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Master in Management

Chair of Managerial Decision Making

The AI revolution in Management: Navigating Ordinary and Extraordinary operations with data-driven decisions

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ABSTRACT

Technological advancements are revolutionizing management practices, with Artificial Intelligence emerging as a transformative force in decision-making processes. This thesis investigates how AI can be effectively incorporated into both ordinary and extraordinary operations while addressing the critical challenges of algorithmic bias, ethical concerns, and the necessity for human oversight. The research examines the delicate balance between leveraging AI's efficiency and maintaining essential human judgment in organizational contexts. The study employs a mixed-methods approach to comprehensively analyze AI's dual role. For extraordinary operations (mergers and acquisitions and crisis management), qualitative research through seven practitioners' interviews reveals how AI tools can enhance target screening, due diligence, and crisis preparedness while highlighting data privacy and accuracy limitations. For ordinary operations, quantitative research demonstrates AI's capacity to improve routine decision-making efficiency while identifying implementation barriers. Findings indicate that despite significant potential benefits in processing efficiency, analytical comprehensiveness, and risk identification, AI implementation faces substantial challenges including data privacy concerns, accuracy limitations, and regulatory compliance requirements. The research demonstrates that successful AI integration requires developing appropriate human-AI collaboration models where technology enhances rather than replaces human judgment. The thesis concludes that effective AI integration depends on the proper achievement of complementarity. By anchoring AI development to established decision theory frameworks while recognizing cognitive limitations, organizations can minimize risks while maximizing benefits. The study offers practical guidance for organizations seeking to optimize AI's potential while reducing inherent risks and ensuring alignment with ethical standards and human values.

TABLE OF CONTENTS

CHAPTER 1

1.1 Introduction

Technological advancements are nowadays revolutionizing many facets of business, employment, and daily life. The most inventive of these technologies is Artificial Intelligence, which has brought a new era of reimagining conventional decision-making procedures and paradigms. Almost every organization has been impacted by AI's capacity to gather, process, and understand enormous volumes of data at previously unattainable levels. Through the improvement of decision-making processes with efficacy, accuracy, and strategic thinking, artificial intelligence holds the potential to totally transform the management industry. Thanks to the ability of robots to behave like humans, seen as the fundamental notion of artificial intelligence, natural language processing, robotics, machine learning, and predictive analytics are just a few of the many applications that can be handled. In the realm of management, these capabilities allow firms to make data-driven decisions that were previously dependent only on human intuition and expertise, automate repetitive operations, and improve complex processes. AI technologies, for instance, can more accurately predict market trends, enhance customer relationship management, and accelerate supply chain operations than humans can. But there are several challenges in incorporating AI into management[1].

In the past, human abilities, critical thinking, and experience have been the foundation of management techniques; however, nowadays, artificial intelligence is increasingly supporting human endeavors. The transition to AI-

[1] S. Ransbotham, D. Kiron, P. Gerbert, and M. Reeves (2017). Reshaping Business With Artificial Intelligence. MIT Sloan Management Review and The Boston Consulting Group.

powered procedures has raised concerns regarding the accuracy of insights produced by machines, and the ethical consequences of giving algorithms sufficient power to make important decisions if left with no human supervision and approval. In a time when enterprises must cope with complex and quickly evolving environments, these factors are especially important. Gaining and maintaining a competitive edge requires the ability to react quickly and efficiently to obstacles but relying too much on AI could have unanticipated negative effects. The use of AI and its tools in the managerial setting is further complicated by both the possibility that biases would negatively affect results and the concerns about data security and privacy. Therefore, despite AI tools offer several opportunities to boost organizational operations and development, its application still requires a careful consideration of the long-term effects, such as how it could affect stakeholders, costumers, and employees.

To sum up, for AI to be implemented successfully, its issues must be handled carefully, particularly those related to biases, ethics, and integrating human expertise into AI-enabled processes. Moreover, revolutionizing the managerial decision-making practices requires AIs to provide businesses with the resources they need to thrive in an increasingly complex and data-driven world.

1.2 Problem Statement and Research Questions

Understanding the main challenge of integrating the technology into the managerial setting requires an in-depth overview of the advantages and disadvantages of AI. Shedding light on the main biases and ethical concerns is one of the aims of this study, since Artificial Intelligence would have the potential to revolutionize decision-making procedures, allowing businesses to operate more strategically, accurately, and efficiently. For instance, it can be implemented in everyday tasks to forecast consumer behavior, manage supply chain operations, and track economic performance in immediate terms. By evaluating intricate datasets and simulating multiple scenarios, artificial intelligence can offer significant insights in unprecedented circumstances, such as crisis management or M&A practices. However, the wish to integrate AI into organizational decision-making requires effortful procedures. Achieving a balance between the effectiveness provided by AI systems and the essential role of human supervision is one of the biggest challenges of this paper since, for instance, AI tools excel at processing big data sets and finding patterns while lack the human manager's ability to take contextual, ethical and nuanced factors into account. Plus, there is the risk that an excessive use of AI tools would result in important decisions being made without enough control from human employees.[2]

Another major obstacle to the application of AI tools into managerial practices can be the possibility of ethical biases to occur. Unfair or discriminating practices can arise from the data used to train AI systems that haven't been properly checked and fixed. For instance, an AI system used for recruitment which has been trained on biased historical data, could enhance disparities in hiring practices. Moreover, privacy and the possible misuse of personal data poses a risk when AI is used for surveillance or customer profiling. This study aims to investigate a number of important facets of AI's application in management. It then seeks to investigate how artificial intelligence might improve decision-making in both ordinary and extraordinary management operations. The paper examines the main operational and ethical issues that generally arise when AI is incorporated into managerial procedures; likewise it aims to understand which are the workable strategies that companies can employ to maximize AI's potential benefits while reducing its risks and limitations. Lastly, the study will try to uncover which could be the optimal combination of human judgment and artificial intelligence that would produce

[2] Gavade, D. (2023). AI-driven process automation in manufacturing business administration: Efficiency and cost-efficiency analysis. Presented at the 7th IET International Smart Cities Symposium, Bahrain

the most effective decision-making outcomes. By tackling these research topics, the study seeks to offer an exhaustive understanding of AI's function in management and pinpoint workable answers to the problems it poses.[3]

1.3 Objectives and Significance of the Study

the main objective of this study is to investigate how AI can be incorporated into managerial procedures, with a focus on its application in both ordinary and extraordinary operations. By focusing on both these organizational operations, the paper seeks to provide insights on how businesses might use AI systems to boost productivity and efficiency to achieve strategic success. Additionally, the study aims to highlight the barriers to AI adoption, such as algorithmic biases, ethical concerns, and the necessity of human oversight, and to offer practical solutions to these problems. The interaction and cooperation among human overview and AI tools in decision-making activities is a secondary objective that will be investigated. Although AI provides the benefits of automation and data-driven insights, human judgment is still necessary for evaluating these insights in the overall setting. The study attempts to offer a paradigm for combining AI with human expertise in a way that optimizes each of their strengths by looking at this interaction.

This study's importance stems from its capacity to close the gap between theoretical and applied viewpoints on artificial intelligence in management. The study adds to the developing body of research on artificial intelligence for scholars by offering an in-depth analysis of its uses, difficulties, and possible solutions. In order to close the aforementioned gap, in chapter three qualitative research will be conducted, specifically with those firms that are approaching or have yet approached AI in their extraordinary operations, aiming to obtain a more insightful and accurate perspective on the use of AI for both Mergers and

[3] Dogru, A. K., & Keskin, B. B. (2020). AI in operations management: Applications, challenges, and opportunities. *Journal of Data, Information and Management*, 2(2), 75–94.

Acquisitions and Crisis management. The respondents will be asked a set of questions about how AI is exploited within their organizations, ranging from general data gathering to its use for strategic-operational purposes. Chapter three will be lastly trying to shed light on the possible concerns that are retaining firms from its everyday usage and how helpful can AI be if properly supported and monitored by humans. All information stemming from the interviews will be then codified and explained within the chapter, with corresponding findings and scientific relevance. Conversely, quantitative research will be conducted in chapter four, which will examine the role of AI in routine operations. The related surveys will be presented to specific employees/executives of the designated companies, and the questions will be ranging from the general internal use of AI to the improvements it can potentially deliver in speed and efficiency terms. Along with graphic representations of the results and an explanation of their scientific relevance, the chapter will include an analysis and summary of the general findings. This thesis also attempts to give practitioners practical guidance on how to use AI in a way that fosters business goals and values. The study highlights for decision-makers the importance of developing legislative frameworks that encourage the moral and responsible use of AI in management. Furthermore, this study is relevant and timely given the increasing application of AI in corporate settings, whose companies will introduce the right company guidelines and policies for the employees to follow. Lastly, understanding the advantages and disadvantages of using AI is crucial for long-term performance and sustainability as businesses navigate the complexities of a data-driven environment, indeed the study aims to provide an overview for companies seeking to optimize AI's potential while reducing its inherent risks by addressing the aforementioned limitations.

CHAPTER 2

2.1 Introduction

Decision-making is a key component of an organization's strategy and its operations' efficiency. However, the theoretical basis for decision-making has changed a lot since the middle of the 20th century. The rise of artificial intelligence as a game-changing force in management has enhanced the conflict between classical rationalist models and empirically based behavioral frameworks which have been at the center of this transformation for a long time. This chapter synthesize theoretical and intellectual currents with contemporary research on AI's dual role in optimizing and complicating organizational decisions. By linking these theories to recent studies on algorithmic bias and strategic AI applications, the chapter creates a framework that draws on several fields to look at how people make decisions in a time when machines are helping them think.

Bounded rationality has changed management theory by criticizing the neoclassical idea of perfect rationality. Simon said that decision-makers have to work within cognitive and environmental limits, thus satisfying instead of optimizing since they don't have enough time or information to do so.[4] This paradigm shift, from homo economicus to cognitively bounded agents, remains pivotal for understanding both human and AI-driven decisions. While AI systems theoretically transcend human computational limits, they inherit designers' biases and environmental uncertainties, creating new forms of algorithmic bounded rationality. For example, when trained on incomplete datasets, large language models (LLMs) in strategic decision-making show

[4] Cristofaro, Matteo. (2017). Herbert Simon's bounded rationality: Its historical evolution in management and cross-fertilizing contribution. Journal of Management History. 23. 170-190.

satisficing behaviors that are similar to how humans rely on heuristics, even though they have more processing capabilities.[5]

Prospect theory, introduced by Kahneman and Tversky in 1979, further dismantled rationalist orthodoxy by demonstrating that decision-makers evaluate gains and losses asymmetrically, prioritizing loss aversion over utility maximization.[6] As will be investigated in the third chapter of this thesis, in many fields from Mergers and Acquisitions to Crisis Management, this nonlinear assessment of risk enquires AI systems, which are generally designed to maximize expected utility.

Gigerenzer's ecological rationality theory stands as a counterpoint, arguing that heuristics are adaptive reactions to environmental complexity. His trees representations, called fast and frugal trees, enable rapid decisions under uncertainty.[7] However, Gigerenzer's emphasis on transparency contrasts sharply with AI's black-box problem, where opaque decision rules hinder organizational accountability. This tension underscores the chapter's exploration of human-AI collaboration since heuristic-driven AI can enhance efficiency (e.g., supply chain optimization) but its alignment with human cognitive frameworks remains uneven.

While triggering both transforming possibilities and ethical concerns, the use of artificial intelligence into decision making offers both opportunities and challenges. Empirical evidence from healthcare diagnostics and strategic planning demonstrates AI's capacity to process vast datasets, predict outcomes, and automate routine decisions. However, as research reveals, these systems sometimes reinforce socioeconomic inequalities by means of flawed training data and designer prejudice. For example, facial recognition systems trained on

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[5] Csaszar, F.A. and Ketkar, H. and Kim, H. (2024) Artificial Intelligence and Strategic Decision-Making: Evidence from Entrepreneurs and Investors.

[6] Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. Econometrica, 47(2), 263–291.

[7] Goldstein, D. G., & Gigerenzer, G. (2002). Models of ecological rationality: The recognition heuristic. *Psychological Review, 109*(1), 75–90.

inaccurate data show racial and gender biases, hence reproducing historical injustices despite claiming to be neutral and unbiased[8]. Such findings call for strict ethical frameworks, combining technical solutions (e.g., bias-correction algorithms) with organizational governance models, prioritizing transparency and inclusion in AI development process[9].

This chapter aims to shed light on these dynamics across three dimensions:

Section 2.2 delineates classical decision theories, bounded rationality, prospect theory, and ecological rationality, to establish their enduring relevance in defining AI's limitations and strengths.

Section 2.3 will evaluate AI's dual role in ordinary and extraordinary operations, drawing on case studies from venture capital and public administration to identify gaps in human-AI trust and collaboration.

Section 2.4 will investigate on ethical challenges, by analyzing how algorithmic bias and opacity can undermine organizational equity despite AI's alleged objectivity. It will synthesize technical interventions (e.g., debiasing datasets) with managerial strategies to propose governance frameworks.

