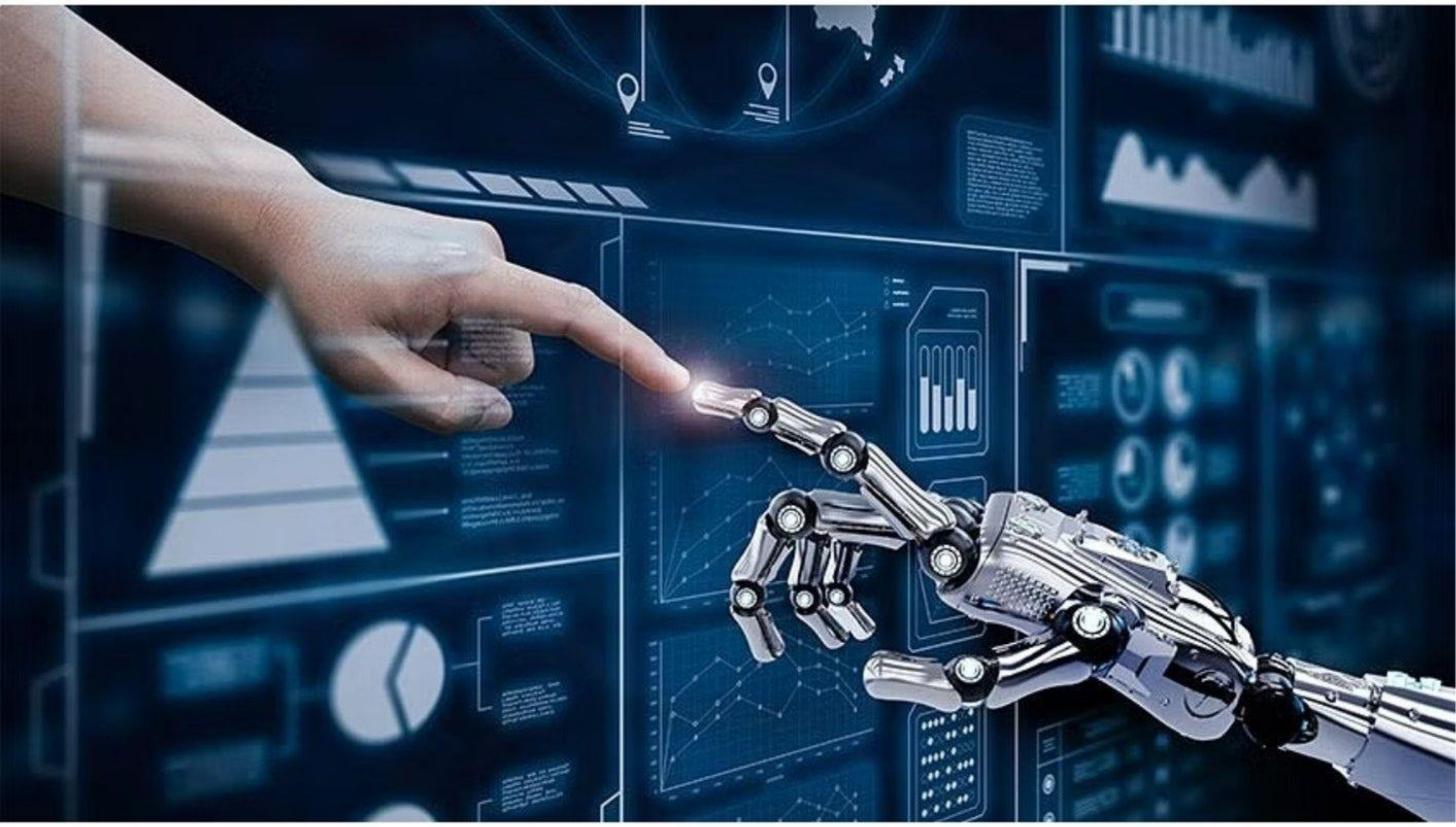
# INSTITUTIONAL LOGICS: GUIDING DECISION-MAKING IN MACHINE LEARNING ADOPTION WITHIN FINANCIAL OPERATIONS

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# Thesis

Institutional Logics: Guiding decision-making in Machine Learning adoption within financial operations

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## Abstract

Technological innovation continues to reshape financial operations within organizations, presenting both opportunities and challenges. Manual tasks in finance which are sensitive to errors and inefficiencies, are now being transformed by advancements in Artificial Intelligence (AI), particularly Machine Learning (ML). These technologies promise to automate routine processes, enhance analytical capabilities, and drive strategic decision-making within finance operations.

To remain competitive and future-proof, finance leaders emphasize the need for enhanced advisory skills and service delivery in an increasingly digital landscape. However, integrating Machine Learning into financial operations requires navigating complex organizational dynamics and aligning with institutional logics. These are unwritten rules, norms, and beliefs that shape decision-making within organizations.

This research investigates how institutional logics influence the adoption of Machine Learning in financial operations. By examining interplay between these different logics and technological advancements, the study provides insights into how organizations balance competing priorities and adapt strategies to align with dominant norms and values that can be generalized for all finance operations. The research focuses on understanding how different institutional logics shape strategies for ML adoption, identifying motivations, challenges, and success factors across diverse organizational contexts.

Empirical findings show the significant role of institutional logics at the profession, corporate, and community levels in driving ML adoption. Professionals seek to enhance their analytical capabilities and maintain a competitive edge through Machine Learning technologies, despite challenges in skill acquisition and organizational resistance to change. Corporations leverage Machine Learning to gain efficiency, reduce costs, and gain strategic advantages in competitive markets. At the community level, collective norms and industry standards guide the adoption of Machine Learning, emphasizing operational efficiencies and competitive relevance.

The study contributes to both academic understanding and practical applications. Practical insights and recommendations gained from this research offer guidance to financial operations seeking to leverage Machine Learning effectively, aligning with dominant institutional logics to enhance efficiency and achieve competitive advantage in an evolving digital landscape.



**Keywords:** Institutional Logics, Finance operations, IT Affordances, Machine Learning (ML), Artificial Intelligence (AI), Decision-making

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# 1. Introduction

## 1.1. Situation and complication

Technological innovation continuously reshapes how finance operates within an organization. Finance tasks are still often done manually, relying on traditional methods that may be time-consuming and prone to error. One of the most promising technological advancements at the moment is the usage of AI and in particular Machine Learning (ML), which has the power to completely transform financial operations, offering opportunities to make processes more efficient (Suryadevara, 2017).

To be future-proof by 2025, finance leaders expect their teams to become more skilled at advising business partners and delivering services to stakeholders in a world that is increasingly digital (Gartner, 2024). They would also need to know how to use Machine Learning as it is a big branch of AI. Moreover, these qualities will also ensure that financial staff members can effectively perform subjective and unclear tasks which will be considered more important to the role of finance when the automation of transactional activities takes place (Gartner, 2024).

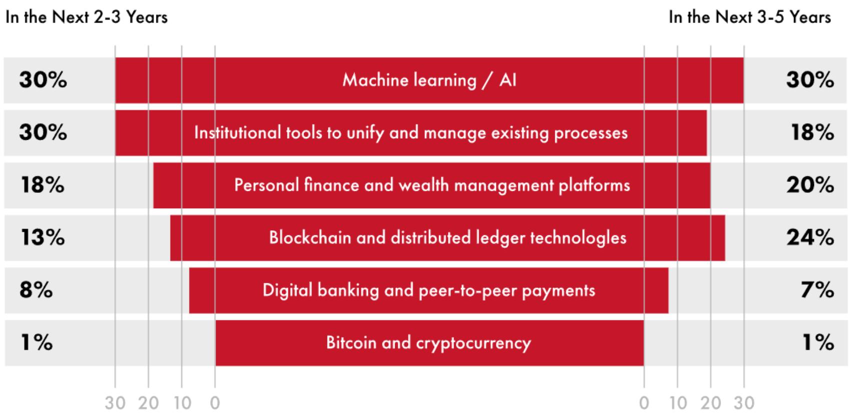


*Figure 1: Forecast of Fintech investment trends (Usachev, 2024)*

The transition to Machine Learning necessitates organizational restructuring to accommodate new roles, responsibilities, and workflows. Automating manual processes traditionally used to perform routine tasks such as invoicing, payroll, accounts payable and receivable, financial reporting, and budgeting allows for more time to focus on strategic decisions (Ng et al., 2021).

This change necessitates retraining current staff in data science, programming, and algorithmic development so that they can enhance the competence of their respective teams in using and managing ML models concerning financial operations (Sofia et al., 2023).

The main aim of this research is to investigate how Machine Learning should be implemented in different organizations, focused on finance operations. Implementing new technologies like Machine Learning isn’t solely done by using the model that works for several different organizations.

It should also fit with the unwritten rules and beliefs also known as institutional logics that are present within organizations. These Institutional Logics are like guiding principles that shape how organizations behave and make decisions (Thornton & Ocasio, 2008).

In finance, there are several of these logics at play, like the goal to maximize profits, manage risks, follow regulations, and build trust with customers. These different logics often clash, making it difficult for organizations to figure out what to prioritize and to make decisions based on the different logics present.

The existence of Information Technology (IT) affordances adds another layer of complexity to this situation. IT affordances refer to the different actions users see as possible when interacting with IT tools, depending on what the user is trying to achieve and the situation (Markus & Silver, 2008). These affordances play an important role in how people use technology and the decisions they make because they shape how users perceive and interact with IT systems.

Understanding the complex connection between institutional logics, the adoption of Machine Learning, and IT affordances is crucial for organizations aiming to improve their financial operations using technology. This is essential for maximizing the potential of technology and achieving significant improvements in operational efficiency and effectiveness.

## 1.2. Research goal

This research will analyse the influence of institutional logics on decision-making regarding the adoption of Machine Learning in financial operations. Building upon the understanding of institutional logics as sets of rules, norms, and beliefs. By examining the interactions between institutional logics and technological advancements, particularly in the context of Machine Learning, this research seeks to provide insights into how organizations navigate between competing logics and adapting their strategies to align with dominant norms and values within their department. The focus of this research will be on the financial operations of organizations.

The primary focus of this research will be on understanding how these institutional logics influence and shape the strategies surrounding ML adoption within financial operations. The research will explore how underlying principles affect the selection of ML technologies. This analysis will help to identify the motivations, challenges, and success factors associated with ML adoption in different organizations. This study therefore seeks to highlight these key areas by answering the following research question:

"How do institutional logics shape the types of Machine Learning adoption in finance operations?"

By answering this question, this research aims to contribute to the academic and practical understanding of how institutional logics shape technological adoption in organizational settings, particularly focusing on the complexities inherent in the adoption of Machine Learning within financial operations.

For financial operations seeking to leverage ML technologies effectively and align with the dominant institutional logics within their operational context, it is expected that the findings will contribute practical insights and actionable recommendations. They can also achieve a competitive advantage through enhancing efficiency. Recommendations from the study will be based on evidence and examples that can be applied in real-life situations.

# 2. Theoretical framework

## 2.1 Institutional Logics

"Institutional logics" refers to the various sets of rules, norms, and beliefs inherent in specific social contexts and institutions (Thornton & Ocasio, 2008). This logic influences how people think, act, and make decisions. Moreover, institutional logics guide organizational practices, structures, and processes, shaping organizational identity and behaviour (Thornton et al., 2012).

(Alford & Friedland, 1985) introduced the concept of "institutional logics" to shed light on the conflicting aspects present in the institutions of modern Western societies. They identified capitalism, state bureaucracy, and political democracy as three separate institutional frameworks, each with its own set of practices and beliefs. These different institutional logics all have a big impact on how people get involved in political conflicts, shaping their interactions with societal norms and structures.

