Publishing) Google Scholar
Wamba-Taguimedje et al. (2020)	Influence of Artificial Intelligence (AI) on Firm Performance: The Business Value of AI-based Transformation Projects	Explore AI's influence on firm performance	AI improves several processes via automation, information and transformation to enhance organizational performance. Success depended on infrastructure and proper management	Builds upon STS notions of organizational and technical interplay. Effective implementation requires coordination across social and technical systems	Science direct & Research Gate
Arakelyan (2024)	EXPLORING FINANCIAL TRANSFORMATION: KEY FACTORS OF AI'S IMPACT ON BANKING SYSTEMS	Identify critical factors in AI deployment	AI transformation depends on tech maturity, cultural alignment, regulation and raises some challenges	Understanding of organizational factors (culture, trust, regulation etc.)	Alternative Quarterly Academic Journal. Google Scholar
Merli et al. (2024)	Artificial Intelligence Approach to Business Process Re-Engineering the Information Flow of Warehouse Shipping	How can AI optimize warehouses	AI significantly reduces errors, cuts labor time and enhances operations. Can be a lengthy process to	Hints at techno-social relations, adaptation, change of workflows (Nonetheless	MDPI Open Access Journals

	Orders: An Italian Case Study		adapt (trial and error)	still highly technical)	
Holdsworths & Zaghloul (2022)	The Impact of AI in the UK Healthcare Industry: A Socio-Technical System Theory Perspective	How does AI interact with public healthcare systems, through theoretical lens	AI improves several procedures and tasks within healthcare institutions. Still early to implement AI on a larger scale. Does not fully replace humans	Uses STS theory in the public healthcare sector. Part of a greater holistic system between human, organization and AI (technology)	CEUR Workshop Proceedings AUB - Google Scholar
Munnisunker et al. (2022)	The Impact of Artificial Intelligence on Agricultural Labour in Europe	Review current and historic impact of AI on EU agriculture	AI helps with labor demands and solves looming issues for EU agriculture. Still early for significant change to occur.	Adresses change in workflow and structure, presents augmentation, no deeper insight.	Journal of Agricultural Informatics AUB - Google Scholar

Table 1: Relevant peer-reviewed studies on the field of AI implementation

1.7.1 Summary

It is relevant to address the theoretical and empirical approaches in the scope of AI literature and address how this thesis can add to the existing scientific field. The field of AI implementation in organizations is very broad and has been done through several different methods.

Despite rapid advances in these fields, the implementation of AI is still in an early embryonic phase, which leaves an academic gap particularly in the long term. Many of these studies emphasize efficiency and automation and to some degree highlight the option or even need for augmentation. Some of the studies include niche models of purpose or acceptance. The study by Holdsworth and Zaghloul provided a very interesting perspective using Socio-Technical Systems theory that better bridges the technical-human divide and accounts for the dynamics that make up an organization. Samuel Fosso Wamba, who is a prominent author about AI, also noted the organizational relevance of AI, seeing it as a part of a bigger system rather than merely a tool.

While the field of AI is very broad, encompassing several public and private spheres. It was therefore imperative to narrow down the field of research. By selecting a more dynamic and interesting sector, it gives the researcher and the reader a more in-depth and reasonable overview of AI. By narrowing down the scope to HR and finance, the number of sources is drastically reduced and allows the thesis to focus on a specific theme within specific fields. These were the frame for the literature review, except for the study by Holdsworth and Zaghloul. This one was included for its theoretical relevance as it was based on Socio-technical systems theory.

While most studies accounted for the potential challenges and risks that may arise with AI, they include arbitrary or surface level guidelines to mitigate certain risks, but do not deliver a framework to holistic address specific needs and issues related to AI. Therefore, it is seen relevant to build this thesis upon Socio-Technical Systems Theory to understand organizational change, human actors, technical tools and the concepts of automation, augmentation, adaptation and joint-optimization. This theory will be supplemented by implementation model which de-constructs the stages of integration such as initiation, adoption, adaptation and routinization and works to explain how change may occur based on organizational factors.

2.0 Theory

In order to assess the research question, it is paramount to introduce theoretical frameworks and the reasoning behind these choices. The chosen theories will be the foundation of the analysis and the discussion and the basis of understanding the empirical case studies. This section will first summarize the core principles and content of the theories Socio-Technical Systems theory, Implementation model as well as the rationale and intuition decision-making models. Then the interplay, use and relevance of each theory will be explained, to better understand the structure of the thesis.

2.1 Socio-technical Systems Theory

Socio-Technical Systems (STS) theory was first presented in the 1950s by researchers at the Tavistock Institute, Eric Trist and Fred Emery. Their early fieldwork in British coal mines showed that new technologies didn’t necessarily improve productivity if they disrupted existing social systems. In fact, these changes sometimes harmed team cohesion, job satisfaction and performance (Miner, 2006). This led to the core insight that technical systems and social systems must be jointly optimized, meaning tech does not work unless it's aligned with people, culture and workflow.

The STS perspective argues that any organizational change, especially technological ones, needs to consider this dual system:

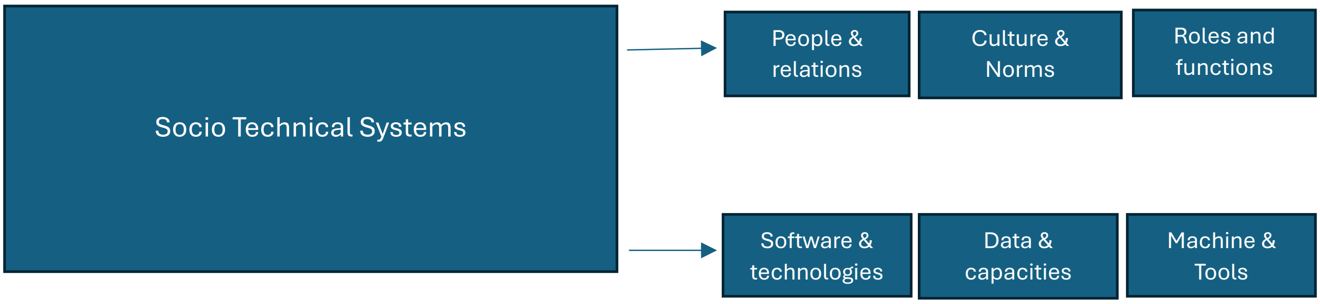


Figure 1.6: Socio-technical components

A key notion is that you can't upgrade one without affecting the other. If a new AI tool is introduced without training, clear roles, or employee input, it might improve efficiency in the short term but lead to burnout or confusion later and vice versa. A strong team without the right tools may underperform. The goal, then, is joint optimization, designing both systems in tandem, so that people and tech support each other rather than clash and the employees feel uplifted.

Another important concept in STS is the "whole task." Rather than breaking jobs into repetitive fragments, STS encourages semi-autonomous teams to handle entire processes. This increases accountability, learning and morale. It also supports better adaptation when tech or roles change.

When applied to AI, STS sees the technology not as neutral or self-sufficient but as embedded in relationships, power dynamics and organizational culture. AI does not operate in a vacuum. It reshapes decision-making, accountability and workflows. So, implementation is not just about deploying a system. It's about how people interact with it, trust it and adjust their roles around it.

In this thesis, STS is used to understand how AI implementation in HR and finance functions interacts with real-world social dynamics. Where AI is framed as just a technical solution, STS helps reveal how it depends on and transforms human factors like autonomy, feedback, routines and ethics. It also makes it possible to analyze whether implementation is truly sustainable, or whether misalignment between systems creates new frictions.

This becomes especially relevant given that modern AI carries more autonomy than past IT systems. With capabilities like predictive analytics, biometric ID and generative text, AI doesn't just support human work. It can replace or reshape it. So, organizations that treat AI as a plug-and-play upgrade may face unintended consequences unless they also adjust to norms, training and structure alongside the tech.

In short, STS offers a way to move beyond seeing AI as a tool and instead analyze how it becomes embedded into everyday organizational life.[26]

2.2 Implementation Model

The foundation of implementation research stems from the seminal work of Pressman and Wildavsky (1973), who revealed how top-down policies often fail in practice due to what they termed the "complexity of joint action." Their insights marked a shift in focus away from policy design and toward the often-fragmented realities of execution. Likewise, Winter (2012) and others have emphasized that implementation is not just implemented in a vacuum, but rather by organizational decisions, resource constraints and local interpretations. Though the notion of implementation research does not constitute a unified theoretical framework in the strict academic sense, it offers a robust body of work that enables researchers to understand how planned change unfolds in complex, real-world contexts. This thesis draws on key contributions from implementation research to structure an implementation model, which serves as an analytical framework for examining how AI technologies are introduced, adapted and routinized within organizations.

Building on these foundations, it is relevant to adopt a model that combines top-down and bottom-up logics of implementation. On one hand, scholars such as Mazmanian and Sabatier (1981) have stressed the importance of central control, leadership and strategic clarity. On the other hand, Lipsky's (1980) concept of street-level bureaucracy highlights the discretion exercised by frontline employees who must interpret and enact change under real-world conditions. Rather than treating these as mutually exclusive, they should be considered complementary, both leadership direction and employee engagement are crucial to implementation success.

More practically, the implementation model used here incorporates insights from Fixsen et al. (2005), who outline specific organizational and technical enablers of implementation. These include:

- **Leadership commitment**: visible support, resourcing and strategic direction
- **Organizational readiness**: alignment of systems, structures and infrastructure

[26] Miner, J.B (2006), p. 169-177

- **Communication and clarity of goals**: understanding the “what” and “why” of the technology
- **Employee engagement and training**: ensuring competence and involvement.
- **Resistance and adaptation**: navigating tensions, skepticism, or resistance
- **Feedback and learning loops**: using user input to improve implementation over time

These factors serve as analytical categories to assess not only *whether* AI is implemented but *how* it becomes embedded into workflows, decision processes and work culture. Importantly, they are not treated as a checklist, but as interdependent conditions that shape implementation trajectories.

This implementation model is not a theory in the traditional sense, it is a synthetic, multi-perspective framework. It integrates structural as well employee insights to unpack how socio-technical change plays out in real settings. By combining macro-level direction (top-down) with micro-level negotiation (bottom-up) and linking them to concrete organizational capabilities of Fixesen et. Al (2005), the model provides a nuanced lens for analyzing AI adoption as a layered, dynamic and context-dependent process. This ties into the philosophical assumptions that will be addressed in section 3.1

In this thesis,the term implementation model will be used to refer to this assembled framework, combining classical insights (Pressman & Wildavsky, Lipsky), strategic governance (Winter, Mazmanian) and operational enablers (Fixsen et al.) to interpret how AI is rolled out, adapted and anchored into organizational contexts. This helps theoretically conceptualize and better explain the patterns and factors that help the implementation processes.[27] [28]

While Socio-Technical Systems (STS) theory provides a holistic lens to understand the interdependence between social and technical elements within organizations, it does not fully account for the processual dynamics of how new technologies are introduced, adopted and routinized over time. For this reason, the Implementation Model is used as a complementary framework. It helps to unpack the practical, stage-wise conditions that shape successful implementation, including leadership support, organizational readiness, employee engagement and feedback loops.

[27] Fixsen, D. L., et. Al. (2005) p. 63-67
[28] Winter, S. C. (2013) p. 3-16

2.3 Rationale & Intuitive Decision-making Models

Rational decision-making focuses on methodical and logical patterns. This approach identifies options, gathers the relevant data, analyzes everything carefully and selects the best solution based on clear criteria. This is the style of thinking that AI systems are built around. Algorithms are designed to process vast amounts of structured information and produce consistent, objective outcomes, often faster and more accurately than humans can.

AI models, for instance, use theories like expected utility theory, which calculate the best possible outcome based on probabilities and predicted benefits. Think of it as a super-powered calculator for decisions. In areas like finance, healthcare diagnostics and supply chain logistics, this structured logic is a huge advantage. However, Herbert Simon pointed out in his concept of bounded rationality that even the most logical decisions are limited by the information and resources we have. AI can help expand those limits, but only within its programmed boundaries.[29]

In contrast, intuitive decision-making is quick, often subconscious and heavily shaped by experience. Instead of analyzing every option, we recognize patterns, feel what's right and draw from past situations to act swiftly, especially when time is short or the data is messy.

Psychologists like Gary Klein argue that professionals such as firefighters, surgeons and military leaders rely on intuition in high-pressure situations. This is considered a subtype within the broader intuition model. Their decisions seem fast and even automatic but are actually grounded in years of practice and deep, internalized knowledge. But intuition isn't perfect. It can be biased, emotional and overly confident. It may be more prone to error and be less calculated than rational decision-making. Still, intuition brings something AI can't: empathy, flexibility and human judgment, things that matter deeply in areas like leadership, ethics and personal connection.

These models will not be used in the core analysis of this thesis, but instead as a framework for discussion. They provide a solid foundation to address the empirical findings of the analysis and to reflect on the broader themes of AI's transformative effect, joint-optimization and the ethical implications surrounding human-AI collaboration.[30]

[29] Simon, H. A. (1955) p. 99-118
[30] Klein, G., (1998)

3.0 Methodology

The following section outlines the methodological framework and considerations for this master's thesis. It covers research design, philosophical assumptions, selection and analysis strategies. By introducing these elements in a coherent section, a more holistic overview of the approach to the thesis is presented.

3.1 Philosophical Assumptions

This thesis is based on a critical realist epistemological standpoint, which forms the foundation for both the study's approach to knowledge and the way AI's role in organizational contexts is analyzed. Critical realism represents a middle ground between objective positivism and the focus on subjective constructions emphasized by social constructivism. In the context of this study, critical realism provides a solid framework for understanding how AI is implemented in organizational processes and how technological and social factors interact.
From a critical realist perspective, it is assumed that there is an independent reality - regardless of our recognition of it. On this matter, it fits the position of the positivistic understanding. But critical realism also differentiates itself from being distinctly positivistic. By recognizing that the world is layered and complex, made up of a multitude of sub-systems and in its essence context-dependent. Things like biology, physical structure, societies, culture all make up systems. While these may exist outside the subjective perception, they can be understood contextually and not always bound by laws or causal explanations. To understand the empirical results and the factual tendencies, the surface-level phenomena and the underlying mechanism, also know the deep stratum are to be iteratively addressed side by side. The term of deep stratum is explained by institutional context, structures, cultures or hidden mechanisms in observations. These contexts are what distinguishes the critical realistic perspective, as it does not deduce observation into one category or explanation. AI's impact on organizations is therefore considered a real phenomenon: AI alters decision-making processes, streamlines workflows and affects organizational structures. However, reality is not directly transparent or fully accessible. Organizations, technologies and human actions constitute complex, layered systems. Here the underlying structures, such as the power relations, cultural norms and technical infrastructures mentioned, shape the observable phenomena and vice versa.