In a world where human intelligence more and more interacts with artificial intelligences, this chapter seeks to reframe decision-making scholarship by combining classical theories with modern AI research. It lays the basis for workable solutions that can leverage AI's potential while mitigating its risks, an essential balance to promote both organizational efficiency and ethical integrity.

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[8] Chen, Z. Ethics and discrimination in artificial intelligence-enabled recruitment practices. *Humanit Soc Sci Commun* 10, 567 (2023).

[9] Nah, S., Luo, J., & Joo, J. (2023). Rethinking Artificial Intelligence: Algorithmic Bias and Ethical Issues| Mapping Scholarship on Algorithmic Bias: Conceptualization, Empirical Results, and Ethical Concerns. *International Journal Of Communication, 18*, 22.

2.2 Overview of Decision-Making Theories Relevant to Management and Evolution

The publication of Kahneman and Tversky's Prospect Theory in 1979 marked a turning point in the decision-making domain. Inevitably, the theory challenged the prior Expected Utility Theory, which said that people make rational choices by figuring out probabilities and benefits. Prospect Theory came up with two new ideas: loss aversion, which means that losses feel worse than gains that of the same size, and nonlinear probability weighting, which means that people think low probabilities are more likely than the high ones. These results were very different from EUT, which showed that framing effects and context can affect how people make decisions. For example, the certainty effect, in which people unreasonably choose guaranteed results over probabilistic ones, directly opposed EUT's principles. Empirical validation revealed that same decisions framed as gains or losses generated reversals in preferences, thus stressing the theory's descriptive power over prescriptive models.[10]

However, several critiques emerged over the generalization of these events. Later studies noted limited replicability of Prospect Theory's paradoxes in broader populations, particularly among individuals with higher literacy. This made researchers wonder if its assumptions were based on broad cognitive processes or specialized heuristics. Even though these objections were made, the theory became a key part of behavioral economics since it linked psychology and economics to explain unusual consumer behavior.

While Prospect Theory focused on deviations from rationality, Herbert Simon's work on bounded rationality gained new relevance in managerial studies after 1979. He stated that decision makers work under cognitive and information

[10] Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. Econometrica, 47(2), 263–291

limitations, which causes them to satisfice rather than maximize. This approach gained relevance in organizational settings where time constraints, limited information, and conflicting priorities demand heuristic-driven decisions. [11] Managers, for instance, may use rules of thumb to speed up difficult choices like giving supplier relationships priority over cost-minimization in supply chain crises.

The 1980s–1990s saw bounded rationality integrated into strategic management theories, emphasizing adaptive decision-making in dynamic environments. According to the researchers Nelson and Winter, businesses establish procedures to deal with uncertainty by striking a balance between exploitation and exploration. These iterative decision-making processes enable businesses to react to changes in the market and has become essential to theories of organizational learning. Empirical studies of industries like automotive manufacturing revealed that bounded rationality explains why firms often stick to incremental improvements rather than radical innovations, a phenomenon termed path dependence.[12]

The realization that natural selection shapes cognitive mechanisms led to the integration of evolutionary biology and decision science in decision-making practices during the late 20th century. In 2012, the researchers Hammerstein and Stevens proposed a Darwinian decision theory, stating that evolved heuristics can optimize fit in several environments. In social decision-making, humans, for instance, exhibit adaptive specialization by reducing association risks by placing trust in their group members.[13] Even if these biases are

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[11] Cristofaro, Matteo. (2017). Herbert Simon's bounded rationality: Its historical evolution in management and cross-fertilizing contribution. Journal of Management History. 23. 170-190.
[12] Foss, N. J. (2002). *Bounded Rationality and Tacit Knowledge in the Organizational Capabilities Approach: An Assessment and a Reevaluation*. The Link Program. LINK Working Paper No. 2002-18
[13] Hammerstein, P., & Stevens, J. (2012). Six reasons for invoking evolution in decision theory. *In P. Hammerstein & J. Stevens (Eds.), Evolution and the mechanisms of decision making* (pp. 1–16). MIT Press.

inappropriate in modern situations, they still reflect evolutionary trade-offs between accuracy and speed.

This viewpoint guided management's behavioral strategy, which looked at how cognitive biases impact competitive dynamics. For instance, CEOs' propensity to overestimate merger synergies can be explained by overconfidence bias, which is a result of status-seeking in evolutionary contexts. In this regard the aforementioned fast and frugal heuristics, like hiring decisions based on recognition, reflect developing systems for making quick decisions in the face of uncertainty. Additionally, the evolutionary models explained the differences in organizational cultures choices since while tech startups use exploratory tactics to manage volatility, companies in stable industries establish risk-averse routines.[14]

The 21st century's computational revolution introduced algorithmic decision-making models, blending insights from Prospect Theory, bounded rationality, and evolutionary principles. Artificial neural networks, for example, simulate human-like learning by adjusting weights based on feedback, a process analogous to adaptive heuristics. Agent-based modeling additionally highlighted how phenomena such as market bubbles or innovation cascades are produced when basic decision rules are aggregated across organizations.[15]

Recent research highlighted the role of reinforcement learning in simulating managerial choices in dynamic settings. By mirroring human strategies under bounded rationality, agents trained on historical data can learn policies that balance and exploitation. Nonetheless, these models show several errors since AI systems trained on prejudiced datasets carry historical injustices like gender

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[14] Kenrick, D.T., Griskevicius, V., Sundie, J.M., Li, N.P., Li, Y.J., & Neuberg, S.L. (2009). Deep Rationality: The Evolutionary Economics of Decision Making. *Social cognition, 27 5*, 764-785.

[15] Kvam, Peter & Cesario, Joseph & Schossau, Jory & Eisthen, Heather & Hintze, Arend. (2015). Computational evolution of decision-making strategies.

inequalities in recruitment processes.[16] This underscores the need for hybrid models integrating human oversight to mitigate algorithmic biases.

Since 1979, decision-making theories have revealed a shift from static, normative models to dynamic frameworks. Prospect Theory's emphasis on psychological realism, bounded rationality's focus on cognitive constraints, and evolutionary models' adaptive lens collectively explain why humans, and organizations, deviate from optimality.
Future studies, lastly, must be able address gaps in temporal factors and cross-cultural integration by applying advancements in economics and machine learning to delineate decision paths across biological, psychological, and organizational dimensions.

2.3 AI's Role in Extraordinary and Ordinary Operations: Current Research and Gaps

The theoretical evolution and the research field of AI's role in organizational operations has broadened both for ordinary workflows (e.g., routine, predictable tasks) and extraordinary operations (high-stakes, volatile scenarios such as mergers and acquisitions and crisis management). This section will analyze AI's distinct contributions to these domains through interdisciplinary lenses, emphasizing operational efficiency, risk mitigation, and ethical challenges.

Ordinary operations, those characterized by repetitive, rule-based tasks, can leverage AI for process optimization and predictive maintenance. AI systems create closed-loop feedback mechanisms that automatically adjust workflows

[16] Hunkenschroer, A., & Kriebitz, A. (2022). Is AI recruiting (un)ethical? A human rights perspective on the use of AI for hiring. *AI and Ethics, 3*, Article 166.

based on performance metrics. For instance, predictive maintenance algorithms in manufacturing analyze sensor data from machinery to forecast equipment failures with reasonable accuracy. These systems can also align with transaction cost economics, where AI minimizes coordination expenses through automated inventory restocking, quality control, and demand forecasting.[17]
Multi-agent systems (MAS) represent a critical advancement in optimizing ordinary workflows. Using decentralized AI agents means, for instance, having the ability to plan delivery fleets routes in real-time while taking traffic, weather or fuel efficiency into account. Similar to this, Robotic Process Automation (RPA) can reduce human error rates by half when streamlining back-office functions like processing payrolls or compliance reporting. The discussion is different when it comes to Static AI models that often facing obstacles in adapting to context changes. For example, reinforcement learning (RL) algorithms optimized for steady-state production may falter during sudden supply chain disruptions, necessitating manual recalibration. Hybrid frameworks like human-in-the-loop (HITL) theory address this by integrating human oversight for exception handling, preserving operational continuity during incremental disruptions.[18]

M&A transactions, a paradigm of extraordinary operations, demand AI systems capable of navigating complexity, uncertainty, and accelerated timelines.
The integration of AI in M&A strategy formulation operationalizes augmented intelligence theory, which posits that human decision-making is enhanced, not replaced, by machine-driven insights. AI systems analyze structured and unstructured data (e.g., financial reports, news articles, social media sentiment) to identify acquisition targets, quantify synergies, and simulate post-merger

[17] Tariq, M. U., Poulin, M., Abonamah, A. (2021). Achieving Operational Excellence Through Artificial Intelligence: Driving Forces and Barriers. Frontiers in Psychology. 12
[18] Mosqueira-Rey, E., Hernández-Pereira, E., Alonso-Ríos, D., Bobes-Bascarán, J., Fernández-Leal, Á. (2022). Human-in-the-loop machine learning: a state of the art. Artificial Intelligence Review. 56. pp. 3020-3025.

scenarios.[19] For instance, Deloitte's AI-driven "nested wargaming" tools enable firms to model competitive counter-moves during target evaluations, thereby reducing biases rooted in CEO overconfidence or herd behavior. These systems leverage structural intersections to expose how organizational hierarchies and cognitive biases intersect, leading to suboptimal target selection.[20]

Machine learning models can analyze market trends, patent portfolios, and competitor behavior to identify acquisition targets with strategic synergies with the aid of their predictive analysis skills. For example, when compared to manual approaches, target identification accuracy is greatly increased by using NLP tools to analyze compliance reports and earning calls for undervalued corporations. Moreover, AI can evaluate intangible assets like intellectual property and human capital to quantify long-term value.[21]

The use of AI in due diligence practices is a prime example of resource orchestration techniques, in which businesses dynamically distribute information assets in order to reduce potential risks. Natural Language Processing (NLP) tools can indeed automate the extraction of contractual obligations, intellectual property disputes, and regulatory violations from thousands of documents, reducing review time by half.

AI-driven due diligence platforms can further address the inefficiencies of traditional methods, where more than half of transactions fail to meet value expectations due to oversight. Deep learning models can indeed parse millions of contracts, financial statements, and emails to flag risks such as hidden liabilities or regulatory non-compliance. The application of these systems can

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[19] Karikatti, M., Kalkoti, N., & Mogare, H. (June, 2024). A systematic review on augmented intelligence: A relation between human intelligence and artificial intelligence. International Journal of Research Publication and Reviews, Vol (5), Issue (6), June (2024), Page – 5448-5454.

[20] Engelbrecht, W., Canon, J., Dilger, E., McKenzie, S., & Dasharath, S. (June, 2024). Artificial intelligence and mergers and acquisitions: Observations from the frontlines and how to prepare for the coming shift. Deloitte Development LLC

[21] Rashid, M. M., Ullah, N., Uddin, M., Rahman, M. (2025). Artificial Intelligence on Merger and Acquisition Processes: Observation from The Target Identification and Due Diligence Perspective. International Journal of Innovative Research in Multidisciplinary Education. 4. 21-27

avoid such time losses and oversights, leading to a better analysis of the required documentation, if the output is correctly monitored and approved by humans.[22]

Post-merger integration (PMI) can leverage AI to operationalize complex adaptive system, where algorithms simulate cultural alignment scenarios by analyzing employee sentiment, communication patterns, and operational workflows.

Moreover, AI enhances PMI through cultural alignment algorithms that analyze employee sentiment surveys, collaboration patterns, and communication styles. For instance, clustering algorithms identify cultural mismatches between merging entities, enabling targeted integration strategies that reduce employee turnover. However, over-reliance on AI risks strategic myopia, as evidenced by cases where automated integration plans neglected regional regulatory nuances, incurring fines.[23]

Crisis management, another extraordinary operational domain, relies on AI for real-time decision-making under existential threats. Exploiting AI's main advantage of not being subject of emotionality, seen as one of the most harmful factors for employees, can play a pivotal role in preventing, facing, and recovering from a crisis.