The concept was further defined by (Friedland, 1991), focusing on understanding the connections between individuals, organizations, and society. They perceive institutions as overarching patterns of behaviour that extend beyond individual organizations, rooted in tangible actions and symbolic systems. These systems are how individuals and organizations shape and maintain their material existence while giving significance to their experiences. Their approach was based on viewing society as a network of institutions interacting with each other, forming an inter-institutional system. In this system, each institution has its own distinct set of principles and values that define its functioning.

The concept of the inter-institutional system presents a framework for understanding different types of institutional logics. This typology identifies seven main institutional logics: the market, corporate, profession, state, family, religion, and community (Thornton et al., 2012). These logics not only shape societal orders but also manifest at the field and organizational levels. They can appear as subtypes of societal logics or as hybrids, blending elements from different logics. For instance, the service logic can be seen as a subtype of the market logic, while the logic of social entrepreneurship combines elements of both market and community logics (Faik et al., 2020).

*Table 1: Inter Institutional System (Faik et al., 2020)*

| Y - Axis: Elemental Categories | X-Axis: Institutional Orders and Corresponding Societal Level Logics | | | | | | |
|---|---|---|---|---|---|---|---|
| | **State** | **Profession** | **Market** | **Corporation** | **Family** | **Religion** | **Community** |
| **Basis of Norms** | Citizenship membership | Associational membership | Self-interest | Firm employment | Household membership | Congregational membership | Group membership |
| **Sources of Legitimacy** | Democratic participation | Personal expertise | Share price | Market position | Unconditional Loyalty | Sacredness in society | Trust and reciprocity |
| **Sources of Authority** | Bureaucratic domination | Professional association | Shareholder activism | Top management | Patriarchal domination | Priesthood charisma | Community values and ideology |
| **Technology Affordances** | Broadening Accessibility and Traceability | Enhancing Knowledge-ability and Autonomy | Stimulating and Controlling Operations | Standardizing and Controlling Operations | (No identified Affordances in Literature) | (No identified Affordances in Literature) | Connecting Members and Opening Governance |
| **Sources of Identity** | Social and economic class | Association with quality of craft/Personal reputation | Faceless | Bureaucratic roles | Family reputation | Association with deities | Shared emotional connection |
| **Basis of Attention** | Status of interest group | Status in profession | Status in market | Status in hierarchy | Status in household | Relation to supernatural | Personal investment in group |
| **Information Control** | Backroom politics | Celebrity professionals | Industry analysis | Organization culture | Family politics | Worship of calling | Visibility of actions |
| **Economic System** | Welfare capitalism | Personal capitalism | Market capitalism | Managerial capitalism | Family capitalism | Occidental capitalism | Cooperative capitalism |
| **Root Metaphor** | State as distribution mechanism | Profession as relational network | Transaction | Corporation as hierarchy | Family as firm | Temple as bank | Common boundary |

Institutional logics are defined by "elemental categories” as seen in Table 1. The range of elemental categories offers research the flexibility to select different methods for distinguishing between different logics. This adaptability has made the institutional logics perspective perfect for connecting individual and organizational behaviours to broader societal phenomena. Specifically, this approach to understanding the multitude of logics at the societal level has yielded valuable insights into the study of institutional change (Faik et al., 2020).

## 2.2 IT affordances

In the literature on institutional logics, particularly within the context of information technology and organizational change, several frameworks offer valuable insights into understanding the interplay between institutional logics and technological advancements. One of these frameworks is the concept of IT affordances. “IT affordances refer to the possibilities of action that users perceive in IT artefacts based on their goal orientation and their use environment” (Markus & Silver, 2008).

(Thornton et al., 2012) propose that the main way institutional logics influence practices is through what they call "focus of attention". They explain that these logics determine what problems and issues are noticed and what solutions are likely to be considered during decision-making processes (Thornton et al., 2012). “The concept of IT affordances highlights the ways in which the attention of the users become intertwined with material elements of IT to produce new possibilities of action” (Faik et al., 2020).

IT affordances theory emphasizes the dynamic relationship between technology and organizational context, highlighting how different institutional logics shape the interpretation and utilization of IT resources within organizations (Faik et al., 2020). Figure 2 shows a model that explains how IT capabilities serve as a connecting point in the interaction between institutional ways of thinking and the use of Machine Learning in everyday situations.

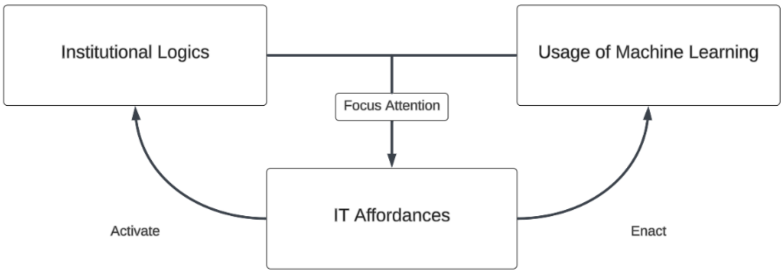


*Figure 2: IT Affordances as a Linking Concept in the Relationship between Institutional Logics and Usage of ML (Faik et al., 2020)*

As people and organizations engage with IT systems, they rely on institutional logics. These logics guide their interactions with technology and influence which features they prioritize. As they interact with IT systems, they focus their attention on specific capabilities, prompting them to activate certain institutional logics (Faik et al., 2020). This process creates a dynamic relationship where IT features shape users' actions, which in turn reinforce specific ways of thinking and operating within organizations. The connection between these concepts is best understood through the actions they enable, such as directing attention or activating logics, highlighting the ongoing and interactive nature of their relationship.

The concept of IT affordances provides a useful way to understand the complex connection between technology, institutional logics, and financial activities. Acknowledging the interaction between IT affordances and institutional logics enables finance operations to effectively utilize technology to address evolving challenges and seize opportunities (Hultin & Mähring, 2014). Understanding how users perceive and interact with IT artifacts within the context of finance is crucial for leveraging the full potential of technology to drive innovation, improve decision-making, and enhance organizational performance.

## 2.3 Navigating Institutional Logics and IT affordances in finance

Understanding dominant logics in finance requires examining broader business logics, shaped by industry type, local context, and culture (Besharov & Smith, 2014). In business decision-making, understanding institutional logics can be useful in understanding how organizations make choices and why they pursue certain strategies. Different Institutional logics may compete or cooperate, and organizations must navigate between these logics to be successful (Besharov & Smith, 2014).

Professions like finance, accounting, and human resources compete, each bringing unique perspectives (Barley & Tolbert, 1991), resulting in differences in their “logics”. These differences in approach contribute to lower compatibility among the various professions within the business ecosystem.

Within finance operations, various institutional logics shape organizational behaviour, ranging from profit maximization and risk management to regulatory compliance and customer trust (Almandoz, 2014). Research by Thornton & Ocasio (2008) has highlighted the coexistence of multiple institutional logics within organizations, emphasizing the importance of understanding how these logics interact and influence organizational processes.

Lounsbury (2002) focuses on status competition and status mobility within the finance operations. He highlights a transition from a regulatory approach to a market-driven mindset, which reshaped how reputation was earned and maintained within the industry. Furthermore, Prato et al (2024) maintain that status is essential for shaping organizational behaviour thereby determining how various individuals operate at individual level, aiming at occupational acknowledgement and recognition collectively.

Professional finance associations played a pivotal role in driving this shift towards a market-driven logic. The rise of professions such as money management and securities analysis has made it easier to spread innovative financial theories like portfolio management and risk analysis (Thornton & Ocasio, 2008). Consequently, individuals' status within the finance field became increasingly tied to their familiarity and expertise with these new theories (Thornton & Ocasio, 2008).

As finance evolved, people's standing in the field became closely linked to how well they knew and understood new financial theories. Individuals striving to enhance their status recognized the importance of aligning themselves with these evolving institutional logics (Lounsbury, 2002). Therefore, active participation in finance associations became not just a means of personal advancement but also a strategic effort to adapt to and thrive within the changing institutional landscape of finance (Lounsbury, 2002).

One important factor contributing to the shift toward a more customer-focused market approach is how financial professionals are now paying more attention to improving customer service, fostering innovation, and embracing competition (Sirri & Tufano, 1995).

Research highlights the role of institutional logics in shaping organizational responses to technological innovations (Suchman, 1995). Another study defines digitalization as the socio-technological process through which digital technologies become integrated into the infrastructure of institutions and society as a whole (Tilson et al., 2010).

Financial operations often operate within a complex environment with different institutional pressures, including regulatory requirements, competition, and market expectations (Arora-Jonsson et al., 2020; Munir & Baird, 2016). These institutional logics do not only inform decision-making but also influence the adoption and implementation of new technologies such as Machine Learning.

Establishing IT affordances as an elemental category and connecting it to the dominant institutional logics within finance involves examining the levels of profession, corporation, and community as provided in Table 2.

Within the profession logic, IT capabilities typically revolve around enhancing knowledgeability and autonomy. This suggests that when professionals are embracing their professional values, prioritize increasing their knowledge and sharing it with others. Moreover, they focus on maintaining autonomy from bureaucratic control (Faik et al., 2020).

In contrast, corporate IT practices commonly emphasize standardization and operational control (Faik et al., 2020). Individuals approaching IT from a corporate perspective prioritize implementing standards and ensuring control over organizational operations. The introduction of new IT into a societal context can increase the prevalence of corporate logic if the technology is perceived primarily as facilitating standardization and operational control (Faik et al., 2020).

The community level is connecting members and fostering open governance. Users drawing from a community logic in their IT usage prioritize creating ties between community members and supporting participatory governance (Karamagioli et al., 2014; Singh et al., 2021). Recognizing these possibilities in IT systems makes the community logic more important among users. For instance, credit unions amplified the community logic when they utilized IT-based financial services to enhance social inclusion, democratize control, and connect union members (Mangan & Kelly, 2009).

## 2.4 Machine Learning in finance

The adoption of artificial intelligence (AI) technologies in finance operations represents the next step in technological innovation, reflecting the industry's increasing reliance on advanced analytics and automation. Research suggests that several factors drive the adoption of AI in finance (Kordon, 2020).

Machine Learning has emerged as a transformative field within the broader scope of artificial intelligence (AI). Artificial intelligence is a branch of computer science dedicated to creating computer systems that can operate like humans. Machine Learning, rooted in mathematical and statistical principles, focuses on the development of algorithms that enable computers to learn patterns from data (Alzubi et al., 2018). Many ML applications are focused on increasing efficiency by automating repetitive tasks, optimizing processes, and improving decision-making.

Machine Learning is employed to instruct machines on handling data more efficiently. In instances where extracting information from data proves challenging even after observation, Machine Learning techniques are applied. It relies on different algorithms to solve data problems. Data scientists emphasize that there isn't a one-size-fits-all algorithm that is best for solving every problem (Mahesh, 2020). The kind of algorithm that is selected depends on the type of problem, the number of variables, and so on. Figure 3 illustrates the application of Machine Learning to a real-world problem.

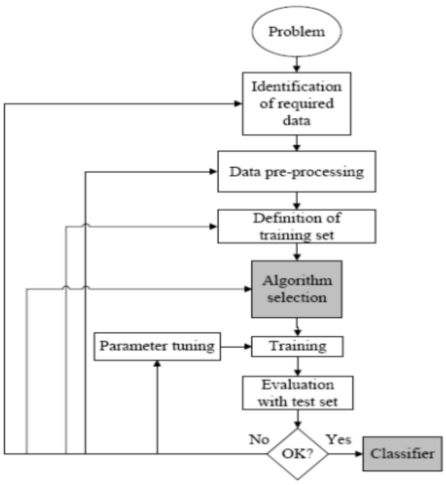


*Figure 3: Machine Learning process (Osisanwo et al., 2017)*

Machine Learning has the potential to transform into a major technological breakthrough across different industries, offering many opportunities for optimizing business processes and improving operational efficiency (Suryadevara, 2017).