In this study, this means that AI's effects are not merely understood as mechanical results of technological innovation. Instead, they are seen as the outcomes of a complex interplay between technological artifacts (such as algorithms and machine learning systems) and social systems (such as employee culture, leadership structures and organizational norms). Reality is understood as composed of both physical technological components and the human interpretations, practices and institutional frameworks in which the technology is embedded.

Critical realism asserts that knowledge of reality is never completely objective or direct. Instead, we attain knowledge through the interpretation of observable patterns and events. In this thesis, knowledge about AI implementation is gained through a combination of analysis of existing empirical studies, case studies and theoretical reflections.

The use of secondary data, such as existing qualitative and quantitative studies, makes it possible to identify patterns, barriers and drivers in AI adoption across organizations. These patterns are interpreted in light of the applied theories, Socio-Technical Systems Theory and Implementation model, to uncover the underlying structures influencing implementation. Knowledge is thus viewed as a continuous, critical process where theoretical insights and empirical observations are constantly compared and developed.

This epistemological approach emphasizes both the observable changes in workflows, decision-making structures and efficiency and the deeper explanations, like cultural resistance, organizational readiness and ethical considerations. The analysis seeks not only to describe 'what' happens with AI implementation but also 'why' and 'how' these changes unfold within complex organizational systems.

The choice of critical realism as the epistemological foundation aligns well with the abductive approach employed in this thesis. Through an abductive interplay between theory and empirical data, the study aims to develop a nuanced understanding of AI's organizational effects, rather than testing specific hypotheses. This approach enables a more holistic analysis, recognizing both technological and social factors as mutually constitutive elements of the implementation process.

The choice of critical realism is furthermore relevant to the theories applied. Socio-Technical Systems Theory specifically emphasizes the interplay between technical and social factors within organizations, while Implementation model focuses on the processes by which new technologies are integrated into practice. Both theories align with critical realism's view of reality as complex and layered, ensuring methodological consistency in the project.

Critical realism provides a methodologically robust foundation for studying AI implementation in organizations. By acknowledging the complex nature of reality and viewing knowledge as an interpretative process, this approach supports an in-depth analysis of how AI changes, and is itself shaped by organizational structures, decision-making processes and work relations. The critical realist perspective thus enables the thesis to contribute nuanced and practically relevant insights into the use and consequences of AI in modern organizations.[31]

3.2 Design

This thesis employs qualitative document analysis as a part of a theory-driven explorative approach to understanding the implementation of artificial intelligence (AI) in an organizational context. By structuring the thesis around multiple case research, the purpose of this study is to understand how AI is employed in workflows, processes, structures and to understand how it affects these elements through augmentation, decision-making, enhancement, automation etc. It is also to explore which factors enable or inhibit proper integration of AI technologies into the operational processes of an organization. The analysis and discussion will be built on secondary literature and secondary data, such as peer-reviewed studies, scientific articles, business case studies, industry reports and publicly available reports that may address AI in a relevant matter. The multiple-case structure consists of examining AI implementation dynamics specifically across the HR and Finance functions within private organizations. Rather than focusing on individual organizations as holistic entities, the study compares how AI affects distinct organizational functions, enabling a sectoral rather than firm-specific insight.

The selection of cases in this thesis is based on a strategic and theory-informed logic, aimed not at statistical generalization but at generating analytical insight. As Flyvbjerg (2011) argues, meaningful case studies are defined by their information richness and contextual relevance rather than quantity. The cases in this thesis have therefore been chosen for their ability to illuminate the complex dynamics of AI implementation across organizational settings. The unit of analysis is specific organizational functions, HR and finance, where AI is actively being integrated. Rather than viewing AI as a general trend, the focus is on how implementation unfolds within concrete work domains. The selected cases represent varied industries, technological maturity levels and organizational sizes, allowing the analysis to capture different configurations of socio-technical interaction, implementation readiness and cultural framing. Given the reliance on secondary

[31] Ingemann, J. H. (2013), p. 88-90

material such as empirical studies, industry reports and organizational documentation, the cases are treated as situated examples of real-world AI adoption. They do not aim to be representative of all organizations but are used to identify patterns, tensions and contradictions that can deepen theoretical understanding.

This strategic selection also supports an abductive research design, where empirical observations are interpreted in light of theoretical frameworks, particularly Implementation model and Socio-Technical Systems (STS) Theory. Rather than testing predefined hypotheses, the goal is to refine theoretical understanding by analyzing how AI implementation is shaped by both technical systems and organizational conditions.[32]

The choice to base the research exclusively on secondary literature is methodically justified by several considerations. Firstly, secondary literature gives access to a broad and nuanced range of existing knowledge. By addressing existing data, a synthesized analysis based on several cross-geographic findings to create more nuance and furthermore add to the knowledge gap by theoretical advancement to reinterpret existing data. In contrast, by gathering primary data the empirical groundwork may be limited by constraints to variation and cases. By critically examining available sources and studies, the study builds on the framework of others, so that points that were vaguely addressed may be further explored and 'answered'. Though, the point of this thesis is not to entirely summarize the literature, but to address the concepts through the chosen theoretical lens to answer the questions research questions. Given the extensive and fast-growing body of high-quality research on AI implementation, secondary qualitative literature and existing case studies are considered sufficient for this study. They provide detailed empirical insights and allow for a critical, theory-driven synthesis of existing knowledge, without the ethical, practical and access-related challenges often associated with primary data collection in private organizational settings. Furthermore, this approach ensures that a wide range of organizational experiences and perspectives are included, offering a more nuanced and comprehensive understanding of the phenomenon.[33]

It likewise reduces ethical constraints related to anonymity or the upholding of GDPR regulation within organizations, if primary data were to be gathered. Some firms or organizations may choose not to participate in a potential interview, if concerns of data-breach or confidentiality risks arise. In

[32] Flyvbjerg, B. (2011) p. 301-311
[33] Ingemann et al. (2018), p. 66-68

addition, organizations or companies may reject an interview on the notion of inexperience. Where AI may be relatively new or underdeveloped, people within these organizations choose not to disclose information fearing that they may not be able to answer questions. Companies are also more likely to be more secretive around their AI softwares or solutions, if it has not been fully rolled out or implemented. While this may be the case for small or medium-size enterprises, who have a lower percentage of AI use than their bigger counterparts. Certain big companies, that have presumably had AI implementation in at least some of their operation, therefore have more AI experience and understanding. Despite this, they can be hard to reach, without internal connection or networking.

The thesis is theory-driven based on two complementary analytical frames: Socio-Technical Systems (STS) Theory and Implementation model. The principles of STS theory create a nuanced perspective on AI, that looks at it as a part of a bigger system of people, organization and culture. By drawing upon these principles, the understanding of successful AI implementation and usage can be better understood as a single technical mechanism or a co-production of several systems. The STS-perspective broadens up the perspective to a holistic analysis, where several factors are drawn upon to understand AI's success. Implementation model adds a structural frame to analyze the organizational and technical aspects, that will be explained further in

3.3 Document Analysis

Document analysis is a qualitative research method that involves systematically evaluating written materials to gain an understanding of a specific phenomenon. In academic research, documents are often treated as empirical data, especially when they provide insight into processes, structures, or organizational practices that are otherwise difficult to access. This method is particularly valuable in exploratory studies where existing research, reports and case studies offer rich sources of information for critical analysis. The reports and studies will be used to triangulate and support the points from the case studies, to address broader tendencies or differences that might be prevalent. Document analysis enables researchers to work with a broad range of materials, from scientific articles and white papers to internal organizational reports and policy documents, thereby offering a multifaceted view of the research topic. Subsequently, the number of documents has been narrowed down from 25 to four, two case studies (as the primary sources) and two empirical reports to supplement.

In this thesis, document analysis is employed as the central method for gathering and interpreting secondary data. The focus is on understanding the implementation of artificial intelligence (AI) in organizational contexts, specifically within HR and finance functions in private and public companies. Though the focus will be primarily set on private institutions and organizations. By systematically analyzing existing documents, this study seeks to uncover how AI technologies influence workflows, decision-making processes, efficiency and organizational structures. Furthermore, the document analysis will facilitate the identification of barriers and enablers in the implementation of AI, as well as the broader organizational consequences associated with these technological changes. The primary source of data will be professional documents that entail existing knowledge on specific topics related to AI.[34][35]

The process will involve a critical selection of sources, focusing on peer-reviewed journal articles, business case studies, industry reports and organizational white papers that directly address AI in HR and finance settings. To some extent, this will also include non-AI or HR sources, as elements related to decision-making, structure, culture, organization etc. can be more broadly interpreted and generalized. Documents will be evaluated for their relevance, credibility and methodological robustness. A thematic analysis approach will be applied to the selected materials, allowing for the identification of recurring patterns, key concepts and theoretical themes relevant to the research question. Through this method, the thesis will not only synthesize existing knowledge but also offer a reinterpretation of how socio-technical and implementation dynamics shape AI adoption in organizational settings. Document analysis is relevant to the aim of this thesis because it allows for the exploration of a complex and evolving field without the ethical and practical challenges of conducting primary data collection within private organizations. Given the sensitivity surrounding AI technologies, data privacy and internal business processes, many organizations may be reluctant to participate in interviews or surveys. Secondary sources, however, often provide detailed and systematically gathered information that can be critically examined to achieve a comprehensive and theory-driven understanding of the topic.

By employing document analysis, this thesis ensures a wide-ranging and systematic exploration of how AI integration transforms key organizational functions. The method supports a theory-driven, abductive research strategy, allowing existing empirical evidence to be reinterpreted through the

[34] Ibid p. 75-76
[35] Brinkmann (2020), p. 185-196

lenses of Socio-Technical Systems (STS) Theory and Implementation model. Thus, document analysis is not only a practical choice but also an academically rigorous method for answering the research questions.[36]

3.4 Data Collection and source evaluation

The data collection process in this thesis was carefully designed to align with the study's abductive, theory-driven methodology and critical realist foundation. Given the focus on how AI is implemented within organizations - particularly within HR and Finance functions - a secondary data approach was chosen. This decision reflects both the theoretical emphasis on layered, socially embedded structures and the practical availability of rich existing knowledge in peer-reviewed literature and industry reporting.

To ensure both depth and breadth in the empirical foundation, a systematic search for high-quality secondary sources was conducted. Academic databases such as Scopus and AAU Library's database (AUB) were used as primary sources, offering access to peer-reviewed journal articles with high scientific credibility. Google Scholar was used to broaden the search, capturing open-access research, working papers and relevant gray literature. Additionally, Google Advanced Search was strategically employed to locate industry whitepapers, consultancy reports and relevant public data not indexed in academic platforms - materials that offer practical insights into real-world organizational AI use. This was also done with the use of AI algorithms like Consensus, that can search several different databases and keywords at once. Such tools have enhanced the searching process, to better and more efficiently find the right field of articles and sources.

The keyword strategy was developed to cover both technical and organizational dimensions of AI implementation. Keywords included combinations such as *"Artificial Intelligence implementation HR organizations"*, *"AI impact decision-making finance sector"*, *"Socio-technical systems AI organizations"* and *"technology adoption"*. Boolean operators and publication year filters (primarily 2019 - 2024) were applied to ensure precision and relevance. Terms like "*AI*" coupled with "*implementation*", "*organization*", "*AI-impact*", "*AI in finance*", "*AI in HR*" etc. were also used in the very early search phase, before being specified into the thematic and theoretical

[36] Brinkmann (2020), p. 185-196

contexts. This can be described as a funnel model, where early on the search was very broad and then narrowed down as the goal and theory of the thesis was forming.

Selection of sources followed clear criteria: peer-reviewed academic studies were prioritized to ensure scientific rigor, with a preference for empirical articles using qualitative methods, case studies, or statistical analysis in real organizational contexts. Theoretical works relevant to Implementation model and Socio-Technical Systems Theory were included to support the study's conceptual foundation. To supplement the academic literature, statistical and industry data were used to ground the analysis in current adoption trends. For instance, Danmarks Statistik provided national-level insight into AI usage across Danish firms, Dansk Industri (DI) contributed sector-specific forecasts, and the World Economic Forum (WEF) offered broader trend on a global plan. This combination of academic and contextual sources ensures that both the depth and breadth of AI implementation are addressed within the study and provide an introductory grasp of AI and its relevance. The Case studies were also selected based on empirical richness, to sufficiently address the dynamics and factors addressed within the research questions.[37]

A central component of working with secondary data is the critical assessment of sources- or source evaluation. This involves systematically reflecting on the quality, credibility and potential biases of the material included in the analysis. In this thesis, source evaluation was guided by the following considerations:

Aspect	**Reflection**
Academic sources	All journal articles were drawn from peer-reviewed publications to ensure a high standard of validity and scholarly reliability. Nonetheless, even within peer-reviewed work, methodological weaknesses or theoretical biases can occur. This risk was addressed by including diverse sources across disciplines and triangulating claims.
Business Case Studies	Business Case Studie (IBM) that present recent insights into AI journeys. The use of business case studies carries certain risks, including the tendency for published cases to emphasize success and downplay challenges, especially when produced by

[37] Flyvbjerg, B. (2011)

	the companies themselves. May include selective or strategically framed narratives that may not reflect the full complexity of implementation processes. Furthermore, the context-specific nature of each case limits its transferability, requiring careful interpretation when drawing broader conclusions.
Statistical data	Official statistics from WEF, DI and Danmarks Statistik were considered highly reliable and were used in the introduction to provide the reader context.
Document selection bias	Relying solely on published materials may leave out failed implementations or internal organizational challenges that are not publicly documented. This limitation was mitigated by ensuring a broad sample of studies, including those reporting implementation failures or mixed results.
Recency and relevance	A focus was placed on sources published between 2019 and 2025 to ensure the material reflects recent trends in AI use. Foundational theoretical texts were included where necessary to support the conceptual framework, regardless of publication date.

Table 2: Systematic source evaluation strengthens the study's methodological transparency and supports the overall credibility of its conclusions.