The Situational Crisis Communication Theory (SCCT) has long served as a foundational framework guiding organizations through crisis response and management. SCCT classifies crises into distinct clusters based on attribution of responsibility: victim cluster (weak attribution), accidental cluster (minimal attribution), and intentional cluster (strong attribution). Each cluster faces

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[22] Wang, H. & Zhou, Y. (2023). Combination of Artificial Intelligence with Mergers and Acquisitions. BCP Business & Management. 39. 235-241

[23] Zhang, H., Pu, Y., Zheng, S., & Li, L. (2024). AI-Driven M&A Target Selection and Synergy Prediction: A Machine Learning-Based Approach. *Journal of Artificial Intelligence General Science (JAIGS) ISSN:3006-4023*, *6*(1), 359–377

different levels of reputational threat and requires tailored communication strategies. Artificial Intelligence technologies, if coupled with SCCT principles, may offer unprecedented opportunities to enhance crisis prevention. AI's grater contribution to crisis management can lie both in its ability to detect potential crises before they fully materialize and in the absence of emotionality, seen as one of the major causes of crises escalation. AI systems can indeed analyze vast amounts of data from diverse sources (social media, news, and internal communications) and provide early warnings such as real-time monitoring tools, thus having the ability to detect sentiment shifts indicative of upcoming crises.[24]

A critical capability for contemporary business organizations facing unpredictable challenges is owning the right mix of tools and skills for real-time crisis management. According to research, firms that incorporate Root Cause Analysis (RCA) systems into their crisis decision-making procedures in real-time can achieve significant advantages through their ability to rapidly identify underlying causes of the crisis, enabling more accurate and focused responses. Addressing accurately and quickly the main symptoms of an impendent crisis allows organizations to deliver an effective response and establishing foundations for long-term resilience. Nevertheless, there are significant obstacles to implementing real-time crisis management tools within firms, especially if no previous training activities have been done neither by the leadership nor the employees. Being prepared for these events plays a key role in how the crisis will be handled during and after a crisis occurs. However, implementing RCA as a tool for crisis management procedures may face obstacles such as time constraints, which can compromise the depth of root cause investigations, creating tension between the need for swift action and

[24] Coombs, W.. (2007). Protecting Organization Reputations During a Crisis: The Development and Application of Situational Crisis Communication Theory. Corporate Reputation Review. 10. 163-176.

thorough analysis.[25] In this setting, AI tools can be paired with or embedded in these systems to accelerate the RCA process, exploiting the ability to analyze large amount of data in short time in an innovative way. These tools, if coupled with the prior governance's duty of redirecting AI's work to the right KPIs to be monitored, can enable organizations to shift toward proactive crisis prevention through predictive analytics that identify potential threats before escalation.

Post-crisis recovery can leverage AI to operationalize organizational ambidexterity, balancing short-term stabilization with long-term innovation. For instance, the ROADS to Health project employs AI to optimize post-pandemic healthcare funding, simulating outcomes for vaccine distribution versus hospital capacity expansion.[26]

Future research must prioritize validating explainable AI (XAI) frameworks that balance algorithmic efficiency with human moral reasoning, a crucial synthesis for sustainable operational resilience. It should then address cross-cultural validity issues since Western-centric AI models often fail in emerging markets where informal networks dictate M&A success or crisis responses. Lastly, research must handle Generative AI risks since, for instance, tools like ChatGPT can accelerate due diligence practices but risk generating hallucinated outputs, thus requiring robust validation protocols.

[25] Aquino, S. R., Kilag, O. K., & Valle, J. (2023). From Preparedness to Action: Effective Real-time Crisis Management. *Excellencia: International Multi-Disciplinary Journal of Education (2994-9521)*, *1*(5), 372-384.
[26] Rainer, K., Kundratitz, V., Hagendorn, M., Neubauer, G., Ignjatović, D., Kutalek, R., & Sturm, N. (2024). Artificial intelligence in crisis management: Potential solutions and challenges. IDIMT-2024.

2.4 Bias, Ethical Concerns, and Human Oversight in AI-Supported Decisions

Artificial Intelligence systems applied in decision-making environments are coming under scrutiny for their potential to reinforce and accentuate cultural prejudices. To understand the causes, manifestations and effects of this intricate phenomenon in organizational contexts, a thorough analysis is required.

In algorithmic decision-making processes, the concept of “bias in, bias out” (Mayson S.G., 2018) has emerged as a critical topic. This phenomenon may produce a self-reinforcing cycle of discrimination when historical inequities that are contained in training datasets are algorithmically processed and projected into future decisions. Indeed, biases can be encoded by AI systems, mirroring implicit human cognitive biases, but with the unsettling feature of operating at scale and potentially projecting an unjustified sense of objectivity. In the corporate setting, where hiring procedures, development prospects, and resource allocation must all conform to fairness and equitable ideals, this becomes very challenging. AI systems’ apparent neutrality frequently conceals the fact that, despite their seeming objectivity, they can systematically penalize particular groups.

In algorithmic systems, bias does not appear on its own, rather it arises from certain causes that needs to be recognized in order to create efficient mitigation techniques. These prejudices may become embedded in organizational procedures without adequate understanding and action, possibly going against moral principles and the legal demands for equitable treatment.[27]

[27] Mayson, S.G. (2018) Bias In, Bias Out. Yale Law Journal 2218 (2019).University of Georgia School of Law Legal Studies Research Paper No. 2018-35. Pp. 2262-2277

The intricate mechanisms involved in converting algorithmic bias into organizational decisions have not received enough attention in the literature to date. Algorithmic bias has been shown to have a substantial impact on fairness perceptions and technology-related behaviors in businesses, such as system adoption, algorithm appreciation, and acceptance of machine-generated recommendations. Contextual elements that differ among organizational contexts mediate these effects, which are not consistent.

Perceived algorithmic bias influences organizational dynamics more broadly than just specific decision points. Customers or staff may become less engaged with technology, lose faith in the company, and even start to withdraw if they believe algorithmic processes are prejudiced. These responses have the potential to erode the advantages of adopting AI while posing new organizational problems with stakeholder relations and employees' engagement.

In addition to bias, the ethical implications of AI-assisted decision-making involve broader concerns like accountability, transparency, and societal impact. The opacity of algorithms presents considerable difficulties in decision-making and accountability for outcomes and users often find it difficult to comprehend the rationale behind decisions. This lack of openness raises ethical concerns and challenges established concepts, especially when decisions affect individuals or social groups.[28]

To facilitate the development and use of AI in decision-making scenarios, numerous ethical frameworks have been proposed, each offering a different viewpoint on how to approach AI's ethical issues.

[28] Osasona, F., Amoo, O., Atadoga, A., Abrahams, T., Farayola, O., Ayinla, B. (2024). Reviewing the ethical implications of ai in decision making processes. International Journal of Management & Entrepreneurship Research. 6. 322-335.

The EMMA framework, Ethical Management of Artificial Intelligence, is one which is worth mentioning. It offers companies a systematic approach for including ethical considerations into the implementation of artificial intelligence across managerial, ethical, and environmental aspects. This framework basically links leadership choices at the strategic, tactical, and operational levels with ethical values. Moreover, its AI Positioning Matrix rates AI projects by their potential for self-learning and human influence, hence stressing high-risk applications needing rigorous ethical scrutiny like human resources algorithms. This approach can further assist managers in transforming abstract ethical theories into useful practices since it guides strategic alignment with organizational codes of conduct, tactical planning, and operational monitoring to handle unintentional consequences like AI systems adopting negative behaviors. By including ethics into the decision-making process and balancing innovation and societal values, companies might use this model to control complex trade-offs and lower operational, legal, and reputational risks.[29]

Human oversight is a regulatory framework that allows people to monitor, affect, and finally take responsibility for actions powered by artificial intelligence. The key factor that led to the introduction of this framework is the awareness of artificial intelligence’s limitations and ethical concerns which makes AI-supported decision-making useless if not properly monitored. Indeed, this framework’s major purpose is risk reduction, hence, people in charge must have sufficient causal power over the AI system and its consequences as well as suitable access to relevant situational characteristics, self-control, and appropriate intentions. The effectiveness of human supervision is influenced by three kinds of elements: the technological

[29] Brendel, A. B., Mirbabaie, M., Lembcke, T.-B., & Hofeditz, L. (2021). Ethical Management of Artificial Intelligence. *Sustainability*, 2021 *13*(4), 1974.

architecture of the system, the personal traits of the oversight staff, and the settings in which they operate. Technical design includes the system's explainability, the presence of notable control mechanisms, and the possibility for human participation. While environmental concerns cover organizational structures, time limits, and power relations, personal qualities encompass the knowledge, skills, and moral conscience of supervisory people. Whether human monitoring is a genuine ethical precaution or only a performative compliance tool relies on how these elements interact.[30]

Regulatory systems have thus begun to formalize human supervision criteria for high-risk AI applications as noted in article 14 of the European Union's AI Act, which will become effective by August 2026. AI system providers must hence follow these rules to incorporate human monitoring mechanisms at all levels of the system lifetime, including design. The role of people in the AI decision-making process shapes the structure, substance, and scope of AI governance, which should be carefully considered in the regulatory framework these systems provide. Still, a significant challenge remains in turning legal requirements into effective monitoring systems.[31]

Studies on algorithmic bias reduction provide some helpful techniques for addressing ethical dilemmas in AI-supported decision-making. Building more objective datasets requires reconfiguring disorganized data, using several data centers in order to offer more precise results, and judiciously deleting data points reflecting past biases. Two strategies to improve this approach can be both understanding the underlying structure of training data and having more equal data sources by correcting data imbalances.

[30] Sterz, S., Baum, K., Biewer, S., Hermanns, H., Lauber-Rönsberg, A., Meinel, P., Langer, M. (2024). On the Quest for Effectiveness in Human Oversight: Interdisciplinary Perspectives. 2495-2507.

[31] European Union (Official journal version of 13 June 2024). Artificial Intelligence Act (Regulation (EU) 2024/1689) – Article 14. Interinstitutional File: 2021/0106 (COD)

Another interesting idea is to increase accuracy and precision by combining both tiny and large data. While small data offers unique, user-specific information that helps to avoid mistakes in causality, big data analysis is generally used to emphasize correlations. This combination of depth and breadth provides a more complex foundation for decision-making and helps to eliminate possible biases.[32] From a human-centered perspective, ensuring diversity and representation in AI research is a crucial step in lowering algorithmic bias. Apart from domain experts and data scientists, such diversity calls for the involvement of significant stakeholders, representatives of underrepresented groups, and end users. Different teams should be involved at every stage of the AI development lifecycle, from defining the initial challenge and creating hypotheses to deploying models across multiple groups and evaluating effectiveness, generalizability, and utility.

Beyond great developments in this field, there are still several theoretical gaps in the knowledge of bias, ethical concerns, and human oversight in AI-supported decision-making. First, additional research is required to understand how biases generated by technology affect organizational decisions and behaviors.

Including ethical frameworks into AI design and deployment offers no practical implementation suggestions. Though many ethical theories exist, it is challenging to convert these detached concepts into exact operational standards and design criteria.[33]

Human supervision systems require significant empirical research to demonstrate their effectiveness. Despite theoretical models for effective oversight have been released, their organizational relevance has received

[32] Chen, Z. (2023). Ethics and discrimination in artificial intelligence-enabled recruitment practices. *Humanit Soc Sci Commun* 10, 567.

[33] Sterz, S., Baum, K., Biewer, S., Hermanns, H., Lauber-Rönsberg, A., Meinel, P., Langer, M. (2024). On the Quest for Effectiveness in Human Oversight: Interdisciplinary Perspectives. 2495-2507.

limited research. Studying how supervision setups work in various organizational settings and decision areas would help to enhance best practices understanding.

Because AI systems may learn and change, it is harder to govern them ethically and reduce bias. It might not be right to use traditional supervision on systems that change when they learn new things and interact with people. To make sure that AI stays ethical in the long term, theoretical frameworks should take this evolutionary part of AI into account.

Furthermore, ethical issues that technical solutions cannot address arise from moral tensions such as precision vs justice or innovation vs safety. Theoretical models that help decision-makers deal with value conflicts and morally good trade-offs would help with AI ethics implementation.

Lastly, to deal with bias, ethical issues, and human oversight in AI-supported decision-making, an interdisciplinary approach is needed, which brings together technical, ethical, psychological, and organizational points of view. Companies might realize the potential of AI while lowering its risks and making sure that it follows social norms and human values if they had more complete theoretical frameworks and useful advice.

2.5 Conclusion

The incorporation of artificial intelligence into organizational decision-making signifies the outcome of decades of theoretical development and a shift in managerial practices. This chapter has shown that classical decision-making frameworks, including bounded rationality, prospect theory, and ecological rationality, remain essential for analyzing AI’s dual role as both an enhancer and a disruptor of strategic processes. It is beyond any doubt that AI systems have overtaken human computational limits, however, they are subject to cognitive constraints due to algorithmic restricted reasoning, satisficing behaviors in data-scarce contexts, and biases present in most of the training datasets. The conflict between AI's ability for rational optimization and its vulnerability to human related errors highlights the need for hybrid models that utilize machine efficiency alongside human judgment.

This analysis has yielded significant insights like the application of AI in routine operations, such as predictive maintenance and supply chain optimization, which illustrates significant efficiency improvements achieved through closed-loop feedback systems and multi-agent coordination. These systems demonstrate fragility in extraordinary operations, where the formulation of M&A strategies and crisis management require adaptive intelligence that integrates algorithmic precision with contextual awareness. The ethical challenges associated with AI-supported decisions, specifically algorithmic bias, model's opacity, and accountability deficits, expose systemic risks that reflect and exacerbate historical organizational inequities. The bias in, bias out phenomenon, as explained above, highlights the necessity for technical solutions such as debiased datasets, in conjunction with structural interventions which include AI systems development along with ethical frameworks like EMMA. Furthermore, human oversight mechanisms, especially those required by emerging regulations like the EU AI Act, must progress beyond mere compliance to facilitate moral agency, integrating explainable AI frameworks with the domain expertise of oversight professionals.

Different areas of study stand out for development of organizational AI systems. Dynamic ethical frameworks are required because of the fluidity of machine learning algorithms while governance models should develop natural adaptation mechanisms to maintain value alignment since algorithms change through continuous data collection and retraining cycles.