The integration of ML technologies in financial operations has gained much attention in recent years, driven by the promise of enhanced efficiency, risk mitigation, and competitive advantage. Using AI-powered Robotic Process Automation (RPA) can assist in automating everyday financial tasks like handling invoices, logging transactions, and generating financial reports. This boosts efficiency and lowers the chance of human errors (Hidayat et al., 2024).

Furthermore, Machine Learning algorithms can be used to forecast a company's financial performance by analysing historical data and external variables. This helps companies in long-term decision-making (Hidayat et al., 2024). These applications leverage Machine Learning algorithms to analyse vast datasets, identify patterns, and make data-driven decisions in real-time.

Machine Learning algorithms can revolutionize the field of financial planning and budgeting by providing personalized advice to organizations based on their financial data, spending habits, and savings goals (Kaur et al., 2023). These algorithms have the capability to analyse large amounts of data and identify areas where organizations can potentially save money and achieve their financial objectives. By leveraging Machine Learning, financial advisors can offer recommendations that take each client's unique circumstances into account. (Kaur et al., 2023).

The current scope of ML applications in finance is primarily driven by the industry's immediate needs and challenges (Bertolini et al., 2021). The applications mentioned above address critical issues such as risk management, efficiency improvement, and regulatory compliance, which are priorities for organizations. Additionally, the narrow scope may also be attributed to the complexity of implementing Machine Learning in highly regulated and sensitive environments like finance.

Deciding whether to adopt Machine Learning in financial operations is a complex process that requires input from various stakeholders. These stakeholders typically include top management, IT departments, data scientists, compliance officers, and relevant regulatory bodies (Markus, 2016). Each stakeholder brings unique perspectives and considerations to the decision-making table.

# 3. Method

## 3.1 Research design

This research adopts a qualitative approach to explore the influence of institutional logics on decision-making regarding the adoption of Machine Learning in financial operations. Qualitative research allows for an in-depth understanding of complex phenomena (Merriam, 2002), such as the interplay between institutional logics and technological adoption.

When discussing a general strategy for analysing qualitative data, it essentially refers to a framework that helps to understand the collected data. Approaches such as grounded theory and analytic induction are frequently characterized as iterative, meaning there's a repetitive cycle between gathering and analysing data (Bryman & Bell, 2011). This means that analysis starts once some of the data has been collected, and the findings from that analysis influence the stages of data collection.

This research is designed around heavy theoretical concepts and adopts a deductive approach, the qualitative processes in this study take a closed design approach. This means that theory leads the research from the beginning, shaping the research questions and data collection methods.

Chosen from the two methodologies, analytic induction was selected because it explicitly considers existing theories, as noted by (Manning, 1982). Using this method involves a process of going back and forth between data collection and theory generation, beginning with a review of the literature to formulate a set of hypotheses. In the case of analytic induction, researchers gather data specifically to test their evolving hypotheses, aiming to construct a theory (Manning, 1982).

The research design was shaped by the central research question and its sub-questions, supported by the theoretical framework. These elements additionally guided the process of selecting cases, collecting data, and conducting data analysis. Data was gathered through interviews with participants, using semi-structured questions to guide the discussions. This approach allowed us to explore the subject deeply without imposing limitations on the scope of the research or the nature of participant responses (Collis & Hussey, 2003).

The interview questions will be based on Table 2 which includes different hypotheses. This method ensured that the discussions remained focused and targeted, enabling the testing and refinement of hypotheses while also uncovering new insights and perspectives from the participants.

*Table 2: Framework hypotheses*

| Logics/Levels | Profession | Corporation | Community |
|---|---|---|---|
| **Status** | Professionals with higher status and influence in the industry will shape the direction of ML adoption in finance operations, relying on their expertise and continuous improvement | The status of a corporation influences the adoption of Machine Learning solutions, affecting both the riskiness and the speed of these changes | Communities, influenced by their status within finance operations, choose to use Machine Learning techniques that fit with the available knowledge within their organizations and their specific application domains |
| **Competition** | In the Competitive finance environment professionals constantly need to develop new skills to excel, influencing the adoption of ML solutions within finance operations | Corporations within finance operations responding to the competitive environment will adopt ML solutions that improve efficiency and automate processes | Communities in the competitive finance environment see their adoption of Machine Learning influenced by efficiency and completeness |

By employing this qualitative approach, this research aims to uncover the underlying motivations, and ethics driving decision-making processes regarding ML adoption in financial operations. This depth of understanding is essential for addressing the relationship between institutional logics and technological advancements within finance operations.

## 3.2 Sampling

Participants for this study will be selected using criterion sampling. This sampling method allows for a selection of individuals who fit specific criteria to make sure they're a good fit for our research goals (Reybold et al., 2013). A participant doesn’t have to meet all the criteria, two out of the three is sufficient. The selection will be made based on several important factors that are key to helping us understand how Machine Learning is being adopted in financial operations.

These factors include:

- Position and Role: Participants must hold positions of authority or responsibility within financial operations. These could be executives or managers who are directly involved in the decision-making process within an organization. They should have a responsibility while adopting new technology.
- Expertise in Financial Operations and Technology: Participants should have expertise or experience in financial operations, as well as a good understanding of technology, particularly Machine Learning and artificial intelligence. This way, they can provide well-informed insights into how Machine Learning fits into financial processes.
- Adaptability and Innovation: Participants should be willing to discuss and adapt to changes in technology and organizational practices. This criterion helps to understand how different ways of thinking within organizations affect decisions. It's all about being able to adjust strategies when faced with different viewpoints and approaches.

For this study, individuals from different types of financial operations will be interviewed. The characteristics of the sample will be representative of the population of people involved in the decision-making process for Technological Innovation, which includes Machine Learning, within the finance industry. The sample should be diverse in terms of the size of the organizations, ranging from SMEs to large multinational organizations, and the specific sector they're in within the finance industry. Table 3 shows examples of participants who will be interviewed.

*Table 3: Examples of participants*

| Participant | Position and role | Expertise in Financial Operations and Technology | Adaptability and Innovation |
|---|---|---|---|

| | | | |
|---|---|---|---|
| Innovation manager<br><br>According to (Kurmanov et al., 2021) | Key decision-makers in large organizations, tasked with driving technological innovation initiatives. | Typically have a solid understanding of financial operations and technology trends, including emerging technologies. | Focused on driving innovation and likely to possess a mindset that embraces change and new technologies. |
| Business Controller<br><br>According to (Hyvonen et al., 2015) | Responsible for financial planning, analysis, and reporting, providing insights to support strategic decision-making within organizations. | Possess expertise in financial operations, budgeting, and forecasting, as well as a solid understanding of technology and its applications in finance. | Often required to adapt to changing business environments and leverage technology to optimize financial processes and drive efficiency. |
| Finance manager (SME)<br><br>According to (Alharbi et al., 2018) | Responsible for overseeing day-to-day operations within financial institutions, making them influential figures in decision-making processes. | Have a deep understanding of financial operations and are increasingly expected to be skilled at using technology to make processes more efficient. | Given the responsibility to enhance operational efficiency, requiring an openness to adopting technological advancements. |
| AI Consultants<br><br>According to (Vial et al., 2023) | Facilitate the development and implementation of AI strategies tailored to specific organizational needs and objectives. | Possess expertise in financial operations and technology, with a focus on understanding how AI fits into organizational processes and strategies. | As a consultant tries to implement AI options that drive organizational growth and competitiveness. |

These examples meet the criteria and represent a diverse range of roles and expertise within the finance industry. This way, the data collection incorporates multiple perspectives, aligning with the principles of triangulation. This aims to strengthen the credibility and validity of the research findings by gathering data from multiple sources or perspectives (Abdalla et al., 2018).

The study sample includes ten participants, each bringing a unique perspective to the research on Machine Learning adoption in financial operations. The participants were selected based on their roles and expertise in financial operations and technology. Figure 4 shows a summary of the participant demographics.

| Age | N | % |
| --- | --- | --- |
| <30 | 4 | 40% |
| 30-40 | 4 | 40% |
| 40-50 | 1 | 10% |
| >50 | 1 | 10% |
| Total | 10 | 100% |
| **Experience** | **N** | **%** |
| 1-9 Years | 4 | 40% |
| 10-19 Years | 3 | 30% |
| 20-29 Years | 1 | 10% |
| 30+ Years | 2 | 20% |
| Total | 10 | 100% |
| **Type organisation** | **N** | **%** |
| Consultant | 4 | 40% |
| Project leader | 1 | 10% |
| Business controller | 4 | 40% |
| Finance Expert | 1 | 10% |
| Total | 10 | 100% |

| Size organisation | N | % |
| --- | --- | --- |
| 1-49 FTE | 4 | 40% |
| 50-99 FTE | 1 | 10% |
| 100-499 FTE | 0 | 0% |
| 500-1999 FTE | 1 | 10% |
| 2000+ FTE | 4 | 40% |
| Total | 10 | 100% |
| **Type organisation** | **N** | **%** |
| Agribusiness | 1 | 10% |
| Consultancy | 5 | 50% |
| Defense | 1 | 10% |
| ICT | 1 | 10% |
| Manufacturing | 1 | 10% |
| Production | 1 | 10% |
| Total | 10 | 100% |

*Figure 4: Demographics of participants*

These demographic details highlight the diversity and range of experience among the participants, enabling a greater comprehension of ML adoption across various organizational settings within the financial sector. This diversity reinforces triangulation which increases credibility and validity by integrating different standpoints into research outcomes.

## 3.3 Data collection

To investigate how different institutional logics affect decision-making towards Machine Learning adoptions within finance, semi-structured interviews were conducted to gather primary data. This choice of methodology is aligned with the principles of deductive coding. As noted by Bryman & Bell (2011), when researchers begin their investigation with a clear focus, semi-structured interviews are often favoured to delve into specific issues related to the research topic.

These semi-structured interviews were carefully planned out with a set protocol to guide the researcher. Although the interviews were structured, they should still provide the opportunity to obtain more details about the subject. By doing these interviews this research aims to explore the thoughts and opinions of participants about integrating Machine Learning into financial operations in depth.

The researcher has a list of questions covering specific topics that need to be addressed to test the different hypotheses included in Table 2. This list is commonly referred to as an interview guide. However, the participant has a lot of freedom in deciding how they want to answer the questions (Bryman & Bell, 2011). During the interviews, questions might not follow the exact order planned, and the interviewer might ask additional questions based on what the participant says. However, all the questions will be asked, and they will be worded similarly for each participant (Bryman & Bell, 2011).

To connect with the organizations relevant to this study, different communication methods were used like phone calls and emails. We reached out formally, explaining our research topic and intentions. The organization providing the internship plays a pivotal role in facilitating access to participants for this research. The organization provides access to its customer base and network of partners to find the right participants based on the criteria. With their assistance, this research was able to connect with a wide variety of participants, which ensures triangulation and enhances the depth and scope of this research.

The interviews will be held in comfortable settings, providing an environment conducive to open discussion. The interviews will last about one hour, giving participants enough time to share their insights on ML adoption. To protect confidentiality, we keep the identities of both the participants and their organizations anonymous.