To summarize, the data collection strategy was built around a structured, transparent and theoretically informed search for high-quality secondary material. Through the use of multiple academic databases, industry publications and official statistical sources, the thesis builds a strong foundation for investigating the organizational implementation of AI. The merging of academic theory with empirical findings ensures the study remains both analytically grounded and practically relevant. The inclusion of explicit source evaluation further ensures that the chosen materials are critically assessed in terms of validity, reliability and relevance - fully aligned with the abductive, critical realist approach. abductive reasoning moves iteratively between data and theory to develop plausible explanations. This is particularly useful in exploring under-theorized but empirically rich phenomena such as AI implementation in organizations.

Several sources were excluded because they did not sufficiently relate to the specific focus areas of this thesis - namely, AI implementation within HR and Finance functions. Some case studies involved AI in broader organizational or industrial contexts (e.g., manufacturing or marketing) but lacked clear relevance to the functional domains under investigation. Including such cases would have diluted the analytical focus and weakened the study's ability to draw meaningful insights tailored to HR and Finance. Secondly, some literature was excluded due to its highly conceptual or speculative nature. These sources often presented interesting theoretical arguments or normative perspectives on AI (such as ethical debates, philosophical critiques, or long-term predictions), but they did not contain empirical data or concrete examples of implementation processes in real-world organizations. Since this thesis is built on an abductive, theory-informed but empirically grounded approach, such conceptual works are excluded. This exclusion process was not based on the perceived quality of the discarded sources alone, but rather on their fit with the research questions, theoretical framework and analytical goals of the thesis. Cases were selected based on their empirical richness and relevance to the topic.[38] In this way, the opt-out process functioned as a form of quality assurance, ensuring that the selected material best supports the abductive reasoning and critical realist perspective of the study.[39]

3.5 Strategy

To optimally and systematically analyze the empirical data, so that it matches the theoretical framework and assesses the research questions, it's essential to include a strategy for handling the data. This is especially relevant when handling several different sources and types of data.

As explained earlier, the analysis takes a theory-informed approach based on Implementation model and Socio-Technical Systems (STS) Theory. The aim is to explore how AI is implemented in organizations and what shapes that process, particularly within HR and Finance functions. As noted in the literature review, previous studies often lack a holistic integration of technical and organizational perspectives. This thesis addresses the gap through a combined STS and implementation model applied via document analysis. The empirical material consists of two cases as the primary sources and two supplementing sources (see section 3.5). The coding framework, which is presented in this section, serves as a practical tool to structure the analysis. Each case study is treated as an example that can help uncover broader patterns, tensions and processes. Rather than

[38] Flyvbjerg (2011)
[39] Ingemann et al. (2018), p. 87-116

looking at sources in isolation, the analysis focuses on how they relate to the main themes outlined in the framework. and how they help shed light on what happens during AI implementation.

Coding Category	Sub-Codes / Focus Areas	Theoretical Reference
Technological Integration	- What types of AI systems are used? - Automation or augmentation? - Degree of system integration - Top-down or bottom-up	STS + Implementation model
Organizational Readiness	- Infrastructure and data quality - Leadership support and investment -Employee enablement - Skills and training -Technical Capacities	Implementation model (partly STS theory)
Socio-Technical Interaction	- Interaction between humans and AI -Co-evolution & joint-optimization - Changing work roles - Trust or mistrust toward technology	STS Theory
Decision-Making	- Is AI used for decision support or replacement? - Rational vs intuitive approach? - Task-delegation	Decision-Making Models (Rational/Intuitive) STS
Ethical and Normative Concerns	- Bias and transparency - Algorithmic accountability - Fairness in processes (e.g., HR, Finance procedures) - Black box	STS (Values and Systems)

	-Technilogical determinism	
Implementation Barriers	- Technological resistance - Lack of cultural anchoring - Data ethics and compliance -Tension	Implementation model
Outcomes and Effects	- Increased efficiency and time savings - Improved output quality - Increased pressure on employees -Enhanced employee experience	STS + Implementation model
Organizational Learning	- Adaptation and feedback loops - Adjustments in procedures and strategy due to AI	STS Theory

Table 3: codes

Sources are coded manually using the predefined categories to keep the process consistent, but also flexible enough to allow for variation and complexity across cases. The goal is to pick up on recurring dynamics, key contrasts and deeper mechanisms that explain both challenges and outcomes in real-world settings. Particular attention is paid to how human and technical systems interact and to the organizational conditions that either enable or inhibit implementation. This approach allows the analysis to stay grounded in theory while remaining open to what the data shows. The theory provides the lens to analyze and derive inference from the material, particularly since the theories revolves around dimensions that in themselves, often are hidden or implicit. This plays into the critical realist understanding of a layered reality that does not appear clearly on the surface and allows for an abductive exploration of AI implementation. Abductive reasoning allows for connecting empirical findings with the theoretical frameworks, in the cases of both direct and more implicit findings. Furthermore, it provides a clear structure without reducing the complexity of the topic and helps build a solid foundation for answering the research question in a meaningful way. The use of generative AI tools, other than research purposes, also included discussing ideas for the thesis. Generative AI tools were occasionally used during the early thesis stages to brainstorm approaches and reflect on the structure of the work. This was done to supplement the critical analysis, writing and reflecting of this thesis in accordance with the recommendations and rules for the use of generative AI at AAU.

3.6 Case presentation

Title	Purpose	Method	Origin
Strategic Change, Antenarratives and AI: A Case Study of OP Financial Group	The case study explores how managers at OP Financial Group make sense of the ongoing implementation of AI technologies. It examines both the positive and negative narratives (antenarratives) that shape organizational change and strategic decision-making. It particularly focuses on how AI is embedded within cultural, strategic and operational contexts at Finland's	**Design:** Embedded qualitative single case study (Yin, 1994) **Analytical Framework:** Thematic analysis (Braun & Clarke, 2006) **Data Source:** 25 semi-structured interviews from a larger dataset of 230 interviews conducted by the SALP research group	This case was published in the *Electronic Journal of Business Ethics and Organization Studies* in 2019. The author is Dinesh Poudel, a PhD candidate at the University of Jyväskylä.

	largest cooperative bank.		
Impact of AI on the Banking Industry in Europe and Beyond (ARIX Research) Will be supplementary to the Financial Case-study.	This study investigates how artificial intelligence affects the banking sector and its employees across Europe. It explores adoption trends, workplace transformations and responses to digitalization and the COVID-19 pandemic. It assesses both the benefits and risks of AI integration, drawing on secondary research and expert perspectives to	**Secondary Research**: Analysis of existing surveys, industry data and literature on AI, digitalization and COVID-19's effects on banking across Europe EBF. **Qualitative Survey**: Conducted 20 structured expert interviews (Zoom/Teams) between April 17–28, 2023, across 10 European countries. The sample included employer association and trade union representatives to gather diverse perspectives EBF.	Commissioned by the European Social Partners in the banking sector and produced by ARIX Research, the study was finalized and presented at a conference in Brussels in May 2024

	provide a holistic understanding of AI's impact on banking organizations and workforce.		
The Business Case for AI in HR: Building Trust and Value	To demonstrate how IBM has implemented artificial intelligence in its Human Resources (HR) functions to improve decision-making, employee experience and business outcomes.	This is a **practitioner-driven corporate white paper** based on internal case analysis. It includes: • Descriptions of IBM's AI tools (e.g., Watson Recruitment, chatbots). • Implementation approaches (MVPs, feedback cycles). • Performance metrics (ROI, NPS).	Industry white paper / internal business case documentation from IBM's website

		• Quotes and reflections from internal HR leadership and practitione	
Madanchian & Taherdoost (2025): Barriers and Enablers of AI Adoption in Human Resource Management: A Critical Analysis of Organizational and Technological Factors	To identify and critically analyze the key organizational, cultural and technical factors that either enable or hinder the adoption of AI in HRM settings, with special attention to ethics, leadership and employee trust.	**Critical literature review** supplemented by **expert interviews**. Integrates insights from both **empirical studies** and **theoretical literature** on AI implementation, digital transformation and HRM systems.	Peer-reviewed academic journal article

4.0 Analysis

4.1 How is AI used and implemented

4.1.1 Finance Case

This section addresses the first research question: *How is AI used and implemented?* Using OP Financial Group as a case study, the analysis explores how artificial intelligence is introduced, developed and embedded across core organizational functions. Rather than viewing AI as a singular innovation, this section unpacks its application within specific domains, namely customer interface, operational processes and internal capability-building. The approach draws on Socio-Technical Systems (STS) Theory and Implementation Model to understand how technological integration is co-shaped by organizational structures, strategy and learning processes.

4.1.1.1 Strategic Shift: From Mobile-First to AI-First

The implementation of AI technologies at OP Financial Group reflects a broader, strategic transition from traditional digital tools toward a deeply integrated, AI-driven service model. Central to this transition is the firm's shift from a "mobile-first" strategy to an explicit "AI-first" orientation, which shows a structural commitment to embedding AI into the organization's operational DNA. This transformation is not merely rhetorical, it is substantiated by the development of several AI-powered solutions that span both front-end and back-end domains. These include biometric authentication tools, autonomous loan processing systems and comprehensive internal training initiatives. This deliberate strategic framing positions AI as a long-term enabler of innovation and aligns directly with Implementation model's emphasis on staged, leadership-driven transformation processes.[40]

4.1.1.2 Domain-Specific AI Applications

AI at OP Financial Group is not implemented as a one holistic solution, but as a set of targeted, function-specific tools tailored to distinct organizational challenges. One example is the facial recognition payment project, which operates with a multi-function purpose of identity verification, transaction processing and user interaction. The system allows customers to authorize payments using facial biometrics, replacing traditional authentication methods such as PIN codes or physical cards. As noted by a senior manager, this AI tool enhances not only efficiency but also the customer experience itself. In global pilots, similar systems have been used for loyalty tracking and secure access control, highlighting the multifunctionality and adaptability of biometric AI within financial ecosystems.[41]

Another prominent application is OP's digital home loan service, which leverages machine learning to evaluate mortgage applications. Trained on extensive financial datasets, the AI model

[40] Poudel, D. (p. 26)
[41] Ibid. (p. 25)

autonomously assesses risk and creditworthiness, enabling near-instantaneous decision-making. The system's ability to make "quick decisions" signifies a process in which routine evaluations once handled by loan officers are now conducted by algorithms. This reduces processing time, limits subjective bias and standardizes decision-making criteria, key implementation benefits aligned with both technical efficiency and organizational fairness. These tools exemplify a broader functional typology in OP's AI strategy. Specifically, they serve purposes of automation (e.g., mortgage assessment), augmentation (e.g., biometric payment systems, internal training) and decision support (e.g., AI-guided loan approvals). This multiple function use reflects a holistic integration model that extends beyond basic automation to enhance user interaction and organizational intelligence.[42]

4.1.1.3 Modular Rollout and Pilot Strategy

OP's adoption of AI follows a modular, domain-specific deployment strategy. Rather than implementing large-scale, organization-wide systems, AI tools are piloted in narrowly defined zones, such as facial recognition in retail banking or automated processing in loan services. According to internal documentation: "*OP Group's current facial recognition payment project is one of the many pilot projects being undertaken in the organization*".[43]

This phased, experimental approach minimizes systemic disruption and enables iterative refinement, ensuring that implementation is sensitive to operational feedback and local context.

This aligns with Implementation model's concept of staged rollout, where each implementation phase is evaluated before being scaled. It also reflects STS theory's principle of socio-technical alignment: by adjusting pilot tools within their specific environments, OP ensures that technology evolves in step with organizational needs and user expectations.

4.1.1.4 Ethical Anchoring and Workforce Enablement

OP does not treat AI as a standalone technical upgrade, but as a socio-technical system requiring cultural anchoring and capacity-building. A notable illustration of this is the bank's internal AI training program, which aims to foster ethical literacy and technical competence among staff[44]. This initiative reflects a broader orientation toward organizational learning and responsible innovation.

[42] Ibid. (p. 23-24)
[43] Ibid. (p. 23)
[44] Ibid. (p. 28-30)

By embedding normative values and skill development into the AI adoption process, OP builds internal readiness and reduces the likelihood of resistance or misalignment.

This ethical grounding also contributes to the organization's ability to adapt to regulatory shifts and evolving stakeholder expectations. In this regard, the training program serves dual purposes: increasing technical fluency and reinforcing the human dimension of joint optimization, as emphasized in STS theory. AI systems are not simply imposed, they are co-produced through learning, dialogue and shared norms.

4.1.1.5 Technical Characteristics and Change Governance

Although OP's documentation does not elaborate in depth on the specific algorithmic systems, several technical characteristics can be inferred. The presence of feedback loops, pilot programs and training systems suggest a **supervised, iterative deployment model**, wherein AI tools are refined based on user or employee input. This reflects a hybrid architecture, part automation engine, part responsive learning system, tailored to OP's regulatory and operational landscape.

Governance of this change process is distinctly **top-down**. The shift to an "AI-first" model is framed and directed by senior leadership and AI initiatives, such as facial recognition and mortgage automation, are strategically defined at the executive level and implemented through standardized documents and cross-departmental coordination. This centralization ensures coherence and alignment but also situates responsibility for success or failure squarely within institutional leadership, a hallmark of the **top-down implementation model** in Implementation model.

Despite the systemic nature of this change, the implementation is described as being in an "elementary stage"[45].This suggests an ongoing process wherein AI is not fully mature or ubiquitous, but still under refinement, a perspective supported by OP's use of pilots and modular architecture. Nevertheless, this approach enables future scalability and compatibility, ensuring that AI systems can evolve alongside existing infrastructure and workflows.

4.1.1.6 Summary

OP Financial Group's AI implementation strategy exemplifies a deliberate, staged and institutionally embedded model of technological transformation. Through domain-specific tools, modular rollout, ethical training programs and top-down coordination, the organization has begun

[45] Ibid. (p. 26)

embedding AI deeply into both customer-facing services and internal operations. From an STS perspective, this reflects a high degree of socio-technical integration, where human skills, organizational structures and technological systems co-evolve. Simultaneously, from an Implementation model lens, OP's approach illustrates a context-dependent, leadership-driven process where phased deployment, feedback and cultural anchoring are used to mitigate risks and build long-term capacity. While the current stage is formative, OP's implementation trajectory signals a strategic shift toward sustainable and adaptive AI integration.

4.1.2 HR Case

This section focuses on the specific practices through which AI technologies are introduced, integrated and operationalized in both HR and finance domains. Rather than treating AI as a broader innovation, the analysis emphasizes function-specific applications, rollout strategies and the interplay between human and technological systems. By examining implementation patterns across organizations with varying degrees of digital maturity, the goal is to uncover not only where AI is applied, but how these systems evolve within existing workflows, structures and infrastructures.