Nonetheless, future academic research should investigate on cross-cultural validity differences. Often, the construction of training data and the codification of normative decision rules create prejudices in present AI systems, which could compromise their effectiveness in operational environments spread worldwide.

Furthermore, high-risk operational sectors for generative artificial intelligence call for significant validation protocol creation. In critical services like financial due diligence, where the technology's propensity for factual errors calls for multi-layered verification systems, we should give Large Language Models applications the priority.

This chapter finds that ethical AI integration depends on symbiotic human-machine ecosystems. By anchoring AI development to prospect theory's psychological realism, ecological rationality's adaptive pragmatism, and bounded rationality's cognitive humility, organizations minimize the existential risks of machine intelligence. Technical optimization is insufficient; artificial and human intelligences must work together to achieve efficient, equitable, and evolutionarily robust decision-making.

CHAPTER 3

3.1 Introduction

This chapter will analyze the role of AI in extraordinary operations, characterized as critical, high-stakes business activities that diverge from standard processes and necessitate specialized expertise, increased attention, and strategic decision-making. Although these definitions are at odd with the concept of artificial intelligence, it is believed to be worth investigating these complex dynamics, in which AI integration seems unable to fit in. Mergers and Acquisitions and Crisis Management are two significant areas where AI applications seem to be gaining space, yet they are not fully comprehended in academic literature.

The M&A landscape has experienced a gradual incorporation of AI technologies across the entire deal cycle. However, its deployment is still in the early stages. A 2024 study reveals that only few organizations are currently employing generative AI in their M&A processes, while projections indicate that the number of firms may increase up to four times in the near future.[34] This limited adoption persists despite compelling evidence that nearly half of all transactions fail to meet financial targets due to people-related issues that could potentially be mitigated through AI-enhanced analytics.

Crisis management has concurrently emerged as a significant application domain for AI technologies. AI systems, if applied in this field, can enhance response capabilities, optimize resource allocation, and support critical decision-making processes in emergencies situations. Recent research indicates that AI technologies, such as machine learning, natural language processing,

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[34] Bain & Company. (2024). Global M&A Report 2024: Gaining an edge in a market reset. Bain & Company. Pp. 18-29. https://www.bain.com/insights/topics/global-ma-report/

and predictive analytics, could help organizations in detecting early warning signals, conducting real-time monitoring, and forecasting potential crisis scenarios based on historical data.[35] The evolution of AI in crisis management has progressively extended beyond internal organizational processes to encompass broader external environments, culminating in predictive and integrative empowerment capabilities.

Nevertheless, important knowledge gaps remain on how these technologies are actually applied in practice despite these developments. Current academic research is still missing specific investigation on integration strategies, performance measurements, ethical issues, and the vital interaction between human knowledge and artificial intelligence systems.

This chapter will employ qualitative research methodology, with 7 different interviews, aiming to investigate the implementation of AI in extraordinary operations, with particular emphasis on M&A processes and crisis management. Drawing upon interviews with 7 professionals who have direct experience in these domains, the analysis examines practical applications, success factors, and implementation challenges. Furthermore, this research aims to shed light on the regulatory frameworks, or specific laws, that need to be implemented in order to provide workable solutions for those firms that nowadays are unable to deploy AI tools since it would mean entrusting sensitive information to public domain platforms. This approach fits with the assumption that understanding the complex interplay between technological capabilities and organizational factors requires rich contextual knowledge best obtained through qualitative research.

The following sections will be covering in order: the exploration AI's specific applications in M&A transactions in section 3.2, a thorough investigation on

[35] Banasik, A., & Pikiewicz, P. (2023). Application of AI in crisis management [Unpublished manuscript]. Silesian University of Technology, RMS2

AI's potential role in crisis prevention and management in section 3.3, an analysis of both the fields with particular emphasis on human oversight requirements in section 3.4, before synthesizing key findings in the conclusion. By examining these extraordinary operations through both academic and practitioners perspectives, this chapter aims to retrieve meaningful insights regarding effective AI integration practices while acknowledging the centrality of human judgment in these complex decision domains.

3.2 AI's Role in Mergers and Acquisitions (M&A)

A revolutionary change that is affecting the field of strategic decision-making, operational processes and post-transaction results in Mergers and Acquisitions processes is represented by the upcoming implementation of Artificial Intelligence tools. Its historical configuration defines it as an extraordinarily complicated process which requires careful examination of massive datasets, nuanced strategic planning, and flawless execution. But businesses may now use cutting-edge solutions to increase productivity, precision, and insight generation at every level of the M&A lifecycle thanks to the introduction of new paradigms brought about by AI tools. This section synthesizes empirical insights derived from interviews with industry practitioners from EQUITA Mid Cap, a private equity fund in Milan, a financial consulting company in Milan, L2Capital, and an international banking institution and peer-reviewed academic research to present a comprehensive analysis of AI's applications in M&A. The topic at hand presents AI as a catalyst for reframing human knowledge in high-stakes transactions and as an efficiency accelerator by merging theoretical frameworks with coded interview data. M&A's phases as Pre-due diligence, target selection, due diligence, and valuation modeling, are the ones under investigation to assess whether AI tools can be implemented or not. The objective of this part is to evaluate whether technological innovations have been incorporated into M&A procedures and what businesses and financial institutions require in order to integrate AI technologies into their operations.

Finding possible prospects that fit with strategic objectives, operational synergies, and financial benchmarks requires careful consideration throughout the target selection and screening stage of mergers and acquisitions (M&A). This phases, as Laura confirmed, have historically been resource-intensive and prone to human error due to their heavy reliance on manual examination of structured data, industry reports, and qualitative assessments (Table 4, Appendix). Businesses can now, theoretically, handle enormous volumes of structured and unstructured data more quickly and accurately thanks to the revolutionary efficiencies brought about by the incorporation of artificial intelligence into these phases.

Before official evaluations begin, the pre-due diligence phase represents a crucial point where first assessments determine strategic direction. At this early stage, AI applications are varied and getting more complex, with a primary focus on data aggregation, preliminary market analysis, and communication preparation.

Financial professionals currently leverage AI for comprehensive market mapping and sector analysis during pre-due diligence activities. As noted by Lorenzo Gabrielli, an analyst in a private equity investment team, “When we are about to analyze an investment opportunity, we do market studies and sector studies, and there it is useful for me to carefully use AI tools to map the market and sector” (Table 2, Appendix). Despite the absence of proprietary tools for several reasons that will be covered later, the implementation of public domain tools for ‘general information gathering’ accelerates the initial evaluation process, allowing investment teams to develop more informed preliminary hypotheses about target sectors.

AI tools also demonstrate significant utility in automating routine communication tasks during early engagement stages. Andrea Taurelli Salimbeni, managing partner at L2Capital, explains that his organization uses AI i.e., "in drafting letters or emails to contact companies to test their openness to capital operations" (Table 3, Appendix). This functionality streamlines initial outreach efforts, enabling more efficient allocation of human resources toward higher-value activities.

Language processing capabilities represent another valuable AI application in pre-due diligence activities. Gabrielli highlights AI's effectiveness as a translator, noting that "translating a document or simplifying it with ChatGPT is much better than with other tools on the market, and it generally doesn't make mistakes" (Table 2, Appendix). This functionality could, for instance, be particularly effective in cross-border transactions where language barriers might otherwise impede efficient analysis of foreign-language documents.

However, language can represent a barrier when dealing with AI tools, since most of them are trained with their original language and used to process queries accordingly. Some of the professionals interviewed provided evidence on the importance of this topic, highlighting that LMs (Language Models) work better when those who are in charge of desk research are trained on the prompting technology of the models, thus being able to know how to ask questions properly, that will be translated from natural language into queries, from which the machines will work on (Table 1 and 6, Appendix).

Furthermore, industry practitioners express general limitations regarding pre-due diligence AI applications. Giuseppe Renato Grasso, CEO of Equita Mid Cap Advisory, observes that "there are no artificial intelligence tools that can replace one of our analysts. There are artificial intelligence tools that greatly help our analysts, but unfortunately or luckily, they are not capable of replacing them yet" (Table 1, Appendix). This sentiment reflects the prevailing industry view that AI currently serves as a complementary tool rather than a substitute for human expertise during initial assessment phases.

Target screening represents a fundamental M&A function where AI demonstrates particularly compelling advantages. Traditional approaches to identifying acquisition targets often involve laborious manual research processes that struggle to comprehensively evaluate vast corporate landscapes. AI-powered screening tools are transforming this domain through enhanced data processing capabilities and pattern recognition algorithms.

The ability to process immense datasets represents a primary advantage of AI-driven target screening. AI-powered platforms can analyze countless businesses public data and help professionals identify potential targets that traditional databases might miss. This capacity for comprehensive market analysis enables more thorough evaluation of potential targets, reducing the risk of overlooking promising opportunities.[36]

Moreover, these tools' advanced screening capabilities enable more precise targeting based on specific strategic objectives and acquisition parameters.

Practitioners confirm the practical value of AI in target screening activities, as Salimbeni states that AI "has helped a lot in everything from scouting to origination and assessment analyses", highlighting its utility throughout the target identification process (Table 3, Appendix). This perspective is reinforced by industry research indicating that AI-driven target identification analyzes factors such as financial health, market positioning, and growth potential to assist companies in building a robust M&A pipeline.

Target screening is changing, with a growing emphasis on ongoing observation as opposed to isolated analysis. Contemporary methods entail putting in place

[36] Rashid, M. M., Ullah, N., Uddin, M., Rahman, M. (2025). Artificial Intelligence on Merger and Acquisition Processes: Observation from The Target Identification and Due Diligence Perspective. International Journal of Innovative Research in Multidisciplinary Education. 4. 21-27.

automated systems that search the market constantly for possible targets, assess how well they align with the goals of the company, and rank them according to established standards. Compared to conventional periodic assessment approaches, this programmatic approach to M&A target investigation offers a considerable breakthrough.[37]

Despite these advantages, practitioners emphasize the continued importance of human judgment in target screening decisions. Salimbeni clarifies that AI can never replace human decision-making but can be helpful in speeding up and make more efficient and effective the processing of data, the preparation of tables, low-level work involving large datasets (Table 3, Appendix). This perspective underscores the complementary relationship between AI capabilities and human strategic insight in effective target identification.

Perhaps the most data-intensive stage of M&A transactions is due diligence, which entails a thorough assessment of the operational, legal, financial, and strategic aspects of possible transactions. AI applications demonstrate particular utility in this domain through automated document analysis, risk assessment, and pattern recognition capabilities. As Laura stated, in the last 40 years this phase has been continuously reshaped, starting from a manual job done by analysists, whose primary work was to analyze long reports and summarize key insights, to the most recent developments that led algorithmic tools alongside analysts in the research processes (Table 4, Appendix).

In due diligence procedures, document analysis can be one of the main areas of development for AI systems. Studies show that artificial intelligence can improve the creation of useful insights as well as the correctness of data analysis, hence allowing users to quickly examine huge data sets, reduce risks and make wise judgments. This capability addresses the fundamental challenge

[37] Nima N. (2023) Transforming the M&A Process: The Current and Future Role of Artificial Intelligence. IMAA Institute.

of processing voluminous transaction documentation within constrained timeframes.[38]

According to Lorenzo Gabrielli, having specific AI functionalities in due diligence including document categorization and content extraction can assist in identifying, classifying, organizing, prioritizing and highlighting documents that are relevant in the context of the transaction in a more effective time and cost manner (Table 2). These features simplify time-consuming document evaluation procedures that often require and consume considerable expert resources.

Financial statement analysis represents another valuable AI application in due diligence processes. AI systems can scrutinize financial statements, profit/loss records, tax filings, and annual reports combining both public sources and proprietary information. But this combination would be effectively implemented only if the providers of AI tools will be able to ensure data protection for all those firms willing to implement their tools. Moreover, finding these patterns would provide analysists that often struggle to find a unique output to rely on, rather than having to compare different data to obtain the same information. This functionality will further improve the identification of financial irregularities that might otherwise remain undetected through conventional review methodologies.

Industry practitioners confirm the practical value of AI in due diligence processes while acknowledging important limitations. Grasso notes that in due diligence, especially on contractual or fiscal parts, when there are many data to analyze, AI would certainly be very effective, while emphasizing that there’s also a problem of confidentiality and data ownership (Table 1, Appendix). This perspective highlights the tension between AI’s analytical potential and practical implementation challenges in confidential transaction contexts.

[38] Emmi, P. A. (2025). The impact of artificial intelligence on M&A deals—Part I. The Journal of Robotics, Artificial Intelligence & Law, 8 (2), 125–146

Gabrielli similarly observes that AI could help a lot in our job on the output formatting side, while noting that there's not an artificial intelligence tool that reworks, synthesizes, and draws conclusions (Table 2, Appendix). This assessment reflects the current industry reality where AI could effectively automate specific analytical tasks, but there are several privacy concerns and general skepticism that is preventing firms to implement these tools.

Valuation analysis through comparable company benchmarking and multiple applications represents a critical M&A function where AI demonstrates significant potential through enhanced data processing capabilities and pattern recognition algorithms.