A few days before the data collection was conducted, an interview orientation was sent to the participants. This interview orientation includes the topics to be discussed, ensuring that participants are well-prepared and have a clear understanding of the focus areas for the discussion without knowing the actual questions.

With consent from the participants, interviews were recorded until theoretical saturation was achieved (Bryman & Bell, 2011). The interviews will mostly be conducted in Dutch. Afterward, the interviews will be transcribed and translated into English. The list of questions used during the interviews can be found in Appendix 1.

## 3.4 Data analysis

Analytic induction involves a series of steps (as seen in Figure 5) to build a theoretical explanation based on the cases examined. The researcher starts with the initial cases and develops a theory based on the connection between institutional logics and the adoption of

Machine Learning within financial operations. The researcher then seeks negative/deviant cases, aiming to test and refine them further through a deductive approach (Hyde, 2000).

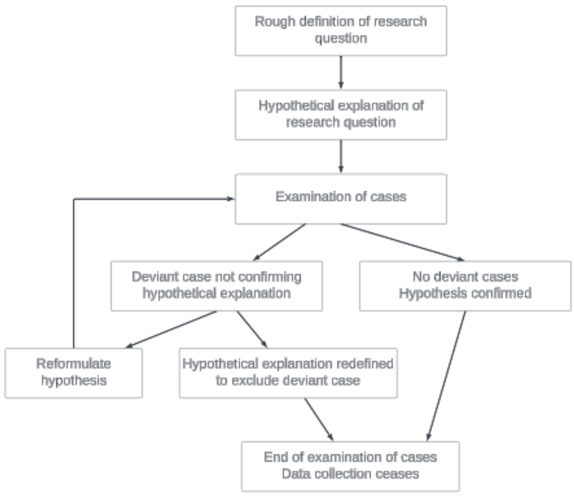


*Figure 5: Analytic induction process (Bryman & Bell, 2011)*

Through a series of iterations, the goal is to connect the findings with existing literature on institutional logics, adopting Machine Learning, and decision-making in finance operations, aiming to contribute valuable insights to answer the central research question and refine the theory until it can explain all the cases examined.

To identify dominant logics and answer sub-question one the research will utilize the inter-institutional system framework outlined by (Thornton et al., 2012) in the interviews. This framework allows categorization of the institutional logics shaping decision-making processes in finance. During the interviews, indications of various institutional logics such as profession logic, corporate logic, and community logic, will be observed and coded.

The analytic induction process starts with outlining the research question to understand the influence of institutional logics on decision-making regarding Machine Learning adoption in financial operations. This starting point gives a basic understanding of what's being investigated, laying the groundwork for the different hypotheses stated in Table 2.

These hypotheses are formulated to understand how the research question is structured or how its parts are linked together (Bezerra et al., 1998). They are based on existing theories, literature, and ideas. These hypotheses provide a theoretical basis for exploring how institutional logic and the adoption of Machine Learning interact.

Each case is methodically analysed based on the hypotheses that have been formulated. The interview transcripts from every case have been examined to see if the observed facts match up with the explanations suggested in this research.

In cases where the observed facts don't align with the hypothesized explanations, deviant cases/negative are identified. These instances represent deviations from expected patterns, leading to further examination and refine the hypotheses (Bryman & Bell, 2011).

Hypotheses will be refined or adjusted if deviant cases between observed facts and initial explanations are identified. This iterative process may involve revising the hypotheses, redefining the research question, or considering alternative explanations.

If necessary, the hypothetical explanation of the research question is adjusted to either exclude deviant cases or include revised hypotheses. This iterative cycle of testing and refining hypotheses continues until a thorough and complete understanding of the phenomenon is achieved.

After conducting successful hypothesis testing and refinement, a common relationship or pattern might become evident across cases. When there are no deviant cases and the observed facts consistently support the hypotheses, the initial explanations are confirmed, offering empirical validation of the theoretical constructs (Bryman & Bell, 2011).

When all the steps are successful, the confirmation of hypotheses and the establishment of universal relationships, the investigation into the influence of different institutional logics on decision-making regarding Machine Learning adoptions within finance concludes. Data collection ceases, and the findings derived from the analysis contribute to the conclusion section of this research.

## 3.5 Ethical considerations

This research, which was based on interviews with employees from all levels of the business hierarchy, took several ethical guidelines into account to ensure the well-being and confidentiality of participants and the integrity of the research process (Arifin, 2018).

All participants involved in the study have received informed consent forms which include the purpose of the research, their rights as participants, and the procedures involved in data collection and analysis (Arifin, 2018). The interviews are conducted voluntarily, giving participants the freedom to choose whether or not they wish to participate.

The identities of both the participants and their organizations will be kept anonymous in all research data to maintain confidentiality. Participants will be assured that their answers will only be used for this research and will not be shared with any third parties without their consent.

Ethical considerations also apply in the interview process itself. The researcher will maintain professional and respectful behaviour throughout the interview process, ensuring that participants feel comfortable sharing their perspectives openly (Arifin, 2018). After finishing the interviews, participants were allowed to share any thoughts or questions they may have had during a debriefing session. By strictly following these ethical guidelines, the integrity and reliability of the research findings will be maintained.

# 4. Results

This section shows the results of this study that examines the main research question:

"How do institutional logics shape the types of Machine Learning adoption in finance operations?”

The information was organized to show how different dominant institutional logics impacted the findings. In using these layers, we see how norms, values and beliefs within finance affect integration and application of Machine Learning technologies. It explains the subsequent sections in each level that provide a comprehensive understanding of how Machine Learning can be applied differently in various stages of its adoption into financial operations.

The findings identified the dominant institutional logics influencing financial operations. These logics are divided into three categories: profession, corporation, and community as seen in Table 4 with each having themes of Status and Competition affecting them (Faik et al., 2020; Lounsbury, 2002; Munir & Baird, 2016).

*Table 4: Dominant logics within finance based on (Faik et al., 2020)*

| Y - Axis: Elemental Categories | X-Axis: Institutional Orders and Corresponding Societal Level Logics | | | | | | |
|---|---|---|---|---|---|---|---|
| | State | Profession | Market | Corporation | Family | Religion | Community |
| Basis of Norms | Citizenship membership | Associational membership | Self-interest | Firm employment | Household membership | Congregational membership | Group membership |
| Sources of Legitimacy | Democratic participation | Personal expertise | Share price | Market position | Unconditional Loyalty | Sacredness in society | Trust and reciprocity |
| Sources of Authority | Bureaucratic domination | Professional association | Shareholder activism | Top management | Patriarchal domination | Priesthood charisma | Community values and ideology |
| Technology Affordances | Broadening Accessibility and Traceability | Enhancing Knowledge-ability and Autonomy | Stimulating and Controlling Operations | Standardizing and Controlling Operations | (No identified Affordances in Literature) | (No identified Affordances in Literature) | Connecting Members and Opening Governance |
| Sources of Identity | Social and economic class | Association with quality of craft/Personal reputation | Faceless | Bureaucratic roles | Family reputation | Association with deities | Shared emotional connection |
| Basis of Attention | Status of interest group | Status in profession | Status in market | Status in hierarchy | Status in household | Relation to supernatural | Personal investment in group |
| Information Control | Backroom politics | Celebrity professionals | Industry analysis | Organization culture | Family politics | Worship of calling | Visibility of actions |
| Economic System | Welfare capitalism | Personal capitalism | Market capitalism | Managerial capitalism | Family capitalism | Occidental capitalism | Cooperative capitalism |
| Root Metaphor | State as distribution mechanism | Profession as relational network | Transaction | Corporation as hierarchy | Family as firm | Temple as bank | Common boundary |

Status affects how people behave in the organization as well as what they do as individuals pursuing professional acclaim and recognition within the profession and industry at large (Prato et al., 2024). It necessitates constant searching for improvements and differentiation to outcompete rivals.

During the interviews, several persons indicated that the finance environment is very fast-paced. One participant stated:

"*I really think developments are moving so fast that many people in fixed positions don't catch everything that's happening*" (Interviewee 2).

This underscores the rapid evolution within the financial sector, where staying ahead requires continuous adaptation and innovation.

Consequently, financial operations have to cooperate with their competitors in order to be up-to-date with the latest developments. Additionally, competition ensures that financial operations change over time such that they are now regarded as prestige and essential for survival in a competitive environment (Arora-Jonsson et al., 2020).

"*Machine learning offers automation opportunities even within constrained budgets, such as automating tasks like invoice categorization or status confirmation, thereby significantly improving operational efficiency*" (Interviewee 2).

AI complements these efforts by highlighting trends and supporting decision-making across departments, although human analysis remains essential for interpreting complex data and translating it to different departments (Interviewee 4).

By focusing on these sector-specific details, this research unique characteristics of finance, including complex data management, continuous improvement, and competitive pressures, influence Machine Learning adoption.

For instance, finance departments must handle large volumes of financial data and want to do it as quick as possible to enhance their decision-making speed and overall operational efficiency. This shapes their approach to adopt Machine Learning differently compared to departments like marketing or HR. This comparison highlights the unique challenges and opportunities faced by finance, showing how its needs and constraints are different from those in other departments of organizations.

## 4.1 Profession logics and Machine Learning adoption

At the professional level, ML is adopted to enhance skills and extend competencies through lifelong learning. Industry leaders apply their expertise to exploit advanced ML techniques thereby setting standards for their colleagues. In this competitive environment, finance experts are forced to include machine learning solutions that enhance their analytical skills and keep them ahead technologically, confirming the hypothesis that in the competitive finance environment professionals constantly need to develop new skills to excel, influencing the adoption of ML solutions within finance operations.

Within finance, tools like Generative AI have raised data entry accuracy and analytical skills in reducing manual errors and accelerating the analysis process even though AI-generated data is still not reliable enough (Interviewee 4). This adoption tends to lean towards both automation, in terms of handling repetitive tasks, and augmentation, enhancing the capabilities of professionals in performing complex analyses.

Augmentation with machine learning can lead to significant efficiencies by taking over routine cognitive tasks and allowing professionals to focus on higher-order analytical work.

*“Machine learning can take over certain cognitive tasks from financial professionals to a certain extent. I don’t think human judgment will become obsolete or in danger anytime soon. People are still needed to validate and test the results from machine learning processes”* (Interviewee 8).

This shift can improve the reliability and accuracy of financial processes, fill gaps in the labour market where there is a shortage of skilled workers, and ultimately enhance the overall quality of financial administration by freeing up human experts to apply their judgment and expertise where it is most needed.

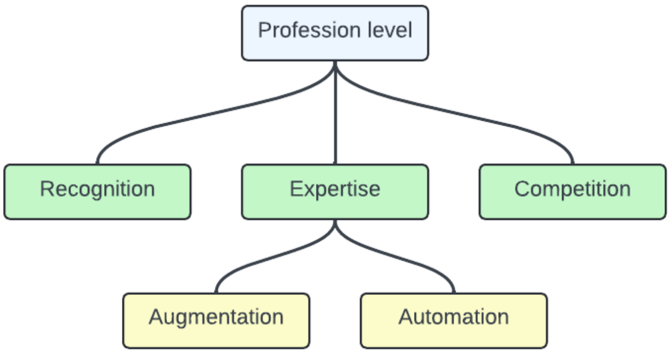


*Figure 6: Profession level influencing ML adoption*

As technology progresses, repetitive tasks will be automated, but this shift also highlights the growing importance of soft skills.

*"Processes remain, but you constantly adapt to the times. It's getting faster and the computer can do more for you. Those who do repetitive work and cannot keep up with new skills will have a problem. Soft skills are also becoming increasingly important; you need to be able to explain what is happening and involve others in the changes"* (Interviewee 10).