4.1.2.1 Modular, Task-Specific Deployment

IBM presents an interesting and phased strategy for AI deployment within HR functions, characterized by a modular, task-specific implementation approach rather than a unified, one-size-fits-all platform. Instead of enforcing organization-wide transformation, AI is introduced through discrete tools tailored to operational needs such as recruitment, learning, compensation and internal mobility. This ensures that each application is context-dependent and compatible with existing workflows and legacy systems, minimizing disruption and enhancing adaptability.[46]

For instance, in recruitment, Watson Recruitment leverages historical hiring data and biographical indicators (e.g., leadership history, educational background) to rank candidates and predict time-to-fill. In learning and development, the Watson Career Coach provides personalized career pathing based on employee profiles and historical mobility trends[47]. For onboarding and employee inquiries, IBM deploys AI-powered chatbots that handle routine questions across areas, freeing HR professionals to focus on strategic, interpersonal and analytical tasks. These tools operate within narrowly defined decision zones, screening, recommending and responding, thus augmenting rather

[46] IBM. (p. 10, 25)
[47] Ibid. (p. 12, 17)

than replacing human agency. The effects of these tools on task distribution and role transformation are further explored in section 4.3. This design-logic reflects the socio-technical co-evolution emphasized by Trist and Emery (Miner J.B 2006), where the role of technology is to enhance, not override, social systems.[48]

4.1.2.2 Implementation Model and Iterative Rollout

This implementation logic also aligns strongly with key principles from Implementation model. IBM's use of Minimum Viable Products (MVPs), small-scale, functional AI tools tested in live environments, represents a clear commitment to iterative change. Each MVP undergoes performance testing and feedback evaluation before being scaled organization-wide, allowing IBM to make continuous improvements without causing organizational disruption[49]. This stepwise strategy mirrors Implementation models' emphasis on adaptive learning, structured leadership support and resource planning. It reflects a practical understanding that change is not linear, but emergent, requiring organizational readiness, stakeholder inclusion and agile revision. The role of employee feedback and adaptive learning as acceptance mechanisms is further elaborated in section 4,4. Feedback loops and performance metrics are used not just to fine-tune technology, but to anchor it in daily practice, promoting legitimacy and buy-in from users.[50]

4.1.2.3 Technical Configuration and Interoperability

On the technical side, IBM leverages both rule-based algorithms (e.g., for parsing resumes) and machine learning models (e.g., predictive scoring tools), thereby matching task complexity with algorithmic sophistication[51]. This balance ensures that high-volume, low-variability tasks are automated, while more interpretive or sensitive processes retain human oversight. Data infrastructure investments support interoperability across systems, enabling seamless integration between AI tools, HR databases and legacy systems[52]. Transparency is also embedded at the system level, where managers can review, override and question AI-driven insights, thus retaining agency

[48] Ibid. (p. 14, 17-18)
[49] Ibid. (p. 25-26)
[50] Ibid. (p. 27-28)
[51] Ibid. (p. 25)
[52] Ibid. (p. 26-27)

and trust[53]. These technical considerations signal deliberate resource allocation and attention to socio-technical interface points. Further discussion on transparency, bias mitigation and ethical concerns appears in section 4.5.2.

4.1.2.4 Partial Alignment with STS: Participation and Values

Despite this operational alignment with STS principles, IBM's approach diverges in notable ways from the deeper, normative commitments of the theory. STS is not merely a framework for optimizing system compatibility; it is a socio-philosophical model that emphasizes co-construction, participatory governance and a balance between efficiency and worker empowerment.

While IBM promotes user feedback post-deployment, strategic control over AI innovation remains top-down. As highlighted in the source, "*IBM's CHRO and her direct reports work to identify the ideas with the most promise*"[54]

revealing a centralized process where senior leadership curates project priorities. This managerial curation stands in contrast to STS's call for co-optimizing design and collective sensemaking, where frontline employees play an active role in shaping not only the tools they use, but the logics that govern them. Moreover, IBM's framing of success in the following passage:
"*Throughout the employee journey, it's about driving the right experience, measured by NPS and driving the right business results, measured through ROI.*"[55]
signals a metric and instrumentalist orientation that prioritizes quantifiable performance over relational or ethical outcomes. These tensions between measurement logic and worker-centered values will be addressed in sections 4.5.2 and 6.0.

STS emphasizes that metrics like job satisfaction, autonomy and worker identity are integral to socio-technical success, not peripheral. Yet these are largely absent or subordinate in IBM's performance framework. While IBM rightly addresses and incorporates issues of transparency, fairness and bias mitigation, these are treated as essential co-constitutive elements of system design but do not supersede the instrumentalist notions.

4.1.2.5 Summary

[53] Ibid. (p. 28, 30)
[54] Ibid. (p. 27)
[55] Ibid. (p. 20)

In summary, IBM’s AI strategy illustrates a highly structured, data-driven and modular model of technological adoption. Instead of pursuing wholesale transformation, IBM deploys task-specific tools such as Watson Recruitment, Career Coach and AI-powered HR chatbots to address discrete functions like hiring, onboarding and employee development. These systems are integrated through Minimum Viable Products (MVPs), performance testing and compatibility with legacy systems. This phased, feedback-driven approach aligns with core principles of Implementation model, particularly its emphasis on adaptive rollout and iterative learning. Technically, IBM balances rule-based systems with machine learning models, automating high-volume, structured tasks while maintaining human oversight in more interpretive areas. Transparency mechanisms, including managerial review and override options, support operational control and accountability. The broader implications for decision-making authority (4.3), organizational acceptance (4.4) and ethical alignment (4.5) are considered in subsequent sections.

4.2 *What* organizational, cultural and technical factors affect the successful integration of AI?

4.2.1 Finance

4.2.1.1 Organizational Factors

The implementation model at OP Financial Group is strongly shaped by organizational readiness and top-down coordination. The transition to an “AI-first” strategy marks not only a branding shift but a strategic decision to embed AI across core processes. As explicitly stated, “the strategy is transforming into ‘artificial intelligence first,’” indicating a long-term institutional commitment. This strategic framing sets a clear tone from leadership, reinforcing the importance of AI as both a competitive driver and a structural feature of the organization. These factors such as leadership commitment, alignment of goals and strategic clarity, are central within the Implementation model, which identifies them as key enablers for effective rollout.
OP’s approach is top-down, reflected in how domain-specific pilots (e.g., facial recognition payments, AI-based mortgage assessments) are implemented under a unified strategic framework. Internal consistency is reinforced through the organization-wide adherence to the strategy:

“*Every unit follows standard strategy. Hence, strategy practices are congruent*.”[56]
This coherence supports system-wide integration and reduces fragmentation across departments. It also signals that leadership has actively allocated resources and set expectations uniformly factors closely tied to the coding category of Organizational Readiness, particularly regarding leadership support and alignment of internal systems. However, the rollout is not without barriers. While high-level coordination appears strong, interviews with mid- and upper-level managers suggest that absorptive capacity, the organization’s ability to process, adapt and embed change varies across units. For example, one senior manager reflected:
“*Time to time I think we are really rushing with AI.*”[57]
This indicates that the strategic pace may not be fully matched by operational capacity. In implementation terms, this mismatch represents a breakdown in stage-wise alignment, where rollout goals are outpacing on-the-ground preparedness an important concern under Implementation Barriers. While leadership pushes forward, not all departments seem equally equipped in terms of staff readiness, infrastructure, or clarity on new workflows.
Similarly, another practitioner noted:
“*Yes and it seems surprisingly challenging to implement in everyday life. In a way the lines are drawn too far away and then here closest things are undone…*”[58]
This doesn’t necessarily reflect resistance, but a gap between strategic vision and practical embedding, tied to issues like role clarity and workload redistribution, both socio-technical concerns.

4.2.1.3 Cultural Factors

Despite these frictions, OP shows strong signs of internal preparedness and cultural orientation toward change. The bank has a long-standing innovation culture that frames AI not as a disruptive force but as a natural continuation of digital modernization. This ties into the broader organizational culture, that ties AI together with existing workflows. Employees often expressed openness rather than skepticism. One internal observation reads:
“*Readiness to change appeared more than resistance to change*.”[59]

---

[56] Poudel, D. (p. 24)
[57] Ibid. (p. 26)
[58] Ibid. (p. 26)
[59] Ibid. (p. 25)

This finding is important within the Organizational Readiness and Socio-Technical Interaction categories. Culturally, OP seems to have preconditioned its workforce to treat technological evolution as standard practice, a feature of high organizational adaptability.

Training and capacity-building are essential in supporting this transition. OP's internal AI training program is a tangible example of competence development, enabling staff to engage meaningfully with new systems. Rather than treating AI as a technical layer, the organization invests in developing staff knowledge on ethical use and responsible operation. According to STS theory, this kind of investment in the "human component" is essential for joint optimization, ensuring that technology functions in harmony with user skills, ethical norms and operational expectations.
This cultural disposition is further reinforced by narratives that normalize change. Practitioners spoke of AI as a "new normal," indicating not just passive tolerance but active adaptation. This aligns with Implementation model's emphasis on cultural anchoring and communication as enablers of successful change. The absence of strong resistance also suggests that employee concerns have been anticipated and addressed early, reducing implementation friction. [60]

4.2.1.4 Technical Factord

On the technical side, OP's strategy relies on modular, domain-specific pilots. Initiatives such as facial recognition payments and automated home loan evaluations are launched in controlled settings, under shared governance but adapted to local contexts. This staged approach supports scalable, context-dependent integration, in line with Implementation model's principle of phased rollout. It also reflects attention to technological compatibility, new tools are embedded into existing systems, not overlaid on them. This helps ensure backward compatibility and reduces the risk of disruption. While IBM focuses on in-house solutions, as they are a tech-company.[61]
Moreover, this modular technical strategy is paired with a commitment to employee preparedness. OP's emphasis on ethical training during AI deployment reflects a dual investment, in infrastructure and in people. This mirrors the STS principle of joint optimization, which holds that technical systems and human roles must be developed in tandem. Without that pairing, systems risk becoming misaligned, underused, or mistrusted.
In this context, OP's implementation approach shows strong technical infrastructure, backed by consistent leadership and workforce enablement. However, barriers remain, especially related to

[60] Ibid. (p. 25-26)
[61] Ibid.

uneven absoprtive capacity and localized tension in adjusting workflows. These issues reinforce that successful implementation depends not only on having the right tools or strategy but also on how the rollout interacts with daily routines, expectations and readiness levels.[62]

4.2.1.5 Summary

In sum, the organizational and technical factors influencing AI integration at OP reflect both structured planning and emergent complexity. Leadership commitment, training, cultural openness and modular rollout provide a strong foundation. Yet real-world frictions, uneven pacing, unclear task shifts and resource strains, highlight the importance of aligning high-level ambition with operational and human realities. These findings underscore that implementation is not linear but contingent, requiring feedback loops and iterative adjustment.

4.2.2 HR Case

4.2.2.1 Technical Factors

At IBM, several technical factors have been pivotal to the successful integration of AI in HR functions. A core strategy involves the use of Minimum Viable Products (MVPs), AI tools that are initially deployed at a limited scale to test functionality, user fit and business impact before being scaled across the organization. This phased implementation allows technical issues to be identified and addressed early without disrupting broader operations[63]. In parallel, IBM has invested heavily in its data infrastructure, establishing robust data pipelines that connect AI modules with live HR databases and legacy systems. This interoperability is essential for maintaining real-time relevance and performance while minimizing friction with existing systems. It also reflects deliberate and strategic resource allocation, a core principle in Implementation model. Sufficient resource allocation is a major factor in driving implementation, highlighting technical capabilities to support the AI. The system architecture supports both rule-based tools (e.g., resume parsing) and machine learning models (e.g., predictive scoring), allowing technical complexity to be matched with task demands, an approach that supports scalability and adaptive deployment. Additionally, IBM avoids fragmented solution silos by ensuring AI tools are interconnected across HR domains, enhancing systemic synergy in areas such as learning, compensation and recruitment. To build trust and foster adoption, IBM prioritizes explainability: variables influencing AI-generated outputs are made transparent, enabling managers to review, question, or override system suggestions, thereby

[62] Ibid. (p. 23)
[63] IBM. (p. 27)

preserving human agency. The broader role of trust and user involvement in tool refinement is addressed in section 4.4.2.[64]

4.2.2.2 Organizational Factors

Organizationally, IBM's internal environment plays a foundational role in supporting AI adoption. A key enabler is strong leadership commitment, with senior HR executives anchoring AI projects to clearly articulated business cases. This alignment not only legitimizes implementation efforts but also ensures access to the necessary resources and organizational legitimacy. Multidisciplinary team structures, bringing together HR experts, data scientists, technical architects and UX designers foster inclusive and context-aware development processes. Equally important is IBM's emphasis on HR upskilling: employees are encouraged to develop analytical and technical literacy to engage more confidently with AI tools, reinforcing long-term adaptability and reducing resistance. Implications for shifting skill requirements and changing roles are adressed further in section 4.3.2. The organization also fosters readiness for change through regular feedback cycles, where users contribute to the refinement of tools post-deployment. This iterative process creates a culture of adaptive learning and local tailoring. While the process is to a large degree fostered by individuals higher up in the system. The annual cycle in which:

"*IBM's CHRO and her direct reports work to identify the ideas with the most promise*"[65]

suggests a top-down logic that limits deep frontline co-creation. Moreover, IBM frames AI success through output-driven metrics such as Net Promoter Score and Return on Investment, stating that the employee journey should be evaluated by "*driving the right experience, measured by NPS and the right business results, measured through ROI*"[66].These are factors that can be highly attributed to the organizational structure and to some degree culture. The relevance and impact of the feedback loops are to be further addressed (4.4). Furthermore, IBM embeds AI deployment within an ethical oversight framework, prioritizing fairness, transparency and bias mitigation, principles operationalized through explainability tools and audit capabilities. These organizational factors collectively contribute to a strategically aligned and culturally supportive environment for AI

[64] Ibid. (p. 25-29)
[65] Ibid. (p. 27)
[66] Ibid. (p. 30)

implementation. Some of the culturally relevant points overlap with points in the upcoming section (4.2.2.3).[67]

4.2.2.3 Cultural Factors

For instance, IBM encourages "technical curiosity" and openness toward digital experimentation, an indicator not only of existing culture, but also of the company's intended cultural trajectory. This active cultivation of a pro-innovation mindset demonstrates how organizational culture itself becomes an enabler of technology adoption, reflecting STS Theory's emphasis on socio-technical interdependence. Like described previously, the use of AI also suffers from a degree of short-termism, highlighted by the use of ROI's and NPS to direct the AI implementation. From such standpoints, it can be attributed to some degree a metric-driven culture. An interesting aspect that IBM seems to address is also the regional culture of their sub-departments:

"*An AI solution designed in one region of a multinational organization's operations may need to be entirely retrained before deployment in another region – even if the same language is spoken in both areas*."[68]

Which shows the organization's consideration of internal customs of each department. Where some regions may use such and such tools in such and such ways, another place may not be as willing to go about the same way.