The identification of relevant comparable companies constitutes a fundamental valuation challenge that AI systems can effectively address. Grasso explains that AI has the potential to identify companies that are in the same sector under examination and the output can be used either to find targets to acquire around the world or to find comparables or to make a valuation. This functionality is currently unexploited since the available databases on the market consider the classification of economic activity itself, thus providing an imprecise output. Integrating AI tools which can exploit the current information available on those databases can enhance the accuracy of valuation analyses through more precise identification of genuinely comparable entities (Table 1, Appendix). This capability can address a fundamental challenge in traditional valuation analyses that often rely on imperfect comparable company selections.

However, practitioners note important limitations in AI-based valuation analyses, highlighting the challenge of data availability in transaction-based valuation methodologies. This challenge is further confirmed by Salimbeni, who observes that "the valuation and negotiation have never been helped much because probably even comparable multiples like EV/EBITDA are not yet reliable in our view since comparables indexes information is usually private" (Table 3, Appendix).

Transaction efficiency, accuracy, and strategic insight can achieve significant benefits thanks to the implementation of AI technologies in M&A processes. These advantages manifest across multiple dimensions, from accelerated analysis timeframes to enhanced risk identification capabilities.
Maturo offers tangible evidence of current efficiencies gained through database tools: 'if we go to research a sector's comparables, and market indices and so on through databases, we can take 1 to 2 hours' compared to a process that can last days when done manually. This illustrates the significant potential for AI to further accelerate these processes, particularly in the 'preliminary phase' of M&A transactions, which Maturo identifies as the area where AI could deliver the most substantial time savings (Table 5, Appendix).
Processing efficiency represents perhaps the most immediately evident AI benefit in M&A contexts. Industry research indicates that AI applications can yield faster company and market analysis compared to traditional methodologies. This dramatic acceleration of analytical processes enables transaction teams to evaluate more opportunities within constrained timeframes, potentially identifying valuable acquisition targets that might otherwise remain unexplored.[39]
Enhanced analytical comprehensiveness constitutes another significant AI advantage. Indeed, AI systems are capable of processing vast amounts of diverse data that would take too long for human analysts to manually review. This feature guarantees more comprehensive transaction evaluations that take into account larger data sets, perhaps revealing insights that could not otherwise be found.

[39] Zhishuo, H. (2024) Does AI Adoption in M&A Teams Improve Deal Performance? pp.17-21.

Risk identification represents a critical M&A function where AI demonstrates particular value. According to research, machine learning algorithms while swiftly evaluating enormous volumes of data, can identify hazards that could otherwise go overlooked. In this way, transaction teams may handle possible issues sooner in the process thanks to this improved risk recognition capabilities, thereby preventing expensive shocks later on.[40]

Accuracy improvement represents another significant AI benefit in M&A processes. Recent studies highlighted the effects of artificial agents in evaluating M&A deals, highlighting the potential for these tools to distinguish between value-creating and value-destroying deals. Moreover, the possibility for AI systems to identify financial irregularities, unusual legal clauses, or signs of underperformance in potential acquisition targets was emphasized. This enhanced pattern recognition capability would enable more precise identification of anomalies that might indicate underlying issues requiring further investigation.[41]

Process standardization constitutes an often-overlooked AI benefit in transaction contexts. Grasso observes that M&A is "a very structured business because you know what needs to be done: contracts are almost all the same. The phases are the same, due diligence is done on the same bases, so there's nothing to invent apparently. But humans' ability to grasp cultural, language and strategy nuances can't be replaced by artificial intelligence" (Table 1, Appendix). The processes' standardization makes M&A look particularly suitable for AI applications that excel at executing well-defined analytical methodologies, but it's lacking nuances understanding, as the ones mentioned above, that only a human can recognize.

[40] Pieretti, C., Papanastasiou, D. (2025). GenAI-powered Research Assistant drives significant efficiency gains for financial services industry. Moody's Reports

[41] Mirzayev, E., Vanneste, B., Testoni, M. (2025). Artificial Agents and the Evaluation of M&As.

Despite significant potential benefits, AI implementation in M&A processes faces several substantial challenges that constrain practical application. These limitations span technical, organizational, legal, and philosophical dimensions that collectively moderate the transformative impact of AI technologies in transaction contexts.

Data privacy represents perhaps the most frequently cited challenge in AI implementation. Gabrielli explains that for privacy and data sensitivity reasons, I personally don't feel secure putting sensitive documents into AI systems (Table 2, Appendix). This concern reflects the fundamental tension between AI's data processing requirements and the confidential nature of transaction information.

Data ownership constitutes a related challenge that particularly affects generative AI implementations. Grasso observes that "if I upload sensitive or proprietary data to public domain tools in order to obtain syntheses or reports, the information I uploaded no longer mine, and I have no intention of doing so because I sell that information; I don't make it available for free to these tools" (Table 1, Appendix). This perspective highlights the conflict between proprietary information ownership and AI systems that potentially incorporate training data into broader models.

Both the concerns raised by Grasso and Gabrielli are partially addressed by the CEDPO Institution, whose study highlighted the issues related to the sharing of confidential or personal data and goes through the possible solutions to this issue. Among others, those of Privacy Enhancing Techniques (PETs) and Synthetic data seem to be the most efficient solutions to ensure data ownership and confidentiality but have not yet been implemented.[42]

Accuracy limitations represent another significant challenge in AI implementation. Practitioners report that outputs often require substantial

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[42] CEDPO AI Working Group. (2023). Generative AI: The data protection implications. Confederation of European Data Protection Organisations

verification. Salimbeni describes an example where AI "greatly sped up the process, making the construction of the database and the retrieval of initial information more efficient. Then, I gave it to my team of analysts to complete, verify, and in some cases redo. So, in this case, AI sped up the decision-making process because it helped build a quick initial base of information, but someone still had to work on it because the information was often imprecise and imperfect" (Table 3, Appendix). This experience highlights the practical reality that AI outputs typically require human verification, moderating efficiency gains.

Technical limitations affect current AI implementations in M&A contexts. Grasso explains that "to have the full power of an LLM and maintain data ownership, there is a very high minimum threshold. Today, there are smaller elements with fewer billions of parameters that work and cost less and can function on less powerful servers" (Table 1, Appendix). This technical constraint currently necessitates trade-offs between analytical capability and practical implementation considerations.

Bias potential represents a significant AI risk in M&A applications. Research indicates that AI systems are only as unbiased as the data they are trained on. This presents a challenge in M&A activities, where biased historical data can lead to skewed analyses and decisions. This concern highlights the need for careful consideration of training data characteristics to avoid perpetuating historical biases in transaction analyses.[43]

Regulatory compliance presents an emerging challenge for AI implementation in European contexts. Academic research notes that companies deploying AI tools must make sure that their AI systems comply with the provisions of the recently approved European Union EU AI Act, which lays out criteria for the development and deployment of AI technology. This regulatory dimension

[43] Fu, R., Huang, Y., & Singh, P. V. (2020). AI and algorithmic bias: Source, detection, mitigation and implications. SSRN

introduces additional compliance considerations for transaction teams implementing AI solutions.[44]

Fundamental process limitations constrain AI's transformative potential in certain M&A domains. Grasso emphatically states that "an M&A process cannot be managed only by artificial intelligences; there's no way. A negotiation process cannot be managed by artificial intelligence today; there's no way" (Table 1, Appendix). This perspective highlights enduring human-centric transaction elements that remain beyond current AI capabilities, particularly in negotiation contexts requiring emotional intelligence and relationship management skills.

While data privacy concerns dominate industry discourse, Maturo offers a more balanced perspective on information sharing: 'if there was approval also from the client, I wouldn't see anything wrong with it.' His viewpoint acknowledges the increasing trend toward financial transparency: 'We are moving more and more towards a transparent communication of financial data, but also non-financial ones to the outside' (Table 5, Appendix). This suggests that with appropriate permissions and safeguards, certain data could be shared with AI systems for collective benefit.

Despite current limitations, industry practitioners and researchers anticipate continued evolution of AI applications in M&A processes. This forward trajectory encompasses both technical advancements and cultural adaptations that collectively promise enhanced integration potential.

Technical advancement represents a primary dimension of AI's evolving M&A role. Grasso anticipates that "within some time, we will get there" regarding more sophisticated AI implementations, that will require both regulatory evolutions, to protect proprietary data or sensitive information, and scalability

[44] Artificial Intelligence Act (Regulation (EU) 2024/1689), Official Journal version of 13 June 2024. (Art.2) *Interinstitutional File: 2021/0106(COD).*

of LLMs that will be introduced in the coming months (Table 1, Appendix). This optimistic view reflects the accelerating pace of AI development that continues to yield increasingly sophisticated capabilities and the arising need for workable solutions. Evolving implementation approaches are indeed a core dimension of how AI's will be embedded into M&A processes. Successful AI integration demands a strategic shift in how firms approach M&A operations including: adapting processes, upskilling teams, and fostering a data-driven culture. This perspective highlights the organizational transformation required to fully exploit AI's potential benefits.

Domain-specific applications represent a promising direction for future AI development in M&A contexts. Gabrielli anticipates that "it will be used more in our sector. From now to five years, I don't think there will be particularly significant upheavals in our sector. The work will be more or less the same; we will make more use of artificial intelligence in more operational activities where you need to put less thought into it" (Table 2, Appendix). This assessment suggests continued evolutionary rather than revolutionary AI adoption in M&A processes.

Human-AI collaboration models represent an emerging paradigm that acknowledges the complementary strengths of automated systems and human expertise. This collaborative approach promises to maximize combined analytical capabilities while preserving essential human judgment in strategic decision contexts. Its potential benefits to achieve the complementarity aimed at the beginning of this thesis, along with the barriers that currently prevents AIs to work side by side with humans, will be explained in paragraph 3.4.

Industry-specific customization represents another dimension of AI's implementation's efforts. Salimbeni observes that "given the sector-specific nature, when you do an operation, every sector, every vertical has its dynamics, its niches that can't be uncovered from the outside" (Table 3, Appendix). This perspective highlights the need for specialized AI implementations tailored to specific industry contexts rather than generic solutions.

In conclusion, AI technologies are progressively transforming M&A processes across multiple dimensions while facing significant implementation challenges. Current applications demonstrate particular utility in data-intensive functions including target screening, due diligence analysis, and comparables identification. Benefits include enhanced processing efficiency, analytical comprehensiveness, and risk identification capabilities. Limitations encompass data privacy concerns, accuracy constraints, technical implementation challenges, and fundamental process boundaries in negotiation contexts. Looking forward, continued development promises increasingly sophisticated capabilities while requiring careful attention to regulatory compliance, organizational adaptation, and appropriate human-AI collaboration models.

3.3 AI-Driven Solutions for Crisis Prevention and Management

The conceptualization of crisis within contemporary organizational frameworks has evolved considerably, transitioning from simplistic incident response models to complex, multidimensional approaches that acknowledge the interconnected nature of modern threats. This section synthesizes empirical insights derived from interviews with industry practitioners from Barabino&Partners and an international IT Company and reviewed academic research to present a comprehensive analysis of AI's applications in the Crisis Prevention and Management setting.

Crises, by their fundamental character, represent critical inflection points that necessitate rapid decision-making under conditions of high uncertainty, significant consequence, and often severe time constraints. These high-stakes scenarios demand both strategic foresight and tactical agility, precisely the domains where artificial intelligence systems have demonstrated remarkable potential.

Corporate crises today manifest across multiple typologies, each with distinct characteristics requiring specialized prevention and mitigation strategies. This section focuses on the breadth of crisis management application across various industrial sectors, highlighting both the universality of crisis vulnerability, and the necessity for tailored approaches, aiming to understand how the artificial intelligences could provide support before, during, and after these rare events occur.

In the corporate communication context, crises frequently bifurcate into operational and reputational dimensions, though these categories are inherently interconnected rather than separate. According to Massimiliano Parboni, partner at Barabino & Partners, a corporate communication consultancy: "reputational crises are often triggered by operational crises that can occur in a company, so we think of the classic warehouse fire or, unfortunately, a workplace accident or a natural disaster that may create a physical problem for the company. Often, the way the company reacts to this operational crisis then has a reputational impact on the company" (Table 7, Appendix). This finding highlights how crises can spread outside their origination boundary, with operational failures often leading to reputational harm, especially when organizational response mechanisms fall short of stakeholder expectations or are insufficient.

The crisis landscape has changed significantly as a result of the growth of digital communication channels, with social media platforms increasing the hazards to firms' reputation and speeding up the spread of information. As noted from Parboni, crises can arise "purely in relational contexts; for example, we think of a top manager of a company who makes a mistake and posts something on social media that has a political connotation or creates problems with some stakeholders" (Table 7, Appendix). This scenario illustrates how modern crises can emerge and escalate rapidly within digital ecosystems, requiring organizations to develop sophisticated monitoring and response capabilities that operate at unprecedented speed. In this respect, Artificial Intelligence tools can provide an unforeseen support, but only if properly trained with detailed documentation sets in which firms' KPIs and KRIs are well explained by who is in charge to define them.