This confirms the second hypothesis. Professionals with higher status and influence in the industry will shape the direction of ML adoption in finance operations, relying on their expertise and continuous improvement.

Some finance professionals find enjoyment in exploring and implementing new technologies to make their work smarter and more efficient. Tools like Power Apps are being utilized to get more work done with fewer resources (Interviewee 10). A participant stated:

*"I think the company can benefit from it if they fully invest in a culture where people want to organize their work efficiently so they can focus on the analytical part"* (Interviewee 1).

A shift in job competencies towards embracing efficiency and prioritizing analytical tasks is crucial. However, there remains a challenge in getting everyone involved.

One participant pointed out that while the knowledge of how these tools work and how to use them isn't fully there yet, it's crucial for individuals to gain experience and skills on their own (Interviewee 1). Finance remains heavily reliant on Microsoft Excel, and not everyone possesses the necessary skills to transition to more advanced tools.

Nevertheless, there is an agreement that critical thinking and a strong analytical foundation remain essential. Machine learning can certainly assist, but it will not replace human judgment in the next few years. Financial professionals are still needed to validate and evaluate machine learning outcomes (Interviewee 2; Interviewee 8).

## 4.2 Corporate logics and Machine Learning adoption

Organizations invest in the latest Machine Learning technology to enhance their operations and improve and strengthen their positions within the industry. Within finance operations, Machine Learning must be adopted due to competitive pressures, focusing on cost reduction and efficiency improvements. Machine Learning is implemented to automate repetitive tasks, increase operational efficiency, and changing roles of professionals into more supervisory ones (Interviewee 3; Interviewee 4). The adoption of these technologies represents a strategic response to competition within finance.

*"You can read a whole document with AI. With invoices, you can read a whole invoice with all the invoice lines, which a human wouldn't be able to do so quickly. So you also have a lot more data that you can use in your own systems and that you can match as a financial picture in your own systems, for example with the payments you have to make to your suppliers. Or payments that are still outstanding where you still have to receive money from customers. Then you can take action much faster because you get that data much faster into your systems"* (Interviewee 5).

In finance operations across various sectors, automation is driven by anticipated growth, in finding new hires, or the desire to do more with fewer people (Interviewee 1). For example, RPA can automate invoice categorization or status confirmation, significantly improving speed and quality while saving time and resources. This automation can reduce department sizes and enhance efficiency, with tasks like invoicing now taking seconds for AI/ML compared to hours manually (Interviewee 3).

In the competitive finance environment, the drive to maintain efficiency and reduce costs is crucial. One participant noted:

*"You can never completely eliminate people, but if there's an opportunity for efficiency, you must take it"* (Interviewee 1).

This confirms the following hypothesis: Corporations within finance operations responding to the competitive environment will adopt ML solutions that improve efficiency and automate processes.

Machine Learning can help with simple, repetitive tasks that previously took considerable time manually. One participant explained:

*"We continuously assess if a robot can handle a task and if it is worth the effort to build one"* (Interviewee 3).

This approach ensures that automation efforts are justified and beneficial and this will work the same for Machine Learning. AI technologies can also analyse large documents quickly, extracting data for financial systems, thus enabling faster financial reporting and more efficient action on outstanding payments.

Cost reduction is another critical factor driving ML adoption. Automation can reduce costs, allowing companies to achieve higher margins on their products or services and offer lower prices or higher profit margins than competitors (Interviewee 5). The increasing use of modern technologies, such as generative AI, demonstrates how companies are replacing older automated models with more advanced solutions to stay competitive (Interviewee 5). The digitalization of financial accounting systems has also made processes more efficient, facilitating the implementation of Business Intelligence and other digital solutions.

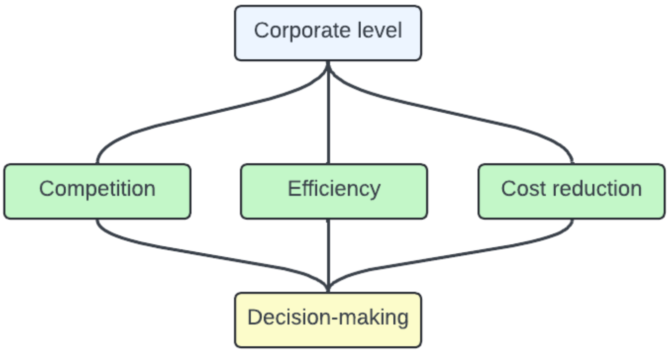


*Figure 7: Corporate level influencing ML adoption*

Machine learning algorithms can handle tasks that are time-consuming or inefficient for humans, creating significant efficiency gains. This allows employees to focus on more complex issues, where strategic and managerial insights are most valuable (Interviewee 8).

However, in large organizations, status and hierarchical structures can slow down decision-making processes. One participant observed:

*"In the really larger organizations that are still quite traditional, you see extreme forms of vertical layers that hinder the ability to innovate quickly or at all with new technologies"* (Interviewee 5).

Top-down decision-making in large organizations can involve multiple layers of management, which not only slows down innovation but also complicates the adoption of new technologies (Interviewee 1; Interviewee 5). Smaller organizations, in contrast, tend to have more collaborative and faster decision-making processes. This confirms the following hypothesis: The status of a corporation influences the adoption of  Machine Learning solutions, affecting both the riskiness and the speed of these changes.

In large organizations, decisions regarding the integration of Machine Learning into finance operations are made with input from multidisciplinary teams, which can further slowdown the process due to the need to balance different interests and gain an agreement (Interviewee 10). Financial constraints also limit the ability to hire extra staff or engage external parties, forcing organizations to depend on their current staff for innovation in finance operations (Interviewee 8).

On the other hand, large organizations firms can deal with the risks associated with new technology projects since they have a large financial base. They are able to take on higher-risk projects including ML solutions which may be too much for smaller companies. This makes it possible for them to implement innovative technologies experimentally without threatening their financial well-being as a whole. One participant stated:

*“Yes, suppose you have a large organization. They have millions, so such a decision has less impact, and you make that choice faster. For the other party, it is a matter of life or death, so to speak”* (Interviewee 7).

As a result, although the process of adopting this technology in financial operations might take longer due to complicated decision-making structures, the size and financial capacity of large enterprises can bring huge returns in successful ML implementations over time due to the riskiness of the methods introduced.

## 4.3 Community logics and Machine Learning adoption

At the community level, collective norms and competition within financial operations influence the adoption of Machine Learning. Standardization therefore happens when industry communities look for machine learning solutions that are widely accepted and based on their collective knowledge thereby standardizing practices.

However, during the interviews, it was evident that the community level was less present within finance compared to the profession and corporate levels. This difference shows that although community level logics have an impact on Machine Learning adoption, it doesn't influence it as much as profession or corporate level logics.

Competition within finance operations drives communities towards adopting ML technologies that help improve performance while keeping them relevant in their respective industries. For instance, operational efficiencies can be improved and costs reduced by applying AI together with RPA technologies thus resulting in a competitive advantage.

Community-driven competition plays a role in shaping ML adoption. One participant noted the potential of ML to handle tasks currently inefficient for humans, thereby creating efficiency gains and freeing up time for more complex strategic issues.

*"For example, automation: you can train a relatively simple model that can significantly impact and save on FTEs, allowing people to focus on other tasks. For instance, in finance, you could train a supervised learning model to automatically categorize invoices, or even post them, and someone could review it at the end of the month"* (Interviewee 7).

Completeness in data, achieved through Artificial Intelligence and Machine Learning, simplifies analyses, and reduces manual errors, enhancing overall efficiency within finance (Interviewee 4). This confirms the following hypothesis: Communities in the competitive finance environment see their adoption of Machine Learning influenced by efficiency and completeness.

However, the challenge within finance operations lies in making Machine Learning knowledge accessible and affordable. As one participant mentioned, the knowledge required to effectively implement ML is not cheap. Government investment could play a crucial role in democratizing this knowledge, making it more accessible and cost-effective (Interviewee 7). This accessibility is crucial for widespread adoption, making knowledge affordable for organizations, and leveraging Machine Learning to its full potential within finance.

Societal expectations and trends often drive technological adoption within communities. However, these trends require concrete implementation and skilled employees to realize their potential (Interviewee 1). This shift necessitates a cultural change where individuals recognize their initial lack of competence but eventually see the positive impact of ML on financial processes. One participant stated:

*“This also involves behaviour, culture, and attitude, but people often find it a threat when you proceed. Everything you make more efficient eventually poses a threat”* (Interviewee 2).

This highlights how the interaction between technological innovation and human factors shapes how these technologies are adopted. This confirms the following hypothesis: Communities, influenced by their status within finance operations, choose to use Machine Learning techniques that fit with the available knowledge within their organizations and their specific application domains.

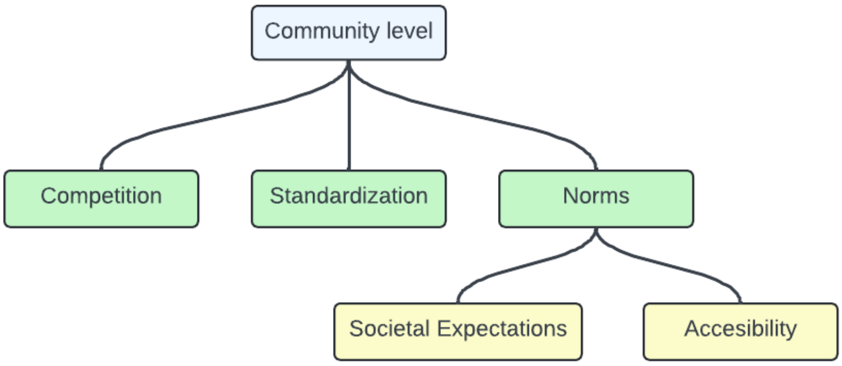


*Figure 8: Community level influencing ML adoption*

The accuracy and reliability of ML in handling routine tasks within finance also play a significant role in community acceptance. Manual processes are prone to errors and inefficiencies, which Machine Learning can address by automating data reading and processing tasks (Interviewee 5). This automation reduces the likelihood of human errors and enhances the quality and speed of financial operations.

# 5. Discussion and conclusion

## 5.1 Discussion

As Machine Learning technologies become increasingly integrated into the financial sector, understanding the influence of institutional logics on their adoption is crucial. This study reveals how profession, corporation, and community logics shape the implementation of ML in finance operations, highlighting the interplay between industry norms, competitive pressures, and technological advancements.

The analysis clearly shows that institutional logics play a significant role in shaping how Machine Learning is adopted in finance operations. Different aspects of finance, with status and competition being the most present during the interviews each influence how ML technologies are embraced and utilized.

### 5.1.1 Automation and Augmentation

Trends towards both automation and augmentation through ML adoption reflect strategic alignments with organizational goals. Finance professionals are using Machine Learning to boost their analytical skills, setting new industry standards for technological ability. At the same time, corporations are driven by the efficiency gains from automation, employing technologies like RPA with the inclusion of Machine Learning to streamline operations and stay competitive.

At the profession level, ML adoption serves as a tool for augmenting the skills of finance professionals, enabling them to excel in competitive environments by enhancing their analytical capabilities. This augmentation not only improves individual performance but also promotes a culture of continuous improvement and professional growth. One participant mentioned that their manager had indicated the work would shift from manual tasks to supervisory roles with the introduction of automation, which has proven true.

Working closely together with the technologies seems to be the most effective way of working at the moment. The accuracy of most Machine Learning and AI models isn’t perfect and by monitoring the outcomes, mistakes will be minimized. At the corporate level, the focus is on automation to enhance efficiency and reduce costs, as it is often less expensive than manual labour, enabling competitive pricing or higher profit margins.