This approach closely aligns with both STS Theory and Implementation model. The emphasis on cross-functional team structures, adaptive feedback mechanisms and localized system customization reflects STS Theory's principle of joint optimization, where technical and social subsystems are co-designed to enhance both performance and human well-being. Similarly, IBM's model embodies the key constructs of Implementation model, where committed leadership, sponsorship, resource mobilization, capability-building and iterative learning are prerequisites for sustainable adoption. However, while IBM's approach is much aligned with the factors within the implementation model, it also diverges in meaningful ways from the normative ideals of STS. Notably, user feedback is incorporated largely by post-deployment and strategic decisions remain concentrated in top-tier leadership. This efficiency-oriented framing diverges from the broader STS and implementation model vision, which advocates a richer consideration of human-centric values such as trust, agency

[67] Ibid. (p. 26-30)
[68] Ibid. (p. 28)

and participatory governance. IBM does address internal culture as a concern for implementation, seeing it as contextually important. Thus, IBM's implementation reflects a technically sophisticated, strategically grounded approach and culturally aware, yet to some degree remains bounded by managerial priorities, illustrating both the strengths and limitations of pragmatic, top-down-led AI adoption. Culture and change readiness are also reflected in how AI affects work organization, covered in the next section.

4.3 How does AI influence task-distribution, workflows and decision-making?

4.3.1 Finance Case

4.3.1.1 Evolving Work Roles and Task Redistribution

A subtle yet significant theme that emerges from the case of OP Financial Group is the evolving nature of work roles in response to AI implementation. While not always explicitly framed in terms of formal task redistribution, interview data reveals a narrative of occupational transformation and gradual functional redefinition. Employees, particularly those with long tenures, reflect on how AI has modified the expectations and routines of their roles. One upper manager recounted:

"*The work has changed so much… maybe it is that I started as a banker in the 90s, I remember there was a panic… we no longer need the cash transactions, but we are still here*."[69]

This statement exemplifies a common theme: continuity amidst change. It signals that while specific tasks, such as manual transaction handling, have diminished, the essence of human involvement remains, albeit in updated forms.

From a Socio-Technical Systems (STS) perspective, such reflections highlight a co-evolution process, where technological tools do not entirely replace human functions but rather reconfigure them. AI, in this sense, serves as an augmenting layer, streamlining specific operational functions while pushing employees toward more interpretive, supervisory, or client-oriented roles. This is echoed in sentiments such as:
"*It's nice to be working in a job that has been in place… but I like the whole thing changing and the people involved*"[70] which illustrates a workforce increasingly engaged with dynamic rather than

[69] Poudel, D (p. 25)
[70] Ibid.

static job definitions. Importantly, there is little evidence of direct job displacement or automation anxiety in the empirical material. Instead, practitioners appear to normalize the idea of shifting roles, embracing adaptation as a professional ethos. One operative noted:
"*AI is super useful… it helps automate our work saving time but not always… much better when a person from bank calls… robot making mistakes*."[71]

This suggests a retained preference for human judgment in relational or interpretive tasks, even as automation absorbs more routine functions. This division aligns with STS's concept of joint optimization, where AI systems take over standardized or repetitive operations, while human employees handle contextual decisions and interpersonal interaction.

4.3.1.2 AI and Decision-Making Dynamics

The implementation of AI at OP Financial Group introduces both opportunities and uncertainties in decision-making. While AI tools are positioned to support rather than replace strategic judgment, internal perspectives suggest a cautious stance on the organization's readiness. One manager remarked, "*how we are going to be capable of using these information is an important question*"[72], indicating concerns about data interpretability and strategic alignment. Given that AI at OP is primarily deployed in modular, pilot-based projects such as digital loan processing and facial recognition, the trend appears to favor further automation of already automated or routine processes, while more complex, human-centered tasks remain augmented:
"*It supports in decision making, it sure help us in leadership…*"[73]

As noted in 4.1.1, further adding to the augmentation-oriented approach in human-related functions. This suggests a division in AI's functional role: streamlining routine operations with automation while supporting, but not displacing, higher-order decision-making and human-oriented functions. From an STS lens, this reflects a cautious co-evolution of technical systems and managerial capacity.

4.3.2 HR Case

4.3.2.1 Task Distribution and Augmentation

[71] Ibid. (p. 27)
[72] Ibid. (p. 26)
[73] Ibid. (p. 26)

One of the defining features of IBM's AI strategy is how it shifts work processes focusing on task augmentation rather than replacement, particularly within HR functions. AI tools like Watson Recruitment and Career Coach are designed to handle specific, repetitive, or data-intensive subtasks, such as resume screening or career pathway suggestions, allowing human professionals to focus on higher-order activities like strategic planning, interpersonal engagement and policy alignment. As the study notes:

"*Responsibilities are changing rather than disappearing... The parts of jobs that are gaining in importance are analytical thinking, strategizing and driving change*"[74]

This shift reflects a reallocation of cognitive and administrative effort, with AI absorbing routine load while enhancing the capacity of HR professionals. Importantly, IBM encourages a collaborative dynamic where "decision autonomy is augmented rather than replaced" ensuring that human agents retain ultimate authority while drawing on machine-generated insights for support. This design philosophy exemplifies the co-evolutionary logic of STS theory, which emphasizes the need for technological artifacts to enhance, not override, the social structure of work. It also aligns with Implementation model's recognition that task realignment must be accompanied by role clarity and employee confidence in using new tools.[75]

4.3.2.2 Workflow Reconfiguration and Efficiency

AI implementation at IBM has significantly contributed to workflow streamlining and role realignment within HR functions. By automating time-consuming processes such as compensation analysis, onboarding support and candidate screening, AI has reduced manual workloads and accelerated service delivery. For example, the use of AI-powered compensation tools has enabled managers to process complex pay decisions in hours rather than days, incorporating several complex variables to enhance the experience. Similarly, chatbots now handle high volumes of routine employee inquiries, allowing HR staff to redirect their focus toward complex, value-adding tasks.[76]

These enhancements have not only improved efficiency but also prompted a shift in HR roles, away from administrative execution and toward analytical and strategic functions. The result is a reconfigured workflow where human professionals act as interpreters and stewards of AI outputs,

[74] IBM. (p. 29)
[75] Ibid. (p. 28-29)
[76] Ibid. (p. 14, 19)

rather than manual processors. This evolution reflects the joint optimization principle of STS Theory, where technical advancements are integrated in ways that elevate human contribution rather than render it obsolete. It also aligns with Implementation model's emphasis on process alignment, whereby structural changes in task distribution are accompanied by resource support and role adaptation to maintain continuity and performance.

4.3.2.3 Decision-Making Support and Managerial Discretion

Building on this reconfiguration of workflows, IBM's AI systems also play a central role in enhancing decision-making through predictive and real-time support. Rather than making autonomous judgments, AI tools at IBM provide data-driven insights that enable managers to make more informed, consistent and timely decisions. For instance, Watson Recruitment generates predictive scores based on candidate profiles, estimating success likelihood and expected time-to-fill, while compensation systems integrate dozens of internal and external variables to assist in equitable pay planning.

These tools act as decision advisors, surfacing patterns and recommendations that would be difficult for humans to synthesize manually, especially at scale. Crucially, the AI outputs are not prescriptive; managers retain discretion and can override or modify system suggestions based on contextual judgment, a capability that IBM explicitly supports:

"*If compensation decisions are based on just one or two data points, such as tenure and performance, a manager can make the decision without analytical support. But managers should consider many factors, such as market rates and propensity to learn…*"[77]

This balance between algorithmic input and human oversight ensures that decision-making becomes more evidence-based without undermining managerial authority.[78]

4.3.2.4 Emergent Human-AI Collaboration

This evolving configuration has also led to the emergence of new human-AI workflows, where decision-making is increasingly embedded within dynamic, digital interfaces. HR professionals and line managers interact with AI through dashboards, alerts and real-time nudges, marking a shift

[77] Ibid. (p. 14)
[78] Ibid. (p. 12-14)

from sequential, manual processes to collaborative co-decision environments. One such example is "conversational HR," where chatbots not only respond to queries but also assist in guiding task execution throughout the workflow. From this it becomes clear that AI doesn't remove humans from the core of functions, but automates less intricate work and augments more nuanced ones[79]. These emergent patterns demonstrate how AI becomes a continuous presence in daily operations, not as a replacement, but as a partner that shapes decisions and adapts over time. This reinforces STS Theory's emphasis on co-evolution and human-machine interdependence, as well as Implementation model's call for phased refinement grounded in practical engagement and user-centered design.

4.3.2.5 Transparency, Trust and Accountability

A central design principle in IBM's AI implementation is the preservation of transparency and managerial control in decision-making. AI tools are developed not as autonomous authorities, but as advisory systems whose logic and influence are made fully visible to users. Managers are provided with insight into the data sources, variables and reasoning that underpin AI-generated recommendations, allowing them to accept, override, or challenge outputs based on contextual factors or professional judgment. As mentioned in section 4.2.2, the systems are built with a degree of transparency. This transparency reinforces trust and accountability, ensuring that human actors remain at the center of critical decisions, particularly in ethically sensitive areas such as hiring and compensation. By making the algorithm's decision path interpretable and reversible, IBM avoids the risk of "black box" decision-making. From this it can be inferred that humans maintain responsibility and majority decision-making power in their work.[80]

4.3.2.6 Summary and Theoretical Alignment

The analysis of IBM's AI implementation in HR reveals a clear alignment with both STS and Implementation model. From an STS perspective, IBM emphasizes task augmentation, human oversight and role preservation, which reflect the theory's principle of joint optimization between social and technical subsystems. Workflows are redesigned to elevate human value through strategic

[79] Ibid. (p. 14, 18-19)
[80] Ibid. (p. 28-30)

redeployment, while decision-making processes incorporate AI-generated insights without removing managerial control. This reflects a co-evolutionary approach where AI is integrated as a partner in daily operations rather than a replacement.

In terms of Implementation model, IBM meets key success factors such as leadership engagement, process support, transparency and employee enablement. Decision tools are framed as advisory systems and their deployment is linked to measurable outcomes, aligning well with the theory's focus on structured rollout and organizational readiness.

The main divergence from STS lies in the limited emphasis on participatory design or co-creation with non-managerial staff, which STS regards as central to full socio-technical integration. Similarly, while IBM's strategy follows Implementation model procedurally, it places less focus on deep cultural transformation or bottom-up change, favoring a more top-down, performance-driven implementation logic.

4.4 How do feedback mechanisms and user participation influence the refinement and acceptance of AI tools?

4.4.1 Finance Case

4.4.1.1 Finance

OP Financial Group also employs feedback mechanisms to smoothen out the implementation process. A central aspect of how OP Financial Group refines and integrates its AI systems is the incorporation of user feedback and experiential input into development cycles. Unlike static technology rollouts, the implementation process is characterized by iterative refinement, as illustrated by one upper manager's remark:

"*As the technology is new, it is important to collect feedback on any fears and apprehensions users may have. Based on what we learn, we will then be able to take the right next steps in development*."[81]

This statement underscores an interactive and responsive approach to implementation, where feedback does not merely inform usability improvements but also addresses emotional and ethical

[81] Poudel, D (p. 25)

considerations, such as fear, control and data privacy. In line with STS theory, this suggests an adaptive infrastructure in which AI technologies are not simply imposed but are negotiated and evolved through user engagement. However, the acceptance of these tools is not uniform or unconditional. An earlier quote that was mentioned also ties into this topic, expressing concerns about the pace and depth of implementation, which can act as barriers to broader buy-in: "*Time to time I think we are really rushing with AI*."[82]
This sentiment reflects a tension between strategic ambition and cultural anchoring, indicating that participation in AI development is not just a technical issue but also a matter of perceived readiness and trust. These concerns highlight that feedback mechanisms are not only a matter of usability, but also serve as cultural and organizational anchoring tools, aligning technical development with social expectations.

Furthermore, the boundaries of AI acceptance are clearly marked by the perceived reliability of human interaction in high-stakes contexts. A practitioner reflects:
"*AI is super useful… it helps automate our work saving time but not always… much better when a person from bank calls… robot making mistakes*."[83]
This remark underscores the conditional nature of trust in AI systems, where human presence is still seen as indispensable in tasks requiring empathy, discretion, or contextual judgment. Feedback in this context functions less as a tool for system optimization and more as a dialogue about role boundaries, shaping which functions AI should take over and which should remain human-led. This quote, interestingly catches the duality of AI use within firms, pointing to a degree of mistrust that will be further addressed.

Taken together, OP's feedback mechanisms reveal a nuanced, dynamic co-adaptation between technical design and organizational culture. While the systems are refined iteratively through feedback, the legitimacy and effectiveness of these refinements may depend on how user concerns, trust boundaries and emotional responses are acknowledged and embedded into the evolution of AI tools. These factors help shape the AI trajectory of the firm.
While the presence of feedback-informed adaptation is clearly emphasized, the empirical material offers limited insight into the concrete structures, channels, or frequency of these feedback loops,

[82] Ibid. (p. 26)
[83] Ibid. (p. 27)

leaving some ambiguity about how systematically these inputs are operationalized in the refinement of AI tools.

4.4.2 HR Case

IBM's AI implementation strategy strongly incorporates feedback mechanisms and selective user participation, though the depth and timing of this involvement shape its impact. As previously outlined in section 4.1.2, IBM follows a phased deployment strategy using Minimum Viable Products (MVPs) to test and refine AI tools before scaling them organization-wide. This structure enables feedback to be gathered under live conditions and used to fine-tune functionalities. One example is IBM's performance management chatbot, which was released with the disclaimer that it was "ready but not perfect," and employees were explicitly encouraged to challenge it to accelerate its learning process. As seen earlier, this exemplifies an agile, adaptive implementation process that aligns well with Implementation model's call for iterative learning and stakeholder engagement.