Beyond business settings, the diversity of crises may be found in public settings such as national security concerns, healthcare emergencies, and natural disasters. Early warning systems for earthquakes, floods, and wildfires have been made possible by AI-driven predictive analytics models, according to a systematic evaluation of AI-based emergency response systems. This has allowed for proactive disaster preparedness and risk mitigation. This use of artificial intelligence in disaster risk management shows how the technology can handle crises at different scales, from regional disasters to organizational occurrences.[45]

The dynamic nature of crises has been made worse by the emergence of new risk variables, particularly in the context of cybersecurity. As an organization's operations become more digitalized, it is more vulnerable to cyberattacks, which can quickly escalate into catastrophic organizational events.

Furthermore, crises are becoming more widespread across traditional organizational boundaries, resulting in intricate interdependencies that make conventional management techniques more challenging. This complexity is specifically acknowledged in the UK government's approach to AI emergency readiness, which focuses on ways the government may improve its capacity to identify and get ready for urgent national security concerns associated with AI. According to this government perspective, crisis management has evolved into

[45] Bajwa, A. (2025). AI-based emergency response systems: A systematic literature review on smart infrastructure safety. American Journal of Advanced Technology and Engineering Solutions. Pp.*174-200*

interdependent ecosystems that require coordinated stakeholder solutions that cut beyond organizational boundaries.[46]

Consequently, crises have changed from discrete incidents to complex problems characterized by speed, uncertainty, and the possibility for expanding impacts on the organizational and social levels. This progress necessitates the improvement of management tactics, particularly through the integration of AI-driven capabilities that can enhance both response and prevention abilities.

A key paradigm in modern crisis management theory and practice is the division between crisis preparedness and real-time crisis management. According to this distinction, organizational resilience in dealing with of extraordinary circumstances is determined by two separate but complementary phases. The differential application of artificial intelligence across these phases underscores the technology's versatility as both a preventive and responsive tool in crisis contexts.

Crisis preparation encompasses the anticipatory activities organizations undertake to identify potential threats, develop mitigation strategies, and establish response protocols before crisis events materialize. As articulated by Parboni: "We are increasingly working in this phase, and the crisis management work begins before; therefore, in the phase of prevention, let's define it not so much as prevention, because it is often difficult to prevent a crisis, but it can be 'prepared' instead" (Table 7, Appendix). This clarification highlights an important nuance since, while complete prevention may remain elusive for certain crisis types, methodical preparation significantly enhances organizational readiness and response efficacy.

The preparation phase centrally involves the development of comprehensive crisis manuals that codify organizational protocols and decision frameworks, along with other ostensive routines that should be followed while preparing for

[46] Wasil, A., Smith, E., Katzke, C., Reed, T., & Bullock, J. (July, 2024). AI Emergency Preparedness: Examining the UK government's ability to detect and respond to AI-related national security threats. SSRN

a crisis. These manuals represent structured approaches to anticipated scenarios, providing critical guidance during high-pressure situations when cognitive capacity may be compromised. These scripts typically incorporate risk assessments, stakeholder mapping, communication templates, and decision hierarchies customized to organizational contexts.[47]

The customization of crisis manuals represents a critical component of effective management. Parboni noted that crisis manuals are always customized, in the sense that each company obviously has its risk factors, which are the starting point for drafting these crisis manuals. This tailored approach acknowledges the unique risk profiles of different organizations, incorporating sector-specific vulnerabilities alongside universal risk factors. For instance, food industry companies must address specific contingencies around contamination events, while financial institutions prioritize protocols for data breaches or market disruptions (Table 7, Appendix).

By means of better risk assessment and scenario modeling tools, artificial intelligence has shown great promise to improve the preparation phase. As D'Urso observes: "in my opinion, the main areas where investments can be made to implement and improve crisis management capabilities are: the first is having access to documentary datasets, which can be articulated with agents using natural language to access detailed information about predefined processes. The second one is KPIs and KRIs analyses which, having a clear framework of the parameters to monitor, can be used both as sentiment analysis indicators and to create crisis scenarios to train on" (Table 6, Appendix). Through the examination of historical data, environmental variables, and establishing trends, this use of artificial intelligence, specifically of generative AI models, would enable more advanced scenario planning.

[47] Knight, G., & Smallman, C. (2014). Crisis response: Aligning scripts and actors. SSRN.

Real-time crisis management, on the other hand, includes the active response systems which act only once crisis situations evolve. Often, this stage calls for quick decision-making during high uncertainty and time constraints, so businesses must manage several competing objectives at once. The shift from preparation to active management often challenges organizational capacity and reveals fractures in planning assumptions.[48]

The unique difficulties of real-time crisis management become particularly explicit in the cybersecurity field, where handling incidents calls for strategic communication as well as technical knowledge. D'Urso emphasizes how AI systems and their ability to foster automation, categorization, and event correlation can help businesses in this phase by identifying situations that could cause crises. These features allow for faster detection and reaction to developing dangers, perhaps reducing crisis effects before they completely manifest (Table 6, Appendix).

Communication represents a critical component of real-time crisis management, particularly in reputational contexts. Parboni emphasizes how its firm intervenes "when the triggering event of the crisis occurs; from that moment on, there is a need to manage and therefore do real Crisis Management in the strict sense of the word" (Table 7, Appendix). This phase frequently involves stakeholder communication, media engagement, and reputation preservation activities that must be executed with both precision and sensitivity to contextual factors.

The inclusion of artificial intelligence into both the preparation and real-time crises phases marks a major development in crisis management capacity, showing how AI can improve predictive capabilities and offer decision support to the leadership.

[48] Coccia, M. (2020). Critical decisions in crisis management (Working Paper CocciaLab No. 45/2020). CNR – National Research Council of Italy.

The temporal distinction between preparation and real-time management increasingly blurs as AI systems enable more continuous monitoring and dynamic response capabilities. Research on AI-based emergency response systems indicates that "AI-powered computer vision and sensor-based surveillance technologies have improved incident detection, reducing intervention delays and ensuring more efficient allocation of emergency resources".[49] These technologies effectively compress the time between detection and response, creating more fluid transitions between preparation and management phases.

The distinction between preparation and real-time phases thus represents both a conceptual framework and practical reality in crisis management. While artificial intelligence enhances capabilities across both domains, organizations must develop integrated approaches that leverage AI while preserving human judgment and contextual understanding during extraordinary operations.

Artificial intelligence offers a variety of advantages when integrated into crisis management frameworks, many of which work together to increase organizational resilience when dealing with unusual circumstances. These benefits cover both the planning and reaction stages, utilizing AI tools in pattern identification, data processing, and decision support to enhance conventional crisis management techniques.

A primary benefit of AI integration lies in its predictive capabilities, which significantly enhance early warning systems across diverse crisis typologies. Research on AI applications indicates that AI-driven predictive analytics models can provide advanced predictive maintenance signals and real time monitoring capabilities that can foster resilience of firms. This predictive capacity extends beyond natural disasters to encompass corporate crises, where

[49] Bajwa, A. (2025). AI-based emergency response systems: A systematic literature review on smart infrastructure safety. American Journal of Advanced Technology and Engineering Solutions. Pp.*174-200*

AI systems can also identify emerging reputational threats or operational vulnerabilities before they escalate into full-scale crises.[50]

The efficiency gains offered by AI in information processing represent another significant advantage, particularly during time-sensitive crisis scenarios. D'Urso emphasizes that generative AI can certainly support all aspects of prevention related to vulnerability management and knowing which systems are exposed with a higher level of criticality (Table 6, Appendix). This capability enables organizations to rapidly process vast data volumes to identify vulnerabilities and prioritize mitigation efforts based on potential impact severity and exploitation likelihood.

AI systems further enhance scenario development processes, generating more comprehensive and nuanced projections of potential crisis trajectories. As articulated by Parboni: "I believe that in the phase of preparing for a crisis, exploiting generative AI tools can be absolutely crucial. The idea is that you can create a sort of large pool of data and information, that can then return to me some scenario simulations would represent an incredible technological advancement" (Table 7, Appendix). This application of AI enables more sophisticated contingency planning by identifying potential scenarios that might otherwise remain unconsidered in traditional planning approaches.

Parboni further elaborates on this advantage: "Substantially, this is the keyword, 'scenarios', with which humans have more difficulty. Today, I can say yes, of course, there are possible crisis scenarios, but I can only list a few, not all of them. Not all of them come to mind, and especially... I can miscalculate the probabilities with which these scenarios occur" (Table 7, Appendix). This observation highlights AI's capacity to overcome human cognitive limitations in scenario generation, particularly regarding probability estimation and comprehensive identification of potential trajectories.

[50] Almaiman, S. (2024). The impact of AI on maintenance performance and predictions. SSRN.

Communication efficiency represents another crucial benefit, particularly for reputational crisis management. Parboni notes that "AI tools are used intensively because, dealing a lot with communication, writing, and language aspects, it is obvious that this type of artificial intelligence is the one most immediately associated with its use" (Table 7 Appendix). This application streamlines language and communication development and dissemination during crises, enabling more responsive stakeholder communication when timing is critical.

Furthermore, a particularly valuable advantage of AI in crisis contexts lies in its emotional neutrality during high-stress situations. Parboni observed that "artificial intelligence, being an intelligence, lacks sentiment. From a certain point of view, this is its great limitation, but in crisis situations, it could be a great advantage: let's remember that in crisis situations, the biggest problem for humans is emotionality and impulsiveness" (Table 7, Appendix). This emotional detachment enables more objective analysis during crisis events, potentially counterbalancing human tendencies toward panic or decision paralysis under pressure.

For organizations with established crisis management frameworks, AI significantly enhances accessibility to crisis playbooks and procedures. D'Urso highlights this benefit: "having these assistants that, during crisis management, can be asked to extract specific information such as a statement for a specific case that instead of being searched in the documentary package, is automatically provided updated with the specific crisis data by this agent" (Table 6, Appendix). This capability ensures that crisis response teams can rapidly access relevant protocols without manual searching, potentially reducing response times during critical incidents. But, to do so, the artificial intelligence tools should be trained on both private and public information packages, in order to ensure a continuously updated output.

The analytical capabilities of AI further enhance performance measurement during and after crisis events. D'Urso notes that "another interesting element is again the analysis of KPIs and KRIs, because an agent that clearly knows which elements to monitor, both internal and external factors, can rely on generative AI to understand which trends may impact the organization during this type of crisis" (Table 6, Appendix). This application enables more sophisticated impact assessment and adaptive management throughout crisis duration, potentially improving response efficacy through continuous feedback mechanisms.

Artificial intelligence revolutionary potential in post-crisis recovery has garnered more attention in recent academic literature, especially in light of economic shocks, natural disasters, and public health emergencies, emphasizing AI's potential to improve financial resilience, with businesses implementing AI technologies before crises showing quantifiable benefits. An examination of the effects of COVID-19, for example, showed those businesses with AI patents prior to the pandemic had up to 20% greater cumulative stock returns throughout the crisis peak than non-adopters, combined with lower volatility and better operating performance. This resilience stemmed from AI-driven dynamic pricing algorithms, virtual assistants maintaining customer engagement, and machine learning models optimizing supply chain disruptions. All these capabilities enabled firms to adapt rapidly to demand fluctuations and operational shocks.[51]

The benefits extend beyond pandemics to natural disaster recovery. Another study examining firms exposed to hurricanes and earthquakes found that organizations allocating part of their workforce to AI-related roles recovered almost everything of disaster-induced shareholder value losses within six months, compared to the percentages for non-AI firms. The research attributed

[51] El Moujahid, O., Murtinu, S., & Sekerci, N. (2023). Artificial intelligence and firm resilience (pp. 6–24). SSRN.

this to AI's ability to stabilize production processes during turbulence, moderating the sensitivity of output to labor and capital shortages through predictive maintenance and adaptive resource allocation. However, the same study cautioned that underperforming firms often fail to realize these gains fully due to insufficient complementary infrastructure, such as cloud computing platforms or data governance frameworks.[52] This aligns with D'Urso's thought, who states that the executives who are in charge of providing data governance frameworks, must be as detailed as possible, allowing AI-driven tools not to make mistakes once trained on the correct information set (Table 6, Appendix). Parallel research on disaster management underscores AI's role in crisis response optimization. During Hurricane Sandy, natural language processing algorithms analyzing Twitter data achieved unprecedented accuracy in identifying critical resource needs, outperforming traditional survey methods by detecting real-time patterns in requests for water, medical supplies, and evacuation routes. These AI systems enabled emergency responders to prioritize allocations based on geotagged social media posts, reducing redundant deployments and shortening relief delivery times.[53]
Together, these studies demonstrate AI's dual role in post-crisis contexts: stabilizing economic systems through enhanced corporate adaptability while improving disaster response efficacy via real-time data synthesis.

Taken as a whole, these advantages show how AI may revolutionize crisis management by improving capacities during the planning, reaction, and recovery stages. As organizations increasingly integrate these technologies into their crisis frameworks, they potentially achieve more robust resilience against

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[52] Han, M., Shen, H., Wu, J., & Zhang, X. (Michael). (2023). Artificial intelligence and firm resilience: Evidence from firm performance under natural disaster shocks (pp. 3–25). Forthcoming in Information Systems Research.
[53] Khattar, A., & Quadri, S. M. K. (2020). Emerging role of artificial intelligence for disaster management based on microblogged communication. Proceedings of the International Conference on Innovative Computing & Communications (ICICC) 2020.

diverse threats while optimizing resource utilization during extraordinary operations.