Despite the potential of ML technologies, their adoption within financial operations is not without challenges. An issue is the conflict between innovation and efficiency, especially in organizations with traditional practices and hierarchical decision-making processes. The rapid pace of technological advancements within the competitive finance environment demands continuous improvement, but this need for innovation often clashes with the desire for operational stability.

Participants pointed out the difficulties in managing this issue, highlighting resistance to change in cultures that favour stability over innovation (Interviewee 7). Successfully adopting ML technologies means overcoming this cultural resistance and ensuring that new technological investments align with organizational goals and industry standards. This situation underscores the need for a strategic approach that balances the drive for innovation with the need for operational efficiency and risk management.

Hassani et al. (2020) explores how Intelligent Automation (IA) is evolving to mix human abilities with self-learning artificial intelligence. As IA develops, it is expected to encounter ethical and moral challenges sooner than technical ones. This highlights the need for a strong ethical framework to guide the use of AI and prepare for augmentation. AI will stay in the future and it's powered by human creativity and innovation. Our task is to make the most of AI's potential while carefully navigating its risks and ethical issues (Hassani et al., 2020).

Blending human and artificial intelligence clearly requires careful thought. While AI has the potential to significantly improve workflows in finance, it’s crucial to have a solid ethical framework to prevent issues that could undermine trust and stability in a community. As AI systems become more advanced, they raise important moral questions about their decision-making processes and the impact on human factors in finance.

The use of Machine Learning in finance highlights a strategic move towards both automation and augmentation, improving analytical capabilities and operational efficiency. However, integrating these technologies can be complicated due to the tension between innovation and established practices. To navigate this, organizations need a balanced strategy that encourages improvement, manages resistance, and aligns with their goals. Successfully leveraging the advantages of Intelligent Automation and AI/Machine Learning while addressing their challenges will be key to future success.

### 5.1.2 Conflicts between institutional logics

The study highlights several key conflicts among the dominant institutional logics. Each logic has its own set of priorities and norms, leading to tensions that influence how ML technologies are integrated.

At the professional level, the drive to enhance skills and gain status pushes finance professionals to adopt Machine Learning. They use these technologies to stay relevant. However, this focus on individual advancement can clash with corporate priorities. Corporations are more concerned with improving operational efficiency and reducing costs through automation, which often shifts job roles from manual tasks to more strategic or supervisory positions.

There is also a conflict between professional and community logics. Finance professionals try to adopt the latest Machine Learning tools to enhance their skills, whereas community logics value the importance of sticking to established standards and industry norms. Communities tend to prefer ML solutions that align with established practices.

Similarly, conflicts arise between corporate and community logics. Corporations invest in Machine Learning to boost efficiency and stay competitive by automating tasks and improving processes. However, this drive for innovation can clash with community priorities, which emphasize sticking to established standards and norms. Communities may resist technological changes that challenge traditional practices, preferring solutions that align with existing standards.

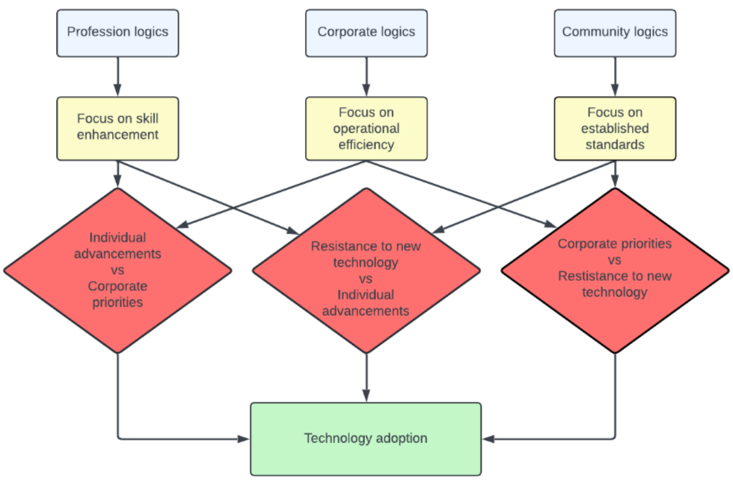


*Figure 9: Conflicts between institutional logics within finance*

Managing these conflicts effectively demands a strategic approach that looks at the needs and priorities of all parties involved. Research by (Battilana & Lee, 2014) emphasizes the need for flexibility and adaptability in managing institutional conflicts. Organizations must align personal advancement goals with corporate efficiency objectives while also considering community standards. It is crucial for developing effective ML adoption strategies that involves finding a balance among the different logics.

(Smith & Besharov, 2019) discovered that organizations effectively handle the tensions between competing logics by using a strategy they termed "structured flexibility". This approach combines stable organizational structures with flexible processes, allowing individuals to navigate and address conflicting demands flexibly. Their research highlighted how both the organizational environment and individual skills play a crucial role in balancing these competing priorities.

Addressing conflicts between different institutional logics in the adoption of Machine Learning within finance operations can be both beneficial and challenging for organizations. On the one hand, recognizing and dealing with these different logics can lead to more well-rounded and effective ML adoption strategies. It allows organizations to integrate diverse perspectives, which can enhance innovation and improve implementation.

On the other hand, managing these conflicts requires careful attention. Balancing personal advancement with organizational efficiency means personal goals should be aligned with the company's objectives. To achieve this, organizations should create an environment that supports both individual and corporate success.

### 5.1.3 Integrating Findings and Theoretical Perspectives

The results section confirmed all of the hypotheses stated in Table 2. Professionals with higher status and influence indeed shape the direction of Machine Learning (ML) adoption in finance. Their expertise and emphasis on continuous improvement drive the integration of ML technologies. Similarly, a corporation's status affects its ML adoption, influencing both the level of risk and the speed of implementation. Communities, too, adopt ML techniques based on their industry status and available knowledge, demonstrating how status impacts their choices.

Regarding competition, the study confirmed that professionals in finance operations are motivated to continuously develop new skills to remain competitive, which drives ML adoption. Corporations, responding to competitive pressures, implement ML solutions to enhance efficiency and automate processes. Additionally, communities consider competitive factors when adopting ML, focusing on efficiency and completeness to maintain their industry standing and performance.

Our findings align with the theory proposed by Faik et al. (2020), which suggests that institutional logics within an industry shapes technological adoption. The study also supports Lounsbury's (2002) and Munir & Baird's (2016) claims that status and competition are crucial factors influencing the integration of new technologies.

## 5.2 Practical implications

While implementing Machine Learning for financial tasks, organizations must consider much more than just the technology itself. When one decides to adopt Machine Learning, it is essential to consider how the organization operates and what its goals are. A considerable part of this understanding involves grasping the different institutional logics at play. This research indicates that finance operations are primarily status and competition driven.

In addition, these findings have gained insights from a range of sectors that are indicative of their implications. Ranging from manufacturing, ICT, healthcare, and other sectors, adeptly navigating institutional logics, and customizing Machine Learning applications are essential for achieving business success.

Organizations can create flexible frameworks that integrate different priorities and facilitate the successful implementation of Machine Learning within finance departments by recognizing the presence of multiple logics in finance departments. In this approach, technological adoption is aligned with organizational strategies and guided by institutional logics. Finance showed an emphasis on a status-driven and competitive nature.

Each sector has unique challenges and opportunities it faces making Machine Learning applications to be customized to fit certain institutional contexts. Once organizations achieve this, they will optimize their Machine Learning initiatives for improved operational effectiveness that will maintain their status and competitive edge in their particular markets.

## 5.3 Limitations

Every research has its limitations, and this is no exception. The author did everything to minimize their effect in the course of research but it's necessary to understand that certain factors contributing to the results can never be fully eliminated.

When criterion sampling is used, participants are chosen by using specific criteria that might ignore perspectives that do not meet the criteria. Even though our participant group is diverse, there is a probability that it may not encompass all the possible opinions concerning adoption of Machine Learning in finance.

The use of semi-structured interviews and pre-established hypotheses introduces a degree of subjectivity into the process of data collection and analysis (Kallio et al., 2016). However, no matter how objective we try to be, there are still some biases that might affect how our data is interpreted or analysed by the researcher or those who participate in the study. Objectivity is always desirable but the human element inevitably introduces some degree of subjectivity into the research outcomes.

Most of the participants have not yet used or may not have been aware they were using Machine Learning. Because it is a fairly new topic, the format of the interview was accessible for all participants who met most of the criteria. However, they may have discussed their insights regarding Machine Learning based on their knowledge of AI because of their lack of knowledge regarding the subject.

Moreover, the time limit for the study and resource constraints may have restricted the depth and breadth of data collected. This might restrict a full understanding of the complex dynamics involved in introducing Machine Learning to financial operations.

## 5.4 Future research

To explore the effects of institutional logics on Machine Learning beyond finance, future research should be done to consider other sectors like healthcare, manufacturing, and retail that provides different components such as regulatory landscapes, competitive dynamics, and operational priorities.

Thus, studying how these factors intersect with institutional logics in shaping Machine Learning adoption strategies would enable a deep understanding of sector-specific challenges and opportunities. Such studies enhance the identification of commonalities between various industries regarding patterns of Machine Learning adoption while at the same time emphasizing specific characteristics that distinguish an industry from others.

For different industries, there needs to be a longitudinal study that tracks the change in strategy of adopting Machine Learning over time. This allows for an investigation into organizational strategy changes as well as technological advancements and regulatory environments thus providing insight into the sustainability and effectiveness of Machine Learning applications. This way researchers can also observe how the strategies have changed throughout time meaning they can predict what is going to happen next with regard to implementation challenges or opportunities in industry-wide Machine Learning.

## 5.5 Conclusion

This research aims to find out how the different institutional logics influence the kinds of Machine Learning found within financial operations. There were three major dominant logics of profession, corporation, and community that involve norms, values, and beliefs which are significant in ML adoption. The findings reveal that the rapid pace and competitive nature of finance necessitate continuous adaptation and innovation, with Machine Learning serving as a tool for enhancing efficiency and staying competitive.

Professionals adopt Machine Learning at this level so as to improve their skills and increase their knowledge base. Advanced ML techniques enable finance professionals to be ahead in technology as they constantly upgrade their analytical capabilities. This kind of adoption is characterized by a focus on both automation and augmentation where routine cognitive tasks are taken over by Machine Learning while professionals focus on higher-order analytic work. The importance of soft skills, such as the ability to explain and involve others in changes, is also emphasized.

In order to improve efficiency and reduce costs, companies invest in ML technologies for operational gains due to corporate logics. This competition-based behaviour drives the need for ML solutions that replace repetitive tasks and speed up financial reporting. Both increasing efficiency and changing professional roles to acquire a more supervisory feature is one such strategic response rooted in competition. Large organizations have the financial strength to undertake higher-risk ML projects, enabling them to explore new technologies putting their financial stability at risk. However, decision-making within their large hierarchical structures may be slow, thereby affecting the pace of ML adoption within the organization.

Community logics are less present than profession and corporate logics within finance. However, it still influences ML adoption through collective norms and industry-wide standards Communities within finance adopt generally accepted ML solutions to improve performance and maintain relevance. The challenge for organizations is making ML knowledge accessible and affordable. Societal expectations and cultural attitudes toward technological innovation also shape ML adoption. They influence how individuals view technology and shape ethical considerations. These factors determine the speed and extent to which ML technologies are adopted in various sectors.

As a general conclusion, this research identifies that the integration and application of Machine Learning in financial operations are significantly influenced by how different logics of profession, corporation, and community levels complement each other. These logics determine if ML technologies will be adopted thus promoting efficiency, competitiveness, and strategic capabilities within finance. Consequently, knowledge from this research can be used as a strong model to understand ML adoption beyond finance due to the generalizability of the findings.