Moreover, IBM incorporates feedback loops into everyday AI use through tools like "Engage at IBM," a platform where managerial input on recommendations informs how the system evolves over time[84]. This real-time refinement fosters both practical responsiveness and user trust. However, as mentioned in section 4.1.2, while these mechanisms ensure functional alignment and incremental improvements, they still occur within a top-down framework. IBM's senior executives, particularly the CHRO and her team, lead the selection of projects and set the strategic direction, which limits the participatory scope envisioned in STS theory. Additionally, IBM places a strong emphasis on transparency and user control to reinforce acceptance. As discussed, managers are given insight into the variables driving AI outputs and retain the ability to override them when necessary. This approach enhances interpretability and preserves managerial autonomy, aligning with both STS principles of human-machine interdependence and Implementation Theory's emphasis on building user competence. Still, as previously noted, such transparency mechanisms are more about safeguarding performance integrity and accountability than enabling co-design or democratic shaping of the tools themselves.

In essence, IBM's feedback strategy is technically sound and methodologically structured, fostering iterative refinement and promoting tool legitimacy. However, as highlighted in section 4.1.2, it does not fully realize the deeper participatory ethos of STS Theory. Instead, it reflects a model of

[84] IBM (p. 13-14)

"managed responsiveness," where feedback serves the function of optimization rather than co-construction. This tension between strategic refinement and genuine user involvement defines both the strength and the boundary of IBM's approach to AI adoption.[85]

4.5 What are the positive and/or negative effects on work and organizational processes AI has

4.5.1. Finance Case

4.5.1.1 Positive Organizational Impacts and Cultural Normalization

A core theme emerging from the case of OP Financial Group is the culturally embedded optimism surrounding AI and its perceived value as a strategic enabler rather than a disruptive force. Unlike many narratives of technological displacement, the empirical material illustrates how AI has been normalized as part of an ongoing transformation, where adaptation, not redundancy, is the dominant outcome. One employee encapsulated this sentiment, reflecting:

"*The work has changed so much… we no longer need the cash transactions, but we are still here*"[86]

This remark highlights a structural transition where traditional tasks are phased out, yet human roles persist through reconfiguration rather than elimination. Moreover, this transformation is framed positively by long-serving employees. One senior staff member noted:

"*I have been here for 20 years now… it's nice to be working in a job that has been in place… but I like the whole thing changing and the people involved*"[87]

Such reflections indicate a workplace culture where change is not only tolerated but embraced, echoing the organization's strategic ambition to reposition itself as a technological frontrunner. The absence of major pushbacks reinforces this cultural disposition. As the report states, "*There was no significant deliberate resistance to AI-led changes… the change is new normal*"[88], underscoring that innovation is institutionally embedded rather than externally imposed. On a functional level, employees also articulated clear benefits associated with AI tools. One manager observed, "*It has good things… many things can be done in a much more straightforward way… Good things have*

[85] Ibid. (p. 28-30)
[86] Poudel, D (p. 25)
[87] Ibid.
[88] Ibid

been done"[89], signaling tangible improvements in operational efficiency. Additionally, AI is recognized not just for task automation but also for enhancing managerial capabilities. As previously noted by a top-level manager, "*It supports in decision making, it sure helps us in leadership…*". This illustrates AI's dual role in augmenting both routine functions and strategic capacities. This quote suggests that one of the central objectives behind OP Financial Group's AI integration is the enhancement of service efficiency. By describing the services as:

"*We are right now in the elementary stage in the way, but good enough from the point of view of customer experience, that the services are pl*easant."[90]

The emphasis appears to be on streamlining processes in a way that improves user interaction without sacrificing quality. This reflects an implementation strategy oriented towards internal process optimization and smoother service delivery. Rather than aiming for radical innovation, the AI tools seem intended to make existing systems more responsive and functional, thereby supporting the broader goal of efficient technological change.

Taken together, these narratives reflect a positive alignment between technological change and organizational culture. From an STS perspective, this supports the notion of joint optimization, where social and technical systems co-evolve in a mutually reinforcing manner. Rather than experiencing AI as a threat, OP Financial Group's employees appear to engage with it as a tool for empowerment, efficiency and professional renewal.

4.5.1.2 Emerging Implementation Barriers and Friction Points

Despite a strong narrative of optimism and strategic alignment, the case of OP Financial Group also surfaces several underlying tensions and critical concerns related to AI implementation. A key element in the negatives is the perceived mismatch between the speed of AI integration and the organization's readiness to support the transition. One upper manager explicitly commented on the rapid pace of AI implementation within the firm, raising questions about information control and the tempo of change. This concern is echoed by another senior manager, who stated: "*How we are going to be capable of using this information is an important question*."[91] This reflects

[89] Ibid. (p. 26)
[90] Ibid. (p. 25)
[91] Ibid. (p. 26)

apprehension about whether internal systems, training and workflows are adequately equipped to manage complex data-driven systems. In implementation terms, it reveals readiness gaps, especially related to infrastructure, role clarity and procedural consistency, all central to organizational readiness and implementation barriers.

Further, this dissonance extends into operational domains. Another manager remarked:

"*It seems surprisingly challenging to implement in everyday life. In a way the lines are drawn too far away and then here closest things are undone…*"[92]

This illustrates that while the strategy may be coherent and centrally driven, its embedding into day-to-day practices remains uneven. These are typical socio-technical friction points, where the technological system outpaces the adaptation of social structures, contributing to role confusion or operational slowdowns. Additionally, concerns over unanticipated risks highlight the limits of predictive planning. One manager warned:

"There is a huge risk; I think we have not identified everything at this moment... we cannot prepare ourselves for this technology."[93]

This signals unease about unintended consequences, not resistance, but a measured caution about the unknowns of early-phase deployment. The concern isn't that AI is unwelcome, but that its impacts may outpace the organization's current capacity to assess, steer, or regulate it. This also reflects a lack of complete joint optimization, where technical development is advancing faster than adjustments in culture, structure, or workflows. This ambivalence extends to frontline interaction. One operative emphasized that while AI supports automation, human presence remains essential:

"*AI makes it easier… but I think they are looking for human contact… much better than robot making mistakes*."[94]

From an STS lens, this quote points to the continued need for relational trust and interpretive judgment, elements that purely technical systems still struggle to replicate. In sum, while AI is framed as a strategic imperative, the case reveals structural frictions, uneven preparation and early-

[92] Ibid.
[93] Ibid. (p. 27)
[94] Ibid.

stage uncertainty. As OP's implementation is still in its formative phase, it remains to be seen how these tensions evolve or are addressed over time.

4.5.2 HR Case

4.5.2.1 Efficiency Gains and Workflow Redistribution

IBM's case presents several positive effects from the use of AI. In example is the deployment of chatbots across HR functions serves as a clear example of how AI can generate tangible efficiency gains in both routine and high-demand scenarios. These chatbots are strategically embedded into workflows where quick response times and scalable support are critical, particularly during seasonal HR peaks, such as benefits enrollment, performance management and compensation planning cycles. During these periods, AI systems absorb high volumes of repetitive queries, allowing HR staff to redirect their focus toward complex or judgment-based issues. In addition to seasonal bots, IBM operates 24/7 chatbots like the "new hire assistant," which alone handles over 700 inquiries daily. The tool plays a pivotal role in onboarding support, particularly by resolving the common barrier of new employees not knowing whom to ask. Furthermore, the overarching goal is to deliver fast, consistent and accurate responses to users while minimizing the operational burden on human HR-teams. This realignment of effort reflects the joint optimization principle in Socio-Technical Systems Theory, where technical subsystems, such as AI chatbots, enhance the functioning of social systems i.e. the employees within IBM's HR. Chatbot integration also demonstrates well-scoped planning and resource reallocation, aligning technological adoption with performance-driven outcomes and strategic timing.[95]

4.5.2.2 Improved Decision-Making

In addition to saving time, IBM's AI systems also seem to contribute to better decision quality, particularly in areas where human judgment can be restricted by time, resources, information overload, or inconsistency. This is especially clear in compensation planning, where AI enables managers to consider dozens of relevant data points, like internal equity, market rates, skill scarcity and historical performance all at once. As IBM puts it:

[95] IBM (p. 15-18)

"*If compensation decisions are based on just one or two data points...managers should consider many factors...With more data points, AI is needed to avoid underpaying some and overpaying others*"[96].

This quote has been used in the previous section but is used here to also highlight the positive effects of AI in decision-making. While the quote refers to compensation planning, it can be used in broader contexts. Rather than replacing human judgment, AI here acts as a decision support layer that helps ensure fairness, accuracy and transparency in outcomes. In this way, it doesn't just streamline HR work, it actively enhances its quality. This builds directly on the previous point: the time saved through automation is not simply a matter of speed, but of enabling more thoughtful and data-informed decisions. It also sets the stage for a shift in roles and responsibilities, where HR professionals move away from repetitive tasks and toward more strategic, analytical contributions, an effect that will be explored in the next section.

4.5.2.3 Strategic Role Evolution

This increased decision quality, supported by AI, naturally contributes to a broader transformation in the role of HR professionals. As routine tasks are increasingly handled by systems like screening, scheduling, or answering standard queries, HR staff are being repositioned to take on more strategic and analytical responsibilities. According to IBM:

"*Responsibilities are changing rather than disappearing... The parts of jobs that are gaining in importance are analytical thinking, strategizing and driving change*"[97].

This quote suggests that AI isn't removing people from the process, it's rather shifting the focus of their work. Instead of spending time on transactional tasks, HR teams are expected to interpret AI outputs, advise on decisions and help design strategies that align with broader business goals. This shift not only enriches the work itself but also encourages upskilling and deeper engagement, as employees must build new capabilities to operate effectively in these augmented roles. From an STS perspective, this is a clear example of co-evolution between technology and organizational roles. And in terms of implementation, it points to the importance of pairing technological upgrades with learning and support systems that ensure people are ready to meet changing expectations.

[96] Ibid. (p. 14)
[97] Ibid. (p. 30)

Together, these changes show how AI is not just altering what work is done, but also who does what and how.

4.5.2.4 Organizational Learning and Engagement

The shift toward more strategic and analytical HR roles also feeds into a broader pattern of organizational learning and skills development. As IBM integrates AI into more parts of its HR ecosystem, the organization actively encourages employees to build the skills needed to work effectively alongside these systems. One example is the company's investment in internal learning platforms and bootcamps designed to help staff develop data literacy and AI fluency even without formal technical backgrounds. This is more than just training; it reflects a shift in IBM's organizational mindset, where continuous learning becomes a structural response to technological change. As noted in the report, IBM has "*demonstrated a statistical link between a worker's amount of learning and their overall level of engagement*"[98],suggesting that AI-driven transformation can also strengthen employee commitment when paired with meaningful development opportunities. From an STS perspective, this reinforces the idea that successful systems depend not only on tool design but on human adaptation and long-term capability-building. And within Implementation model, it speaks to the importance of competence development and organizational readiness not just for the initial rollout, but for sustaining change. In this way, AI doesn't just alter roles or workflows, it pushes organizations to evolve in how they support learning, growth and engagement over time.

4.5.2.5 Scalability and Structural Flexibility

As AI enables HR professionals to focus on higher-value tasks, it also allows IBM to scale its HR services without proportionally increasing cost or headcount. This is particularly important in large, global organizations where maintaining responsiveness across geographies and time zones would otherwise require significant staffing. AI tools, like chatbots, recommendation engines and decision support systems can be deployed consistently across units, ensuring standardized service while still allowing for contextual adaptation. As IBM notes, "AI allows HR organizations to deliver new insights and services at scale without ballooning headcount or cost"[99]. This scalability reflects a structural benefit that goes beyond immediate productivity, it creates a foundation for replicable, flexible service delivery that grows with the organization. From an implementation perspective, this illustrates effective resource optimization and long-term operational alignment, while STS Theory

---

[98] Ibid. (p. 16)
[99] Ibid. (p. 7)

helps frame this as a system-wide integration where technical tools extend the reach of human systems. This ability to scale HR functions reinforces the role shifts discussed earlier and creates the organizational conditions under which broader learning and adaptation, discussed next, can take root. But this scaling may also risk fragmenting work processes and responsibilities, that in the long run may traject decision-making power more into the AI systems. Such considerations will be further addressed in the discussion.

4.5.2.6 Bias and Ethical Risks

While AI has proven to have several positive effects on the organization and the socio-aspect of IBM, it is not without certain risks, particularly around bias. While AI is often presented as a tool for increasing objectivity, the systems IBM employs rely on historical data that can reflect and reinforce existing social inequalities. As the report notes:
"*There is nothing about AI that magically reduces biases... if we aren't careful, [it could] reinforce it... Bias is learned, reapplied, amplified and made systemic*"[100].
This presents a fundamental challenge, as the very systems designed to promote fairness and consistency may, without oversight, risk institutionalizing patterns they aim to correct. From a socio-technical standpoint, this illustrates the importance of recognizing that technologies are not neutral; they are shaped by and embedded within broader social structures. The Implementation Model reinforces this concern by emphasizing the need for ethical readiness and transparency during deployment. If organizations fail to embed bias monitoring and accountability mechanisms into the process, AI can shift from being a solution to becoming a silent source of harm. In IBM's case, awareness of this risk is acknowledged, but continuous attention to ethical safeguards remains essential.

4.5.2.7 Uneven Resource Demands

Implementing AI at IBM also hints at the resource-intensive nature of AI projects, particularly in terms of skills, data readiness and sustained organizational effort. While IBM is proactive in supporting employee upskilling, through bootcamps, internal courses and on-the-job training, it also recognizes that not all employees start from the same baseline. As one report quote states, "Many of our employees are learning these skills via bootcamps or other industry courses... you don't need a degree for these types of roles"[101]. This inclusive message masks a deeper challenge: AI adoption

[100] Ibid. (p. 30)
[101] Ibid. (p. 28)

creates new layers of expertise demands and not all teams or individuals are equally positioned to meet them. Moreover, the company acknowledges that even relatively short AI implementation cycles (6–12 months) require “resources, dedicated effort and data”, a point that relates to section 4.3.2, to succeed, factors that may not be consistently available across departments. This unevenness can result in capability gaps between early adopters and others, leading to internal disparities in tool usage, confidence and performance. From an STS perspective, such asymmetries point to a fragile integration of the social and technical systems, where the potential of AI may be unevenly realized. From the perspective of Implementation Model, this challenge reflects a lack of full organizational readiness and uneven resource allocation. While IBM demonstrates strategic commitment and offers learning opportunities, the broader implementation landscape still reveals gaps in skills, data infrastructure and localized support. These factors make it difficult to ensure consistent, sustainable AI use across the organization. The model shows that without widespread capability-building and equitable access to resources, even well-intentioned AI initiatives can struggle to deliver impact at scale (Fixsen et. Al., 2005)

4.6 Synthesis and summary

4.6.1 Finance

The case of OP Financial Group illustrates a strategically aligned and culturally grounded approach to AI implementation. The organization's pivot from a “mobile-first” to an “AI-first” strategy represents more than a branding shift; it signals a deliberate, top-down transformation initiative. Leadership plays a pivotal role in cascading this vision across all departments, ensuring that strategy practices remain congruent throughout the organization. This coherence supports both Implementation model’s emphasis on staged and guided transformation and Socio-Technical Systems (STS) theory’s notion of integrated system alignment.