Despite the substantial benefits artificial intelligence offers crisis management practices, significant challenges and limitations constrain its implementation and efficacy. These constraints span technical, organizational, and ethical dimensions, collectively moderating expectations regarding AI's transformative potential in crisis contexts.
A fundamental challenge lies in the widespread absence of foundational crisis management frameworks within organizations. D'Urso highlights this concerning reality: "The sad reality is that many organizations, especially in Italy, do not have crisis plans. In the best case, excluding the few percentage points of companies with very high maturity... Most organizations do not have a crisis plan" (Table 6, Appendix). This observation reveals a troubling gap since without basic crisis management infrastructure, organizations lack the foundational elements necessary for effective AI integration. Moreover, this widespread absence of formal crisis frameworks significantly constrains AI's potential value, as the technology augments rather than replaces fundamental crisis management practices.
For organizations that do implement AI in crisis contexts, data quality and availability represent significant technical limitations. D'Urso observes that the first challenge, especially from a technical perspective, is the documentary package or reference data. Without comprehensive, high-quality historical data, AI systems lack the training foundation necessary for accurate prediction and recommendation generation. This limitation particularly affects smaller organizations with limited documented crisis experience (Table 6, Appendix).
The phenomenon of AI "hallucinations", wherein systems generate plausible but factually incorrect outputs, poses particular dangers in high-stakes crisis contexts. Parboni elaborates on this risk: "when there is a big error, a

hallucination, during a crisis when I need to necessarily go out in a press conference within five minutes and make statements. The risk of making them based on incorrect information or a wrong suggestion can lead to worsening the already critical situation" (Table 7, Appendix). This scenario illustrates how AI limitations could potentially exacerbate rather than mitigate crisis impacts if outputs remain unverified, a particularly concerning prospect during rapidly evolving situations with minimal time for validation.

Data privacy concerns represent another significant limitation, particularly regarding sensitive information processing during crises. Parboni notes: "in crisis management, we talk about often very sensitive, delicate information. And it is obvious that knowing exactly the tools we are applying becomes crucial, because if I make the mistake of using the free version of ChatGPT, putting confidential documents in it, I really risk triggering a crisis even worse than the original one" (Table 7, Appendix). This observation highlights how improper AI implementation could introduce secondary risks through data exposure or confidentiality breaches.

D'Urso elaborates on this concern from an implementation perspective: "If the documentary package is deployed is 'on-premise', no. If the deployment is done on the cloud, then the discussion is about how the data is managed on the cloud, despite cloud infrastructures have high security standards" (Table 6, Appendix). This distinction underscores the importance of deployment architecture in addressing privacy limitations, with on-premise solutions potentially offering enhanced security for sensitive crisis data.

User capability limitations further constrain AI efficacy in crisis contexts. D'Urso notes that "a user who deals with artificial intelligence that does not have all the data due to commercial limitations... or due to model biases... thus with an incomplete information to do the question would have an incorrect answer and therefore decrease their confidence in these types of applications" (Table 6, Appendix). This observation highlights how user proficiency in prompt engineering and interpretation significantly impacts AI utility during crisis events.

Studies on explainable artificial intelligence in disaster risk management confirm these constraints by pointing out that present methods have natural obstacles and constraints that have to be resolved to improve explainability and efficacy in critical situtations' decision-making. During crisis circumstances, when decision-maker confidence depends on knowledge of recommendation rationales, this lack of explainability may reduce trust in AI systems.[54]

Cost barriers represent another practical limitation, particularly for smaller organizations. Parboni observes that: "as a small or medium-sized enterprise, could never afford a proprietary model because it has unsustainable costs" (Table 7, Appendix). This economic constraint potentially creates implementation disparities between large corporations with substantial resources and smaller entities with limited technology budgets, despite universal crisis vulnerability.

The integration challenges between AI systems and existing crisis management processes further constrain implementation efficacy. The widespread use of AI in crisis response systems is constrained by issues with interoperability, ethical considerations, cybersecurity flaws, and algorithmic biases. These difficulties and restrictions limit hopes for AI's revolutionary potential in crisis management. Although the technology has many advantages, its successful deployment necessitates filling in basic gaps in user capacity, data quality, privacy protection, and organizational readiness, restrictions that have a big influence on adoption paths in many organizational contexts.

To conclude, the key objectives of artificial intelligence for crisis management in the future will be building predictive analytics, integrating several data

[54] Ghaffarian, S., & Taghikhah, F. (2023). Explainable artificial intelligence in disaster risk management: Achievements and prospective futures.

sources, and strengthening privacy and security policies. Predictive artificial intelligence is expected to enhance scenario modeling by means of probabilistic studies of potential crises and by stressing its revolutionary potential during crisis planning phases. Even if it is still challenging, being able to combine internal documents, historical data, and real-time inputs into unified platforms can enable a more comprehensive crisis analysis. All things considered, artificial intelligence is expected to achieve a considerably wider role in crisis management, but its effective usage will depend on robust governance systems, multidisciplinary collaboration, and the inclusion of human control to ensure moral and efficient use.

3.4 Highlighting the Importance of Human Approval

The inclusion of artificial intelligence into mergers and acquisitions initiatives and crisis management indicates an important shift in how companies manage challenging decision-making activities. Despite AI technologies have grown, their use in these critical areas constantly stresses a fundamental concept: the necessity for human approval, oversight, and intervention. This section will look at the current stage of human-AI cooperation techniques as well as the benefits, challenges, and future expectations for this evolving relationship.

The way AI is now being used in M&A procedures shows caution, with human specialists still having a major say in important choices and using AI for certain, defined jobs. According to Grasso, the application of AI in M&A is primarily concentrated in the preliminary phases: “The first thing and the first phase in which AI serves greatly today is the analysis of comparables, targets, and multiples” (Table 1, Appendix). This selective application reflects broader trends observed in the financial industry, where AI adoption has been most successful in data-intensive tasks with clearly defined parameters.

Gabrielli, further emphasizes this selective application: “I use it more in the pre-due diligence phase. When we are about to analyze an investment opportunity, we do market studies and sector studies, and there it is useful for me to use AI tools to map the market and sector” (Table 2, Appendix). This approach strengthens the assumption that AI tools in financial operations tend to be deployed most effectively in research-oriented and data aggregation tasks rather than in judgment-intensive decision-making.[55]

In crisis management, AI implementation follows similar patterns of selective application with strong human oversight. D’Urso notes that AI has been used for decades in crisis management contexts because it allows optimization, categorization, and correlation of events that can lead to incidents that can lead to crises (Table 6, Appendix). This historical application has primarily focused on information processing and pattern recognition rather than autonomous decision-making, which remains firmly in human hands.

Current AI deployment in both domains reveal a consistent pattern: organizations utilize AI as a supportive tool that augments human capabilities rather than as an autonomous decision-maker. This pattern is consistent with what researchers termed the “augmented intelligence” in AI implementation, where the technology enhances rather than replaces human judgment and efforts.[56] Salimbeni articulates this philosophy clearly: “AI can never replace human decision-making. What AI can do is speed up and make more efficient and effective the processing of data, the preparation of tables, low-level work involving large quantities” (Table 3, Appendix).

The technological infrastructure supporting these human-AI collaborations varies significantly across organizations. Large corporations often develop proprietary solutions that address specific needs while maintaining data

[55] Huang, A. H., & You, H. (2022). Artificial intelligence in financial decision making. Handbook of Financial Decision Making (Forthcoming). HKUST Business School Research Paper No. 2022-082

[56] Sadiku, M. N. O., Ashaolu, T. J., Ajayi-Majebi, A., & Musa, S. M. (2021). Augmented intelligence. International Journal of Scientific Advances, 2(5), 772–776.

security. As D'Urso explains: "My company has a very high attention to data sensitivity and confidentiality. So, for example, the artificial intelligence platform can be implemented 'on-premise' within the organization's infrastructure, consequently, the data never leaves the organization" (Table 6, Appendix). This approach addresses one of the primary concerns limiting broader AI adoption in sensitive domains.

In contrast, smaller organizations typically rely on publicly available AI tools with additional layers of human verification. Gabrielli notes that at his organization, "We are free to use the artificial intelligence tools available on the market. In my work, I often use ChatGPT. We do not yet use artificial intelligence systematically within the company" (Table 2, Appendix). This bifurcation in approaches, proprietary systems for large enterprises versus public tools with heightened oversight for smaller organizations, reflects the economic realities of AI implementation and the considerable investment required for customized solutions.[57]

The procedural integration of AI across both domains follows what researchers describe as a human-in-the-loop model, where AI systems provide recommendations or analysis that human experts must explicitly approve before implementation.[58] This model is particularly evident in Andrea Maturo's description of market analysis processes: "If we go to research a sector with comparables, target screening, and market indices and so on through databases, we can take 1 hour or 2 hours... So, the simplification that this type of technology gives you is huge" (Table 5, Appendix). However, he also emphasizes that these outputs invariably require human verification and refinement.

[57] Wilson, H., & Daugherty, P.R. (2018). Collaborative intelligence: Humans and AI are joining forces to solve business problems and create value together. Harvard Business Review, 96(4), 114–123

[58] Mosqueira-Rey, E., Hernández-Pereira, E., Alonso-Ríos, D., Bobes-Bascarán, J., Fernández-Leal, Á. (2022). Human-in-the-loop machine learning: a state of the art. Artificial Intelligence Review. 56. pp. 3020-3025

In crisis management, the human-in-the-loop model is even more pronounced due to the high-stakes nature of decisions. D'Urso emphasizes that during crises, "leadership must still have a clear understanding of what is happening and be able to make decisions with the most data available" (Table 6, Appendix). AI systems can indeed provide data aggregation and analysis functions, but the critical decisions remain firmly in human hands.
Cautious integration with significant human control best describes the present stage of human-AI cooperation in both fields. This strategy fits with more general patterns in high-stakes decision-making areas, where companies want to use artificial intelligence capabilities even as human judgment remains the last decision-maker.[59]

Combining artificial intelligence features with human knowledge provides great advantages in M&A activities as well as crisis management. These advantages go beyond efficiency increases to encompass qualitative changes in results and decision-making procedures as will be highlighted below.
In M&A contexts, the primary benefit of human-AI collaboration is the dramatic acceleration of preliminary analysis phases. Grasso explains that AI tools "greatly help our analysts, but unfortunately or luckily, they are not capable of replacing them yet" (Table 1, Appendix). This acceleration allows analysts to focus their attention on higher-value activities requiring human judgment and expertise. Salimbeni provides a concrete example of this acceleration: "We're doing a mapping of competitors that install stairlifts and elevators, a list of 151 players. We gave it to OpenAI to map whether they sell only stairlifts or also elevators and if they sell platforms... The mapping was very quick because it did the work that an analyst might do in half a day" (Table 3, Appendix). While he notes that the output required human verification, the

[59] Jarrahi, M.H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision-making. Business Horizons, 61(4), 577–586

initial time savings were substantial. This pattern of significant efficiency gains in specific, well-defined tasks is consistent with researchers analysis of AI's economic impacts, which emphasizes the technology's strength in firms' operations with clear parameters.[60]

Beyond efficiency, human-AI collaboration in M&A can enhance analysis quality through improved pattern recognition across large datasets. The ability to identify patterns and relationships that might escape human attention represents what practitioners' term analytical intelligence, where AI excels at discovering non-obvious correlations within complex datasets.[61]

In crisis management, human-AI collaboration offers distinct benefits centered on rapid information processing and objectivity. As D'Urso explains, AI systems help with collecting unstructured information and extracting KPIs or KRIs for direct evaluation, providing crisis managers with synthesized information essential for effective decision-making (Table 6, Appendix). This capability is particularly valuable during crises, when information overload can impair human decision-making.

Parboni highlights another unique benefit of AI in crisis contexts: emotional detachment. "In crisis situations, the biggest problem for humans is emotionality and impulsiveness. In this sense, artificial intelligence has this huge advantage, removing all those aspects of emotionality that surround us and do not allow us to reason with a clear mind" (Table 7, Appendix). This emotional neutrality can provide a valuable counterbalance to human decision-makers, who may be influenced by stress, fear, or other emotions during crises.

The complementarity between human and AI capabilities creates what researchers termed collaborative intelligence, where each party contributes

[60] Filippucci, F., Gal, P., Jona-Lasinio, C., Leandro, A., & Nicoletti, G. (2024). The impact of artificial intelligence on productivity, distribution and growth: Key mechanisms, initial evidence and policy challenges (OECD Artificial Intelligence Papers No. 15). OECD Publishing

[61] Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service: A customer service revolution. Journal of Service Research, 21(2), 155–172.

distinct strengths to the partnership. Humans provide contextual understanding, ethical judgment, and interpersonal skills, while AI systems offer computational power, pattern recognition, and consistency.[62] Grasso illustrates this complementarity when discussing due diligence: "When you need to examine, for example, the pay stubs of 1,000 employees to see if they were correctly accounted for, the auditing firm takes two interns and puts them there for four days to flip through pay stubs. While a tool can scan it, put it in, and the artificial intelligence will do it easily, but you still need to recheck" (Table 1, Appendix).