# References

Abdalla, M. M., Oliveira, L. G. L., Azevedo, C. E. F., & Gonzalez, R. K. (2018). Quality in qualitative organizational research: Types of triangulation as a methodological alternative. *Administração: ensino e pesquisa*, *19*(1).

Alford, R. R., & Friedland, R. (1985). *Powers of theory: Capitalism, the state, and democracy*. Cambridge University Press.

Alharbi, R. K., Yahya, S. B., & Ahmed, E. R. (2018). Characteristics of manager's and SMEs performance: the role of access to finance as a moderator. *International Journal of Engineering & Technology*, *7*(4), 5115-5119.

Almandoz, J. (2014). Founding teams as carriers of competing logics: When institutional forces predict banks' risk exposure. *Administrative Science Quarterly*, *59*(3), 442-473.

Alzubi, J., Nayyar, A., & Kumar, A. (2018). Machine learning from theory to algorithms: an overview. Journal of physics: conference series,

Arifin, S. R. M. (2018). Ethical considerations in qualitative study. *International journal of care scholars*, *1*(2), 30-33.

Arora-Jonsson, S., Brunsson, N., & Hasse, R. (2020). Where does competition come from? The role of organization. *Organization Theory*, *1*(1), 2631787719889977.

Barley, S. R., & Tolbert, P. S. (1991). Introduction: At the intersection of organizations and occupations.

Battilana, J., & Lee, M. (2014). Advancing research on hybrid organizing–Insights from the study of social enterprises. *Academy of Management Annals*, *8*(1), 397-441.

Bertolini, M., Mezzogori, D., Neroni, M., & Zammori, F. (2021). Machine Learning for industrial applications: A comprehensive literature review. *Expert Systems with Applications*, *175*, 114820.

Besharov, M. L., & Smith, W. K. (2014). Multiple institutional logics in organizations: Explaining their varied nature and implications. *Academy of management review*, *39*(3), 364-381.

Bezerra, R. F., Jalloh, S., & Stevenson, J. (1998). Formulating hypotheses graphically in social research. *Quality and Quantity*, *32*(4), 327-353.

Bryman, A., & Bell, E. (2011). *Business research methods* (3rd ed.). Oxford University Press Cambridge.

Collis, J., & Hussey, R. (2003). *Business research* (Vol. 142). Citeseer.

Faik, I., Barrett, M., & Oborn, E. (2020). How information technology matters in societal change: An affordance-based institutional logics perspective. *MIS quarterly*, *44*(3).

Friedland, R. (1991). Bringing society back in: Symbols, practices, and institutional contradictions. *The new institutionalism in organizational analysis*, 232-263.

Gartner. (2024). What Is Finance Transformation — And What Does It Achieve?

Hassani, H., Silva, E. S., Unger, S., TajMazinani, M., & Mac Feely, S. (2020). Artificial intelligence (AI) or intelligence augmentation (IA): what is the future? *Ai*, *1*(2), 8.

Hidayat, M., Defitri, S. Y., & Hilman, H. (2024). The Impact of Artificial Intelligence (AI) on Financial Management. *Management Studies and Business Journal (PRODUCTIVITY)*, *1*(1), 123-129.

Hultin, L., & Mähring, M. (2014). Visualizing institutional logics in sociomaterial practices. *Information and Organization*, *24*(3), 129-155.

Hyde, K. F. (2000). Recognising deductive processes in qualitative research. *Qualitative market research: An international journal*, *3*(2), 82-90.

Hyvonen, T., Jarvinen, J., & Pellinen, J. (2015). Dynamics of creating a new role for business controllers. *Nordic Journal of Business*, *64*, 21-39.

Kallio, H., Pietilä, A. M., Johnson, M., & Kangasniemi, M. (2016). Systematic methodological review: developing a framework for a qualitative semi-structured interview guide. *Journal of advanced nursing*, *72*(12), 2954-2965.

Karamagioli, E., Staiou, E.-R., & Gouscos, D. (2014). Can open-government models contribute to more collaborative ways of governance? An assessment of the Greek OpenGov initiative. *Open Government: Opportunities and Challenges for Public Governance*, 37-50.

Kaur, K., Kumar, Y., & Kaur, S. (2023). Artificial Intelligence and Machine Learning in Financial Services to Improve the Business System. In *Computational Intelligence for Modern Business Systems: Emerging Applications and Strategies* (pp. 3-30). Springer.

Kordon, A. (2020). Applied artificial intelligence-based systems as competitive advantage. 2020 IEEE 10th International Conference on Intelligent Systems (IS),

Kurmanov, N., Tolysbayev, B., Amirova, G., Satkanova, R., & Shamuratova, N. (2021). Foresight of the innovation manager competencies. *Polish Journal of management studies*, *23*(2).

Lounsbury, M. (2002). Institutional transformation and status mobility: The professionalization of the field of finance. *Academy of management journal*, *45*(1), 255-266.

Mahesh, B. (2020). Machine learning algorithms-a review. *International Journal of Science and Research (IJSR).[Internet]*, *9*(1), 381-386.

Mangan, A., & Kelly, S. (2009). Information systems and the allure of organisational integration: a cautionary tale from the Irish financial services sector. *European Journal of Information Systems*, *18*(1), 66-78.

Manning, P. K. (1982). Analytic induction. *Qualitative methods*, *2*(1), 273-302.

Markus, M. L. (2016). 11 obstacles on the road to corporate data responsibility. *Big data is not a monolith*, 143.

Markus, M. L., & Silver, M. S. (2008). A foundation for the study of IT effects: A new look at DeSanctis and Poole's concepts of structural features and spirit. *Journal of the Association for Information systems*, *9*(10), 5.

Merriam, S. B. (2002). Introduction to qualitative research. *Qualitative research in practice: Examples for discussion and analysis*, *1*(1), 1-17.

Munir, R., & Baird, K. (2016). Influence of institutional pressures on performance measurement systems. *Journal of Accounting & Organizational Change*, *12*(2), 106-128.

Ng, K. K., Chen, C.-H., Lee, C. K., Jiao, J. R., & Yang, Z.-X. (2021). A systematic literature review on intelligent automation: Aligning concepts from theory, practice, and future perspectives. *Advanced Engineering Informatics*, *47*, 101246.

Osisanwo, F., Akinsola, J., Awodele, O., Hinmikaiye, J., Olakanmi, O., & Akinjobi, J. (2017). Supervised machine learning algorithms: classification and comparison. *International Journal of Computer Trends and Technology (IJCTT)*, *48*(3), 128-138.

Prato, M., Ertug, G., Castellucci, F., & Zou, T. (2024). The Status of Status Research: A Review of the Types, Functions, Levels, and Audiences. *Journal of Management*, 01492063241226918.

Reybold, L. E., Lammert, J. D., & Stribling, S. M. (2013). Participant selection as a conscious research method: Thinking forward and the deliberation of 'emergent'findings. *Qualitative Research*, *13*(6), 699-716.

Singh, S., Khare, A., Pandey, S. K., & Sharma, D. P. (2021). Industry and community peers as drivers of corporate social responsibility in India: The contingent role of institutional investors. *Journal of Cleaner Production*, *295*, 126316.

Sirri, E., & Tufano, P. (1995). The Economics of Pooling, In the Global Financial System: A Functional Approach, Eds. *DB Crane, KA Froot, SP Mason, AF Perold, RC Merton, Z. Bodie, ER Sirri, P. Tufano, Harvard Business School Press, Boston MA*.

Smith, W. K., & Besharov, M. L. (2019). Bowing before dual gods: How structured flexibility sustains organizational hybridity. *Administrative Science Quarterly*, *64*(1), 1-44.

Sofia, M., Fraboni, F., De Angelis, M., Puzzo, G., Giusino, D., & Pietrantoni, L. (2023). The impact of artificial intelligence on workers' skills: Upskilling and reskilling in organisations. *Informing Science: The International Journal of an Emerging Transdiscipline*, *26*, 39-68.

Suchman, M. C. (1995). Managing legitimacy: Strategic and institutional approaches. *Academy of management review*, *20*(3), 571-610.

Suryadevara, C. K. (2017). Transforming Business Operations: Harnessing Artificial Intelligence and Machine Learning in the Enterprise. *International Journal of Creative Research Thoughts (IJCRT), ISSN*, 2320-2882.

Thornton, P. H., & Ocasio, W. (2008). Institutional logics. *The Sage handbook of organizational institutionalism*, *840*(2008), 99-128.

Thornton, P. H., Ocasio, W., & Lounsbury, M. (2012). *The institutional logics perspective: A new approach to culture, structure and process*. OUP Oxford.

Tilson, D., Lyytinen, K., & Sørensen, C. (2010). Research commentary—Digital infrastructures: The missing IS research agenda. *Information systems research*, *21*(4), 748-759.

Usachev, D. (2024). The Role of Machine Learning in Finance.

Vial, G., Cameron, A. F., Giannelia, T., & Jiang, J. (2023). Managing artificial intelligence projects: Key insights from an AI consulting firm. *Information Systems Journal*, *33*(3), 669-691.

# Appendix A – Interview Guide

- *Thank you for agreeing to participate in this interview. I'm Bas Geerdink, and I'm studying how institutional logics influence the adoption of Machine Learning in financial operations. May I record this interview?*

**Introduction**

1. Could you introduce yourself and tell me more about your role and the organization you currently work for?
2. Can you describe the challenges the company is currently facing?
   *(And what is being done about it at the moment?)*

3. What is the mission and vision of the company?
4. Can you tell me about your experience with financial processes and technologies such as AI/Machine Learning?
5. How do you think technological innovation, particularly Machine Learning, can help address challenges within finance?

**Institutional Logics**

6. What drives you to come to work every day?
   *(Can you give specific examples of what motivates you?)*

7. How does your position and influence affect decision-making within financial operations?
8. How does the status and reputation of the organization influence decision-making within financial operations?
9. In what ways does the company distinguish itself from the competition?
10. How are new methods and technologies introduced and applied to improve your organization's competitive position?
11. How do changes in laws and regulations affect your strategic decision-making?
    *(Are there specific ways in which IT innovations can be leveraged to ensure compliance while simultaneously increasing operational efficiency?)*

12. How do your expectations regarding profit and efficiency influence decision-making within your organization?
13. How is success measured in the organization?
14. How is success achieved within the organization?
    *(Is this aligned with the mission and vision/company culture?)*

### IT Affordances/ML adoption

15. How has the availability of modern IT capabilities changed the way financial institutions manage and execute their processes?
16. How can Machine Learning improve decision-making within the organization?
17. In what ways can Machine Learning contribute to improving success, especially in a competitive market environment?
18. How do you see the influence of societal expectations on the adoption of new technologies, particularly in the field of Machine Learning?

## Closing the Interview

- Is there anything else you would like to share that we haven't covered?
- Thank you for sharing your valuable insights.