Crucially, this top-down shift is to a large degree met with internal readiness, though some skepticisms do arise. The empirical material reflects a workforce that both accept AI-driven change but actively engages with it. Employees, for the most part, see the evolving nature of their work as positive and express a sense of pride in being part of a technologically progressive organization. OP’s internal AI training programs, focused on ethical and technical literacy, further indicate institutional investment in workforce enablement. This readiness suggests alignment between organizational vision, resource allocation and employee capability, key prerequisites for successful system embedding. On the technical front, OP Financial Group employs a modular, pilot-based rollout strategy. Initiatives such as facial recognition payments and digital home loan processing are implemented within clearly defined operational domains. These projects are embedded into existing workflows, allowing for backward compatibility and reduced disruption[102].

In terms of human-AI collaboration, the implementation model favors augmentation over substitution. AI systems take on routine or standardized functions, while employees shift toward oversight, interpretation and client interaction. This redistribution also goes on to align with the STS concept of joint optimization, where human and technological capacities evolve together to maintain systemic functionality and workplace integrity. Moreover, OP integrates feedback mechanisms to ensure that AI tools evolve in response to user concerns and practical realities further supporting the idea of joint-optimization. As noted in user interviews, the bank actively collects feedback to address fears and refine its systems. However, while the intention is clear, the structure, frequency and formality of these feedback loops remain vaguely articulated in the empirical material, suggesting room for improvement in participatory design and refinement processes.

Finally, the impact of AI implementation is generally perceived as positive, enhancing efficiency, supporting leadership and improving customer service. Yet some concerns persist. Interviewees express caution regarding the rapid pace of AI deployment, the challenges of managing complex data systems and the unknowns surrounding long-term risks. These perspectives highlight a potential mismatch between strategic ambition and internal absorptive capacity, underscoring the need for careful calibration of technical advancement with organizational preparedness.

A comparative synthesis of the OP Financial Group case and the *Arix Research Report: Impact of AI on Banking Employment in Europe* reveals significant points of alignment in how artificial intelligence is being integrated across the financial sector. Both sources underscore the strategic centrality of AI, yet OP's case offers a more grounded, empirically detailed view of how such integration unfolds in practice.

At the strategic level, OP's transition from a "mobile-first" to an "AI-first" orientation mirrors sector-wide trajectories noted in the Arix Research (AR) report, which states that 83% of financial institutions are expected to adopt AI tools by 2027. This top-down implementation model is

[102] Fixsen et. al. (2005)

reflected in OP's centralized planning and standardized strategy practices, aligning with Implementation model's emphasis on structured, staged change and the socio-technical principle of systemic alignment and the cultural alighment.[103] Culturally, both sources underscore the importance of organizational readiness and workforce enablement. The Arix Research report notes that employees engaged with AI tools frequently report increased job satisfaction and optimism. OP complements this with first-hand narratives that show adaptation and pride rather than displacement or fear. However, unlike the broader claims in the AR report, OP's case surfaces localized concerns about pacing and absorptive capacity, offering a more nuanced view of readiness as a dynamic, evolving condition rather than a static state.[104]

In terms of technical implementation, OP's focus on modular, domain-specific pilots such as biometric payments and digital loan evaluations, offers a complementary but distinct picture to the AR report's emphasis on backend AI applications like fraud detection and algorithmic trading. While both prioritize integration into existing infrastructures, OP's pilot-based approach underscores flexibility and minimal disruption, reflecting a preference for localized optimization over wholesale transformation.

The role of AI in shaping human labor is another area of convergence. Both sources stress that AI augments rather than replaces human functions. The AR report indicates that roles involving interpersonal interaction and judgment are expanding, while clerical tasks face automation. OP's data echoes this, with employees describing shifts in tasks but not in job stability, supporting STS Theory's model of joint optimization where human and technical systems evolve in tandem.

Where OP's case provides unique depth is in its account of feedback mechanisms. While the AR report calls for transparency and trust-building, OP offers detailed insights into how feedback loops are operationalized, including employee concerns and iterative system refinement. These examples highlight implementation not as a one-off technical deployment but as a responsive, user-informed process that adapts to emotional, ethical and practical feedback.

Finally, ethical risk and regulatory alignment are central concerns in both accounts. The AR report foregrounds the EU AI Act and the need for algorithmic accountability. OP reflects similar concerns through its ethical training programs and recognition of "unidentified risks." However, the specifics of how OP operationalizes ethical safeguards remain vague, leaving room for future inquiry. Yet,

[103] Arix Research, (p. 88)
[104] Ibid. (p. 87-89)

several divergences also surface. OP presents a relatively confident, culturally normalized view of AI adoption, whereas the AR report highlights sector-wide caution, particularly concerning legal liability and risk ownership. AR managers call attention to unresolved “accountability gaps” in AI decision-making, which are less visible in OP’s internal discourse. From an Implementation model lens, OP displays high organizational alignment, while the AR report reflects external systemic uncertainty.[105]Transparency and explainability also reveal contrast. While the AR report positions them as prerequisites for trust, especially in high-stakes areas like investment advisory OP’s data lacks technical detail on how these are ensured. Similarly, OP’s human-AI collaboration is portrayed as stable and empowering, whereas the AR report surfaces anxiety about the limits of “black-box” AI in complex, interpretive tasks.[106]Infrastructure-wise, OP emphasizes modularity and integration into existing systems yet does not extensively discuss data governance or computational capacity. The Arix Research study, by contrast, identifies robust data pipelines and scalable infrastructure as foundational for AI success, an area where OP’s case remains silent.

Finally, governance structures diverge. OP relies on internal leadership and ethics training, whereas the AR report strongly advocates for external regulatory mechanisms, including adaptive sandboxes and tri-sector governance. This points to differing assumptions about where oversight and trust should be anchored, in institutional culture or in formalized legal frameworks.

4.6.2 HR

IBM case exemplifies a highly structured and technically mature approach to AI integration in HR, one that resonates in many respects with the enablers identified by Madanchian and Taherdoost (2021). Both stress that organizational readiness and strategic vision are central to successful implementation. IBM’s deployment strategy, anchored in strong leadership sponsorship, phased rollout of minimum viable products (MVPs) and cross-functional team composition this is evident by Madanchian and Taherdoost’s emphasis on digital leadership, strategic alignment and coordinated resourcing as critical success factors[107]. IBM’s heavy investment in data pipelines and its technical interoperability with legacy systems aligns closely with the authors’ identification of robust data infrastructure and HRIS integration as core technical enablers. Likewise, IBM’s efforts to foster "technical curiosity" and upskill HR professionals illustrate the importance of capacity-

[105] Arix Research, (p. 108)
[106] Ibid. (p. 81)
[107] Madanchian & Taherdoost (p. 3)

building within the workforce, reinforcing the need for internal capability development to support AI systems over time[108]. However, when viewed through the normative lens of Socio-Technical Systems (STS) theory and in light of Madanchian and Taherdoost's more critical framing, IBM's model reveals important limitations. While IBM integrates ethical safeguards, such as transparency, bias mitigation and explainability, into its AI design, through feedback loops. Other types of mitigations are not addressed in IBM. In contrast, Madanchian and Taherdoost argue that ethical principles must be embedded into the design logic itself, not merely applied as audit features. They stress that algorithmic fairness, employee trust and value alignment must be foundational pillars of any AI strategy, influencing not just how AI is used but why and by whom it is developed (p. 4). Going back to the point in 4.1, looking into the strain between ethics and instrumentalism the authors Madachian and Taherdoost also address this issue stating:' "Although they are often discussed, ethical frameworks are rarely put into practice, which results in varying applicability among enterprises"[109]. Furthermore, IBM's implementation process is characterized by top-down governance and a strategic focus on efficiency and business value. Each year, AI priorities are decided by senior executives based on expected ROI and organizational KPIs, a model that sidelines the role of frontline employees in shaping technological change. Madanchian and Taherdoost caution against this form of centralized technocratic decision-making, arguing that it perpetuates existing power asymmetries and limits the transformative potential of AI systems. They advocate for participatory design and grassroots involvement as essential components of equitable and ethical AI adoption - principles that are underrepresented in some areas through their feedback system and more prevalent in others via their top-down instrumentalist approach, in IBM's model. Finally, while IBM's MVP-based, incremental strategy promotes stability and risk minimization, it also risks entrenching a path-dependent, optimization-focused view of AI that falls short of the deeper cultural and structural shifts envisioned in STS theory. Madanchian and Taherdoost highlight the danger of treating AI as a tool for local process improvement rather than as a catalyst for organizational reinvention. Their critique of the non-disruptive narrative surrounding AI, where it merely enhances rather than transforms existing systems, applies to IBM's framing, which emphasizes efficiency, speed and integration over rethinking work design, employee agency and long-term institutional ethics. Though they do present AI as a powerful tool that can increase efficiency and productivity.[110] In summary, IBM provides a technically exemplary and

[108] Ibid. (p. 4)
[109] Ibid. (p. 12)
[110] Ibid, (p. 11-12)

organizationally coherent case of AI implementation, particularly in its attention to operational alignment, leadership coordination and infrastructure. Yet Madanchian and Taherdoost's study surfaces deeper theoretical tensions: the risk of ethical minimalism, limited employee participation and overreliance on instrumental metrics such as metrics such as ROI and NPS. This comparative perspective reinforces the need to view AI not just as a technical upgrade, but as a socio-technical intervention, one that must engage critically with power, culture and institutional values if it is to achieve truly transformative outcomes. Rather than reducing the AI into an instrumental technical system, that succeeds irrespective of socio-technical dynamics.[111]

5.0 Discussion

5.1 Reflections on AI Implementation in Practice

The findings across both cases show that AI implementation is neither linear nor uniform. Instead, it is characterized by modular deployment, pilot-based strategies and top-down orchestration. In both OP Financial Group and IBM, implementation unfolds incrementally, through small-scale initiatives that are later scaled depending on performance and feedback. These strategies reflect a pragmatic application of Implementation Model, where adaptive rollout and leadership support are viewed as enablers of sustainable change.

However, the real-world execution of these principles reveals certain tensions. In OP's case, there is clear alignment with STS theory's principle of joint optimization, the strategic aim is to embed AI in both technical and social structures. Yet, this ambition is challenged by signs of readiness gaps at the operational level. Interview excerpts pointed to pressure and uncertainty among middle managers, which reflect a disconnect between strategic clarity and day-to-day implementation capacity.

IBM's case presents a more technically mature implementation. The organization makes significant investments in data infrastructure, feedback systems and internal training. Their deployment model centered on MVPs and iterative refinement closely mirrors the implementation model's emphasis on incremental change and cross-functional integration. However, while IBM excels in structural preparation, it shows weaker alignment with the participatory ideals of STS theory. AI systems are

[111] Ibid. (p. 8-11)

largely curated by senior leadership and the strategic logic revolves heavily around measurable outputs such as ROI and NPS. This raises the question of whether the integration process truly fosters a co-evolution between technical tools and human systems, or if it primarily serves managerial priorities.

What emerges across both cases is the recognition that ethical concerns, while acknowledged, often function as secondary layers, visible but not deeply transformative. For example, transparency and bias mitigation are embedded in IBM's AI tools, but these features act more as safeguards than as core design drivers. Similarly, in OP, ethics is addressed through training programs and internal codes, but these are largely geared toward responsible use rather than participatory co-design. In both cases, ethics is operationalized as compliance, not as a central philosophical anchor.

Overall, AI implementation in practice appears as a negotiated process, one shaped by institutional goals, technical possibilities and human limitations. While the theories applied offer valuable frameworks for understanding what *should* happen, the empirical data underscores how implementation is often marked by friction, uneven adaptation and the tension between high-level vision and operational complexity.

One of the most telling contrasts between the two cases lies in the organizational cultures that frame their AI strategies. At OP Financial Group, implementation is tightly connected to strategic vision, with top leadership driving an "AI-first" transition. This creates coherence across departments but also risks overstretching internal capacity. The cultural anchoring is a sign of long-term adaptation, yet the empirical material reveals early signs of fatigue, particularly among mid-level employees tasked with translating vision into practice. Despite the organization's stated readiness, the analysis points to implementation strain, where the pace of change outstrips local preparedness.

In contrast, IBM exhibits a culture of structured experimentation and resourcing. Training, feedback loops and interdisciplinary collaboration are central to their implementation model. This creates a technically robust environment for AI deployment. However, the same structure also carries a risk: a managerial, metrics-oriented logic that frames AI adoption in terms of performance optimization rather than organizational transformation. Phrases like *"driving the right experience, measured by NPS"* exemplify this instrumental approach. While efficient, such logic may sideline broader STS concerns such as worker identity, role ownership and participatory governance.

This contrast invites broader critical questions: Is IBM's strong emphasis on metrics, even if technically sound compatible with human-centered values promoted by STS theory? Does OP's cultural narrative of innovation reflect widespread acceptance, or is it largely driven by a core group of AI advocates? These tensions suggest that cultural anchoring, while essential, is uneven and often symbolic rather than deeply embedded.

A critical reflection on source material is also warranted to address the limits of the cases. The IBM case study is authored internally and likely serves, at least in part, as a strategic branding tool. Its detailed reporting, use of performance metrics, and coherent structure are clear strengths, but the risk of selective storytelling must be acknowledged. For example, challenges such as resistance, ethical tension, or failed implementations are notably underrepresented, raising questions about how comprehensively the data reflects organizational reality. In contrast, the OP Financial Group material, while richer in qualitative depth and internal reflection, is drawn primarily from interview-based insights and document analysis provided through a third-party study. As well as the AI use being in an early phase of their implementation This gives rise to a more nuanced portrayal of internal tensions, including employee ambivalence, readiness gaps, and critical voices. Furthermore it limits the insights from a long-term perspective. Its limited scope and reliance on the researchers' intent and narrative may risk overrepresenting certain perspectives, particularly those of mid- or upper-management, and underrepresenting operational staff or end-users. While both sources offer valuable insights into real-world AI implementation, they do so through different levels of transparency, authorship bias, and narrative intent. These factors must be critically considered when interpreting outcomes or drawing generalizable conclusions.

5.2 Augmentation vs. Automation - Beyond Technical Design

Across both the OP Financial Group and IBM cases, one of the most consistent patterns is the augmentative use of AI. Rather than entirely automating decision-making functions or replacing human roles, AI systems show a conscious design to support existing workflows, enhance operational efficiency, and enable better decision-making. In OP's finance operations, tools such as automated loan assessments are used to pre-process and evaluate applications, but the final decision remains under human control. Similarly, IBM's HR systems, whether in recruitment, onboarding, or compensation provide predictive insights and real-time recommendations, but do not displace managerial agency. This aligns closely with the idea of bounded rationality (Simon, 1972), where human decision-makers operate within cognitive limits, and AI is employed to expand informational access and analytical capacity without removing the human from the loop.

From a technical standpoint, this division of labor between AI and humans reflects a strategic preference for augmentation. Yet, this raises some important questions, is this design choice a matter of deliberate organizational strategy, or rather a reflection of current technological limitations? In other words, are IBM and OP opting for augmentation because it aligns with their cultural and ethical values, or because full automation remains either unfeasible or may experience too much pushback?

The analysis suggests elements of both. At IBM, augmentation is closely tied to control and accountability. AI systems are embedded with transparency mechanisms such as explainability tools and override functions, ensuring that human judgment can always supersede algorithmic suggestions. In this sense, augmentation becomes not only a technical configuration but also an ethical safeguard. It helps mitigate the risk of black-box decision-making and supports compliance with fairness and bias mitigation standards. However, this configuration also aligns with IBM's broader metric-driven culture, where systems are assessed based on ROI, NPS, and efficiency gains. While AI may not currently replace human roles, the pressure to scale and optimize could eventually shift this balance, particularly in high-volume, low-risk tasks.

At OP Financial Group, the augmentative approach is similarly framed as supportive rather than substitutive. AI systems handle standardized processes like digital mortgage evaluations or facial recognition authentication, while human discretion is retained for contextual and ethical judgment. Interview data even suggests a cautious attitude among staff, with concerns about the speed and scope of AI deployment, This hesitance implies that organizational readiness, rather than only strategic design, serves a role in maintaining the current augmentation model. It could be argued as a cautious attitude among staff, with concerns about the speed and scope of AI deployment potentially reflecting deeper anxieties about job displacement, shifting responsibilities, or loss of control. While explicit resistance was minimal in OP's material, the recurring references to being "rushed" or lacking time to adapt hint at an underlying fear: that AI may eventually encroach upon core professional roles or may have unintended consequences. Another perspective is that the fear lies in AI's capabilities, being unable to deliver adequately. Such concerns are not uncommon in financial services, where automation has historically been associated with downsizing, loss of jobs and so on. Even when AI is framed as supportive, the absence of clear boundaries around what will, and will not, be automated can create uncertainty and apprehension, especially in contexts where transparency about future role evolution is limited. From both a socio-technical and implementation lens, these concerns underscore the importance of clear communication, participatory rollout strategies, and reassurances around role security to ensure that augmentation is not experienced as a precursor to replacement. This hesitance implies that organizational readiness, rather than only strategic design, plays a role in maintaining the current augmentative functions. In this way, augmentation can be understood as both a normative choice and a pragmatic adaptation to internal capacity.

From the lens of decision-making theory, the absence of fully autonomous AI decisions in both organizations reflects a continued reliance on human intuition, especially in ambiguous or high-stakes contexts. Intuitive decision-making, grounded in experience and tacit knowledge (Klein, 1998), remains firmly in the human domain. Even the most advanced systems, such as IBM's predictive hiring tools, are deployed within specific functional roles, where AI suggests rather than decides. This boundary ensures that ethical, relational, and context-dependent factors, which resist quantification, are still considered by human actors.

Importantly, this raises normative concerns from an STS perspective. If augmentation is framed only as a transitional phase toward more comprehensive automation, then ethical considerations such as employee agency, trust, and accountability risk being marginalized. Conversely, if augmentation is a deliberate design principle, then organizations must continue investing in training, participatory governance, and transparency, to ensure that human roles are not merely preserved, but meaningfully enriched. Otherwise, the rhetoric of "human-in-the-loop" could become a symbolic safeguard rather than a functional one.

6.0 Conclusion

The purpose of this thesis is to address the following problem definition:

How is Artificial Intelligence (AI) implemented in HR and finance functions and why do organizations choose to leverage AI in their processes?

Based on two organizational case studies, OP Financial Group (Finance) and IBM (HR), the study investigated how AI technologies are concretely applied and integrated, as well as the organizational, technical and cultural factors that shape implementation. The research is theoretically grounded in Implementation model and Socio-Technical Systems (STS) Theory and methodologically based on document analysis.

The analysis of OP Financial Group showed that AI is implemented through a top-down, strategically anchored process with an AI-driven vision. The implementation unfolds gradually through modular phases and is supported by initiatives such as employee training and cultural anchoring. However, the analysis also revealed signs of capacity strain and implementation friction, indicating uneven organizational readiness. From an STS perspective, there was a clear emphasis on joint optimization, yet also tensions between technological ambition and social alignment.

In IBM's HR function, a similarly structured and modular approach was observed, though with greater technical maturity. Here, AI supports specific HR processes such as recruitment, onboarding and compensation planning. The implementation is carried out through MVPs and feedback loops, with a strong focus on system interoperability and decision support. Despite this, the analysis highlighted limited participation from non-managerial staff and a management-driven approach based on ROI and KPIs, rather than deep cultural transformation. This suggests a normative departure from STS theory's emphasis on participatory design and employee involvement.

Across both cases, the analysis found that AI is primarily used as an augmenting tool, not to fully automate, but to enhance existing processes and free up time for more strategic tasks. Both OP and IBM demonstrate awareness of ethical concerns, though they differ in how deeply these are embedded and in how much employees are involved. Furthermore, the implementation agenda in both cases is largely shaped by centralized decision-making, though with limited bottom-up perspectives through feedback mechanisms.

It can be concluded that in both cases, AI is implemented as both an organizational and technical strategy, but with varying degrees of cultural anchoring, participation and ethical reflection. There is a clear movement toward organizational learning and structural adaptation, but also a need to ensure that social systems evolve in parallel with technological solutions. In this way, the study provides a nuanced picture of how AI is implemented in practice, not as a linear process, but as a complex interplay between technology, people and organizational structures.

Literature

- Arix Research. (2024). *Impact of AI on the banking industry in Europe and beyond*: Commissioned by the European Social Partners

- Arakelyan, G. (2024). *Exploring Financial Transformation: Key Factors of AI's Impact on Banking Systems*. ALTERNATIVE Quarterly Academic Journal, 3(2)

- Brinkmann, S. & Tanggaard, L (2020), *Kvalitative Metoder: En Grundbog.* 3. udg. Hans Reitzels forlag

- Danmarksstatistik: *Hver Fjerde virksomhed bruger kunstig intelligens*, (3. september 2021) - Nr. 311

  https://www.dst.dk/da/Statistik/nyheder-analyser-publ/nyt/NytHtml?cid=31880

- Danmarksstatistik: *Flere virksomheder anvender kunstig intelligens* (12. marts 2025) – Nr. 67
  https://www.dst.dk/da/Statistik/nyheder-analyser-publ/nyt/NytHtml?cid=55352

- Dansk Industri - *Halvdelen af danske virksomheder anvender kunstig intelligens inden udgangen af 2025, (*03/03/2025)

  https://www.danskindustri.dk/brancher/di-digital/nyhedsarkiv/nyheder/2025/3/halvdelen-af-danske-virksomheder-anvender-kunstig-intelligens-inden-udgangen-af-2025/

- Davenport, Thomas H. og Mittal, Nitin: *How Generative AI is Changing Creative Work* (2022)
  https://hbr.org/2022/11/how-generative-ai-is-changing-creative-work

- Digitaliseringsstyrelsen: Forside > Kunstig intelligens > Signaturprojekter > Signaturprojekternes erfaringer (Besøgt 18/03/2025) https://digst.dk/kunstig-intelligens/signaturprojekter/signaturprojekternes-erfaringer/

- Fixsen, D. L., Naoom, S. F., Blase, K. A., Friedman, R. M., & Wallace, F. (2005). *Implementation research: A synthesis of the literature*. University of South Florida, Louis de la Parte Florida Mental Health Institute, The National Implementation Research Network.

- Flyvbjerg, B. (2011). Case study. In N. K. Denzin & Y. S. Lincoln (Eds.), *The SAGE handbook of qualitative research* (4th ed., pp. 301–316). Thousand Oaks, CA: SAGE Publications.

- Garcia-Murillo, Martha; MacInnes, Ian (2019): *The impact of AI on employment: a historical account of its evolution*, 30th European Conference of the International Telecommunications Society (ITS): "Towards a Connected and Automated Society", Helsinki, Finland, 16th-19th June, 2019, International Telecommunications Society (ITS), Calgary https://hdl.handle.net/10419/205178

- Gartner: *Gartner Survey Finds 79% of Corporate Strategists See AI and Analytics as Critical to Their Success Over the Next Two Years (*05/07/2023) https://www.gartner.com/en/newsroom/press-releases/2023-07-05-gartner-survey-finds-79-percent-of-corporate-strategists-see-ai-and-analytics-as-critical-to-their-success-over-the-next-two-years

- Hargyatni, T., Purnama, K. D., & Aninditiyah, G. (2024). *Impact Analysis of Artificial Intelligence Utilization in Enhancing Business Decision-Making in the Financial Sector*. Journal of Management and Informatics, 3(2), 282–296. https://doi.org/10.51903/jmi.v3i2.36

- Hmoud, B. (2021). *The Adoption of Artificial Intelligence in Human Resource Management*. Forum Scientiae Oeconomia, 9(1), 97–107. https://doi.org/10.23762/FSO_VOL9_NO1_7

- Holdsworth, M. & Zaghloul, F. (2022). *The Impact of AI in the UK Healthcare Industry: a Socio-Technical System Theory Perspective*. CEUR Workshop Proceedings, STPIS 2022.

- IBM. (2020). *The business case for AI in HR: Building trust and value*. Retrieved from https://www.ibm.com/thought-leadership/institute-business-value/report/ai-in-hr

- Ingemann, J. H. (2013). *Videnskabsteori for økonomi, politik og forvaltning* (1. udg.). Samfundslitteratur.

- Ingemann, J. H., Kjeldsen, L., Nørup, I., & Rasmussen, S. (2018). *Kvalitative undersøgelser i praksis: Viden om mennesker og samfund* (1. udgave). Samfundslitteratur.

- Interaction Design Foundation (24-04-2025)

https://www.interaction-design.org/literature/book/the-encyclopedia-of-human-computer-interaction-2nd-ed/socio-technical-system-design

- Jarrahi, M.H. (2018) "Artificial Intelligence and the Future of Work: Human-AI Symbiosis in Organizational Decision Making," Business Horizons. 61(4).

- Kitek.dk. AI-tænketank https://kitek.dk/hvordan-kan-vi-sikre-ansvarlig-brug-af-ai-i-beslutningstagning/ (11/03/2025)

- Klein, G. (1998). *Sources of Power: How People Make Decisions*. MIT Press.

- Kolbjørnsrud, V. (2017). *Kunstig intelligens og lederens nye rolle: Hvordan AI ændrer strategisk beslutningstagning*. BI Norwegian Business School.

- LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553) https://doi.org/10.1038/nature14539

- Madanchian, M., & Taherdoost, H. (2025). Barriers and enablers of AI adoption in human resource management: A critical analysis of organizational and technological factors. *Information*, 16(1), 51. https://doi.org/10.3390/info16010051

- Merli, M., Ciarapica, F.E., Varghese, K.C., & Bevilacqua, M. (2024). *Artificial Intelligence Approach to Business Process Re-Engineering the Information Flow of Warehouse Shipping Orders: An Italian Case Study*. Applied Sciences, 14(21), 9894. https://doi.org/10.3390/app14219894

- Miner, J. B. (2006). *Organizational behavior 2: Essential theories of process and structure* (1st ed.). Routledge.

- Mukherjee, A. N. (2022). *Application of Artificial Intelligence: Benefits and Limitations for Human Potential and Labor-Intensive Economy*. Management Matters, 19(2).

- Munnisunker, S., Nel, L., & Diederichs, D. (2022). *The Impact of Artificial Intelligence on Agricultural Labour in Europe*. Journal of Agricultural Informatics, 13(1), 46–54. https://doi.org/10.17700/jai.2022.13.1.638

- Murphy, John w., Largacha-Martinez, Carlos: Ai and the Humanistic Organization: Technology and Barriers to Human Flourishing (2024):

- Poudel, D. (2019). *Strategic change, antenarratives and AI: A case study of OP Financial Group*. Electronic Journal of Business Ethics and Organization Studies, 24(2).

- Russell, S. J., & Norvig, P. (2020). *Artificial Intelligence: A Modern Approach* (4th ed.). Pearson.

- Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, 69(1), 99–118.

- Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kamdjoug, J. R. K., & Wanko, C. E. T. (2020). Influence of Artificial Intelligence (AI) on Firm Performance: The Business Value of AI-Based Transformation Projects. *Business Process Management Journal*, *26*(7), 1893–1924. https://doi.org/10.1108/BPMJ-10-2019-0411

- Wang Y. *Ethical considerations of AI in financial decision. Computing and Artificial Intelligence*. 2024; 2(1):1290. https://doi.org/10.59400/cai.v2i1.1290

- Winter, S. C. (2013). *Implementation perspectives: Status and reconsideration*. In B. G. Peters & J. Pierre (Eds.), *The SAGE handbook of public administration* (2nd ed., pp. 255–272). SAGE Publications. https://doi.org/10.4135/9781446200506

- World Economic Forum: *The Future of Jobs Report (*2025) https://www.weforum.org/publications/the-future-of-jobs-report-2025/digest/

- Xin, O. K., Wider, W., & Ling, L. K. (2022). *Human resource artificial intelligence implementation and organizational performance in Malaysia*. *Asia-Pacific Social Science Review*, *22*(4), 144–157. https://doi.org/10.59588/2350-8329.1461