# Appendix B – Hypotheses

*Table 5: Starting hypotheses table*

| Logics/Levels | Profession | Corporation | Community |
|---|---|---|---|
| **Status** | Professionals with higher status and influence in the industry will shape the direction of ML adoption in finance operations | Corporations follow the commonly accepted logics of their industry to maintain their status, adopting Machine Learning methods that align with those logics | Communities, influenced by their status within the industry, choose to use Machine Learning techniques that fit with the existing logics |
| **Competition** | The competitive finance environment driven by professionals will influence the adoption of ML solutions | Corporations within finance operations responding to the competitive environment will adopt ML solutions that align with dominant institutional logics | Communities in the competitive finance environment see their adoption of Machine Learning influenced dominant institutional logics |
| **Regulatory** | The adoption of Machine Learning is influenced by professionals' adherence to regulatory standards, which are shaped by institutional logics | Regulatory standards, influenced by dominant institutional logics, influence the adoption of Machine Learning in corporations | In communities, regulatory standards play a pivotal role in shaping the dominant logics, impacting the adoption of Machine Learning |
| **Expectations** | The expectations of financial professionals regarding profit and efficiency will influence the adoption of ML solutions | Corporations within finance aiming to meet profit expectations and optimize operations will influence the adoption of ML solutions | Communities focus on expectations shaped by institutional logics influence the adoption of Machine Learning |

*Table 6: Reshaped hypotheses table*

| Logics/Levels | Profession | Corporation | Community |
|---|---|---|---|
| **Status** | Professionals with higher status and influence in the industry will shape the direction of ML adoption in finance operations, relying on their expertise and continuous improvement | The status of a corporation influences the adoption of Machine Learning solutions, affecting both the riskiness and the speed of these changes | Communities, influenced by their status within the industry, choose to use Machine Learning techniques that fit with the available knowledge within their organizations and their specific application domains |
| **Competition** | The competitive finance environment, where professionals constantly develop new skills to excel, influences the adoption of ML solutions within finance operations | Corporations within finance operations responding to the competitive environment will adopt ML solutions that improve efficiency and automate processes | Communities in the competitive finance environment see their adoption of Machine Learning influenced by efficiency and completeness |
| **Regulatory** | Professionals' compliance to regulatory standards and reliability influences the adoption of Machine Learning by shaping organizational trust | Regulatory standards, influenced by dominant institutional logics, impact the adoption of Machine Learning in corporations, with completeness being a necessity | In communities, regulatory standards play a pivotal role in impacting the adoption of Machine Learning, requiring complete and thorough adherence to ensure compliance and maintain trust |
| **Expectations** | The expectations of financial professionals regarding profit, efficiency, quality assessment, and impact on the business will influence the adoption of ML solutions | Corporations within finance aiming to meet profit expectations and optimize operations will influence the adoption of ML solutions | Communities focus on expectations shaped by efficiency and automatization within the specific organization, influencing the adoption of Machine Learning |

Initially, this research hypothesized that professionals, corporations, and communities within finance operations would adopt Machine Learning technologies primarily influenced by their respective institutional logics whether based on status, competition, regulatory, or expectations as shown in Table 5.

Through interviews and iterative refinement, these hypotheses needed to be slightly reshaped to the hypotheses shown in Table 6. The researcher started the process of interviewing based on hypotheses that were a bit vague, knowing that rephrasing was part of the process of analytic induction.

It became evident that professionals with higher status and influence shape ML adoption strategies based on their expertise and continuous improvement efforts. Corporations, driven by their status within the industry, adopt ML solutions varying in risk and speed, aligned with dominant institutional logics. Similarly, communities within finance operations adopt ML techniques that fit their organizational knowledge and application domains.

The competitive environment in finance, characterized by professionals striving for skill development, strongly influences ML adoption. Corporations respond by integrating Machine Learning to enhance efficiency and automate processes, optimizing their operational capabilities. Communities, immersed in competitive dynamics, adopt ML technologies to achieve efficiency and comprehensive solutions within their specific contexts.

However, expectations were found to overlap significantly with competition. These were later combined. Regulatory compliance, while crucial, often followed predictable paths and was excluded in the results because it didn't add new and relevant insights.

By narrowing the focus to core logics such status and competition this study aims to provide thorough insights into how institutional logics shape the adoption of Machine Learning in financial operations. This approach ensures a focused and clear examination of the factors that drive ML adoption, providing valuable conclusions that can benefit professionals, corporations, and communities in finance operations.

# Appendix C – Coding hypotheses

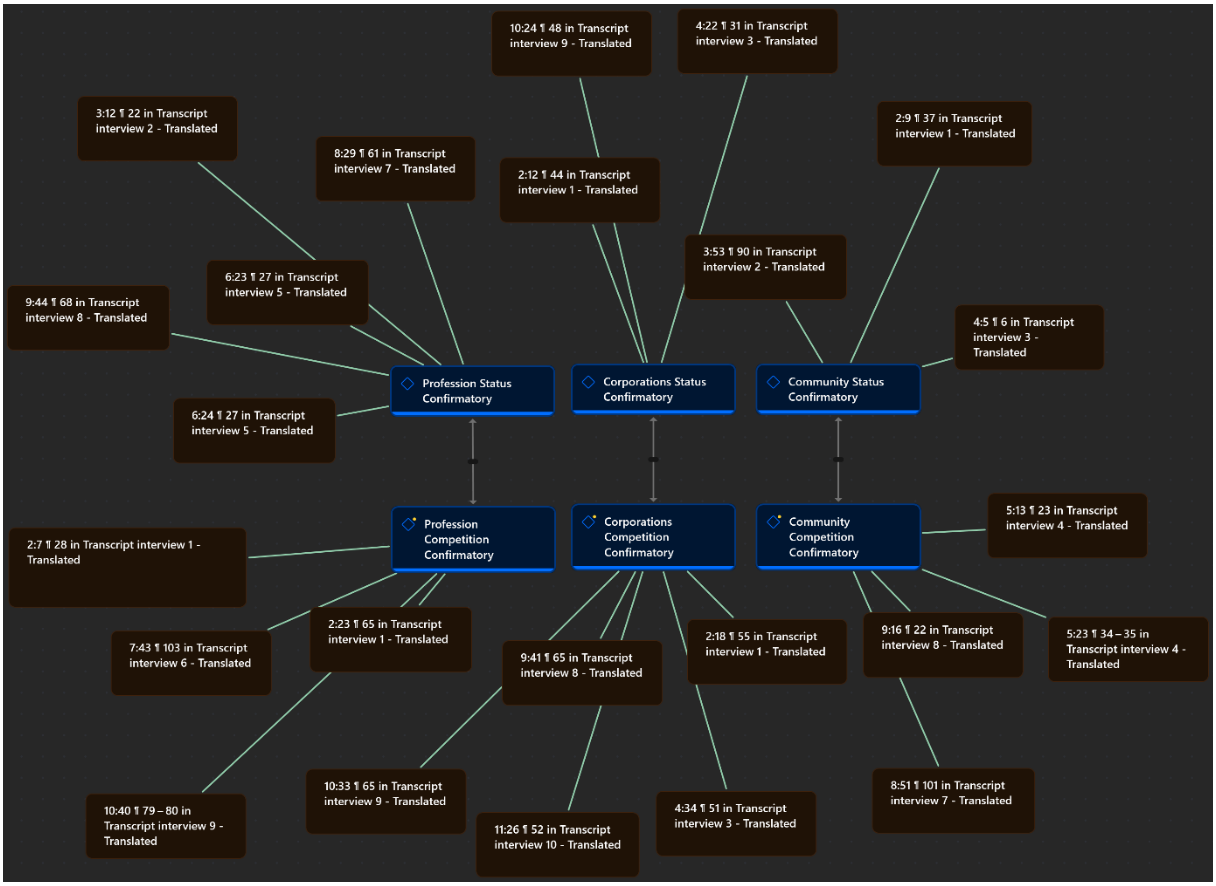


*Figure 10: Coding Atlas.TI*

# Appendix D – Recurring themes

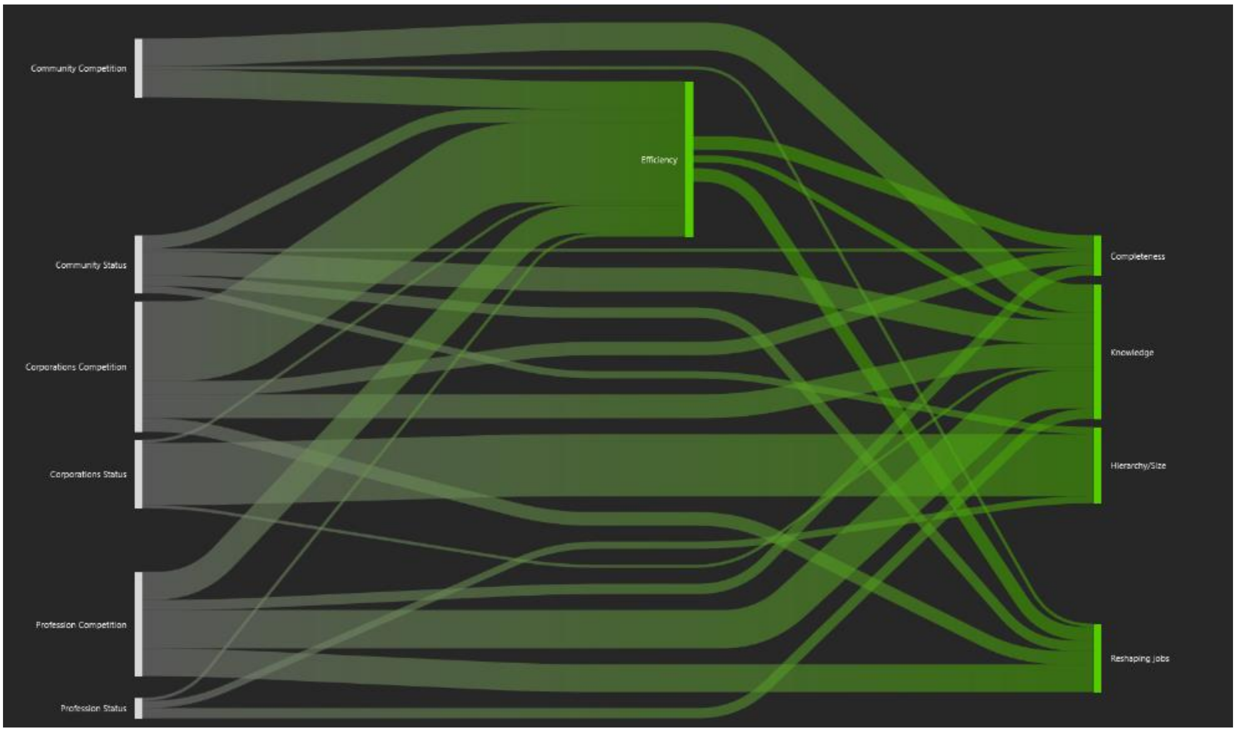


*Figure 11: Recurring themes*

This research used qualitative data analysis to examine the data gathered from the interviews. The primary objective was to confirm our hypotheses regarding the influence of institutional logics on Machine Learning adoption within finance operations.

By coding the data, this research gained a deeper understanding of how professionals, corporations, and communities navigate between competing logics to adopt and integrate ML technologies effectively. These insights are crucial for developing practical recommendations that align with dominant norms and values within finance while leveraging Machine Learning.

The analysis revealed themes that reoccurred through most of the interviews. All the recurring themes identified in the data analysis support the outcomes of the hypotheses but also provide insights into how institutional logics operate within the context of ML adoption in finance operations.

The recurring themes consist of efficiency, completeness, knowledge, hierarchy/size, and reshaping jobs, with efficiency emerging as a most recurring theme as seen in Figure 10. Within the competitive landscape of the financial sector, organizations and professionals alike prioritize efficiency through the adoption of Machine Learning technologies.

In the competitive world of finance, the drive to automate isn't just about making things run smoother, it's also about improving your position in the market. Professionals, particularly those with influence in the industry, drive these efforts as they seek to optimize processes and leverage technological advancements to maintain or improve their position. Thus, efficiency stands out as a central theme, linked with competition, shaping decisions and strategies regarding the integration of Machine Learning in financial operations.