Human-AI collaboration also enhances organizational capabilities for scenario planning and anticipation, particularly valuable in both M&A strategic planning and crisis preparation. Parboni emphasizes this benefit in crisis contexts: "I strongly believe that in the phase of preparing for a crisis, some tools like predictive AI can be absolutely crucial. The idea is that you can create a sort of large pool of data and information that are made available to a mechanism that can then return to me, depending on my company, what it does, what its mechanisms are, how it operates, some scenarios" (Table 7, Appendix). This capability would be critical for organizational resilience, where the ability to anticipate and prepare for multiple potential futures plays a pivotal role.

Laura highlights a practical benefit for workforce management: "The analyst does many low-value-added things. All that apprenticeship serves. One can have various points of view; maybe it still serves. In any case, if there's a tool that helps me and I can spend my time more efficiently, it would be great" (Table 4, Appendix). This quality-of-life improvement for workers represents another potential benefit for human-AI collaboration, where technological efficiency gains translate into improved work-life balance rather than workforce reductions.

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[62] Wilson, H., & Daugherty, P.R. (2018). Collaborative intelligence: Humans and AI are joining forces to solve business problems and create value together. Harvard Business Review, 96(4), 114–123

Importantly, the benefits of human-AI collaboration extend beyond the operational level to include strategic advantages. As D'Urso explains: "effective AI integration can provide a clear, reliable, and trustworthy informational framework that translates a series of quantitative and qualitative information into CRIs, enhancing leadership's ability to make informed decisions" (Table 6, Appendix). This improved decision support system fits with the notion of augmented intelligence, in which technologies increase human cognitive capacity without substituting human judgment.[63]

Even if the advantages cited above are impressive, human-AI collaboration in M&A and crisis management still presents various challenges and limitations that must be thoughtfully addressed. These challenges spanning between organizational, ethical, economical, and technical, show how difficult it is to properly include artificial intelligence in contexts involving significant choices. A primary technical challenge is the insufficient accuracy of current AI systems when handling complex or ambiguous tasks. Salimbeni describes this limitation clearly: "I did a massive download, and I had OpenAI create an Excel file directly with the company names in rows and three columns indicating yes or no for these products. The mapping was very quick because it did the work that an analyst might do in half a day, but it was very imprecise because it could only look at the website up to a certain point" (Table 3, Appendix).
Maturo reinforces this concern regarding current database tools: "When you do this type of research without then adding the consultant support, often totally distorted data arrive that have nothing to do with what you have in mind or with what is the reference sector" (Table 5, Appendix). This limitation necessitates significant human oversight, potentially negating some efficiency gains from AI deployment. Researchers have documented this phenomenon, noting that

[63] Sadiku, M. N. O., Ashaolu, T. J., Ajayi-Majebi, A., & Musa, S. M. (2021). Augmented intelligence. International Journal of Scientific Advances, 2(5), 772–776

the need for extensive human verification can create a supervision tax that reduces the net benefits of automation.[64]

In crisis management contexts, the risk of AI inaccuracy becomes particularly acute. Parboni notes: “There are also problems in crises and applications of artificial intelligence, and we think of reliability with the theme of hallucinations. And if it is true that when I need to design a claim for an advertising campaign and do not get the right result, I can have it redone a hundred times until I am satisfied. It is a problem when there is a big error, a hallucination, during a crisis when I need to necessarily go out in a press conference within five minutes and make statements” (Table 7, Appendix). This concern highlights the critical obstacle biases represent in AI systems, emphasizing the need to predict and constrain the magnitude of potential errors, particularly in high-stakes contexts.

Data privacy and security represent another significant challenge. Grasso articulates this concern when discussing the potential use of LLMs for analyzing equity research: “The ideal would be to have a Large Language Model that based on public information plus our private equity research information, answers our clients’ questions of any kind from that database... Why don’t we do it? Because our information is proprietary! And if I give it to public domain tools, it’s no longer mine, and I have no intention of doing so because I sell that information” (Table 1, Appendix).

Gabrielli echoes this concern from a private equity perspective: “For privacy and data sensitivity reasons, I personally don’t feel secure putting sensitive documents...” (Table 2, Appendix). The reluctance to share sensitive information with external AI systems creates an implementation gap, where

[64] Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. Management Science, 64(3), 1155–1170

theoretical AI capabilities remain unrealized due to practical constraints along with the challenges mentioned above.

The economic barriers to advanced AI implementation represent another significant challenge, particularly for smaller organizations. Grasso highlights this issue when discussing proprietary LLMs: “To maintain proprietary data, we would need a Large Language Model that runs only on our servers, so the problem is that it would cost millions of euros” (Table 1, Appendix). This economic constraint creates both an adoption limitation and a potential source of increased market concentration, where only large organizations can fully leverage AI capabilities.

Laura further emphasizes the cost-benefit considerations that constrain AI adoption: “In the banking sector for every investment you make, you have to demonstrate that it’s remunerative, so it depends. It depends on seeing how much it improves the firm, what the savings are. Assuming I have to find something that maybe I need to develop internally with high standards so it can work well, but what are the actual savings if, in the end, I still need ten analysts?” (Table 4, Appendix).

Perhaps the most fundamental limitation lies in AI’s inability to handle the qualitative, interpersonal dimensions of both M&A and crisis management. Gabrielli emphasizes this limitation in the M&A context: “Dynamics like understanding if a company’s management is good or not, or some corporate governance issues when making an investment, are themes that artificial intelligence cannot yet address” (Table 2, Appendix).

Laura provides a similar assessment: “If you need to do a more complex operation where nothing repeats, each one different from the other, no. I think AI can help in all sorts of analyses supporting some more quantitative elements rather than qualitative ones” (Table 4, Appendix). This limitation aligns with researchers' analysis of task automation potential, which identifies socially complex tasks as particularly resistant to technological substitution.[65]

Parboni highlights the risks of uncontrolled AI adoption: "Companies must do a lot of training on this, especially for their own employees. According to me, they must be quick to adopt internal policies that do not exist today, which prevent individuals from using ChatGPT, Perplexity, or whatever each person finds available. The risk can be that, with a consequent lack of homogeneity in the results, there are also problems, as we said before, of privacy or data security" (Table 7, Appendix). This concern reflects how uncoordinated AI adoption across an organization can create significant risks or worsen an ongoing crisis.

Cultural and linguistic barriers also constrain AI effectiveness in international contexts. Taurelli Salimbeni notes: "Regardless of the AI tool used, you have to consider that the language factor also plays a role, because for example, ChatGPT can be spoken to in Italian and works well. However, its native language is not Italian, so it has different efficiency and effectiveness, even if just analyzing local websites" (Table 3, Appendix). This observation aligns with the need to develop cross-cultural and multilingual capabilities as significant frontiers for AI development.

Future expectations focus on the evolution of more specialized AI solutions designed for particular fields rather than general systems. Industry professionals expect to to have at their disposal private Language Models that can run on restricted, proprietary information domains while preserving security and privacy. At the same time, there is general agreement that further AI usage in high-stakes contexts like crisis management and M&A transactions

[65] Frey, C., & Osborne, M. (2017). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254–280.

depends on strong governance structures. The technological evolution is anticipated to follow a calculated course whereby gatekeepers to broader deployment include reliability and trust.

To systematically modify processes, organizations will increasingly embrace strategic approaches to AI integration, such as establishing specialized leadership positions like Chief Digital Officers (Table 2, Appendix). AI is expected to perform well in data-intensive preliminary tasks like information analysis, scouting, origination, and routine due diligence, while humans will continue to be prioritized for intensive tasks. This expected task distribution between humans and AI will be consistent across domains. While maintaining human oversight on crucial decisions, this selective automation adheres to efficiency standards. Given the cross-functional nature of successful AI implementation, interdisciplinary cooperation between technical specialists and domain experts is probably going to become the norm.

Future M&A and crisis management strategies will still heavily rely on human judgment, even with the expected technical breakthroughs. The complex nature of negotiations, cultural considerations, and emotional intelligence represents an enduring domain of humans. Industry professionals constantly assert that although AI will revolutionize information processing workflows, relationship management, strategic judgment, and contextual understanding will still be dominated by human expertise. The growing body of opinion points to a human-AI hybrid model in which the lines separating technical and human responsibilities are flexible and complementary rather than hostile, with each bringing unique qualities to organizational results.

3.5 Conclusion

A new era of efficiency, accuracy, and strategic insight has been brought about by the incorporation of artificial intelligence into high-stakes corporate operations. However, this has also brought about complicated difficulties that require cautious handling. The significance of artificial intelligence in both mergers and acquisitions and crisis management has been thoroughly examined in this chapter, underscoring its transformative potential while emphasizing the persistent need for human oversight. AI's ability to enhance data-driven decision-making, its role in mitigating risks through predictive and responsive capabilities, and the critical interplay between technological systems and human judgment are the three core themes emerged from the previous sections. AI integration has fundamentally reshaped the M&A lifecycle, particularly in pre-due diligence, target screening, due diligence, and valuation analysis. The capacity of AI to process extensive datasets has revolutionized target identification, enabling organizations to explore global markets for opportunities aligned with strategic objectives. By automating the analysis of financial statements, market trends, and sector-specific data, AI has significantly reduced the time required for initial evaluations, from days to mere hours, allowing professionals to focus on higher-order strategic tasks.

Because of this acceleration, human analysts can concentrate on higher-value jobs that AI is now unable to perform, such assessing management competency or cultural fit.

AI tools are excellent at document analysis, risk assessment, and anomaly detection in due diligence. To identify possible liabilities, such as concealed financial irregularities or non-compliant terms, machine learning algorithms can examine regulatory filings, contractual agreements, and historical performance data. However, practitioners stress that because AI systems can misread contextual nuances or produce partial insights, their outputs need thorough human verification. For example, although AI is capable of quickly classifying and ranking documents, it is yet unable to evaluate the strategic alignment of a target's company culture or synthesize qualitative insights from stakeholder interviews.

AI's ability to recognize patterns has also helped in the valuation analysis phase, especially when it comes to finding similar businesses and improving financial forecasts. AI systems create more accurate benchmarks for measures by evaluating global datasets, which minimize the need for faulty manual selections. However, because many valuation multiples are still privately held, getting proprietary data continues to be difficult, which restricts the comprehensiveness of AI-driven analysis.

Despite these advancements, AI adoption in M&A faces systemic barriers. Data privacy concerns dominate industry discourse, with practitioners reluctant to share sensitive information with public-domain AI platforms due to risks of intellectual property leakage. Regulatory frameworks, such as the EU AI Act, further complicate implementation by imposing strict requirements on data governance and algorithmic transparency.[66] These constraints highlight the need for secure, proprietary AI solutions, a resource currently accessible only to large firms with significant financial and technical resources.

AI has also changed crisis management practices, especially during the planning and real-time response stages. Organizations may discover vulnerabilities, create contingency plans, and model various crisis scenarios with predictive analytics. AI-driven risk assessments, for instance, can simulate the ripple effects of operational interruptions on financial and reputational outcomes, such as supply chain breakdowns or cybersecurity breaches. By using these technologies, businesses can reduce response times during real crises by proactively allocating resources, creating communication templates, and establishing decision-making rules.

AI can improve situational awareness during current crises by aggregating and analyzing data in real time. While machine learning models rank replies according to impact and severity, natural language processing tools keep an eye

[66] Artificial Intelligence Act (Regulation (EU) 2024/1689), Official Journal version of 13 June 2024. (Art. 2) *Interinstitutional File: 2021/0106(COD).*

on internal communications, news sources, and social media to identify new risks. AI systems in cybersecurity can automatically categorize issues, correlate security events, and suggest mitigation techniques, allowing for quicker breach containment. Significantly, AI's emotional neutrality serves as a vital counterbalance to human decision-makers, who could be prone to cognitive errors brought on by stress in high-pressure situations.[67]

But there are clear limitations to AI in crisis situations: when unreliable AI suggestions are used to inform urgent decisions, such as public pronouncements or evacuation orders, hallucinations pose serious risks. Furthermore, the majority of small and medium-sized businesses lack crisis plans, and many organizations lack the fundamental infrastructure needed for successful AI integration. Poorly documented previous crises or disjointed internal databases restrict the amount of training data available for prediction models, which further reduces the effectiveness of AI.

A common theme in both M&A and crisis management is that although artificial intelligence is great at improving human abilities, it cannot replace human expertise in understanding context, ethical judgment, and relationship building. Especially for positions requiring innovative thinking, stakeholder management, or negotiation, the human-in-the-loop idea remains vital.[68] AI, for instance, can generate the initial outreach emails during M&A target screening;, but human refinement will be required for the deeper interactions in order to manage cultural sensitivities or build rapport. Similarly, even when driven by sentiment analysis generated by artificial intelligence, crisis communication strategies would need human empathy to fit external message with stakeholder expectations.

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[67] Jarrahi, M.H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision-making. Business Horizons, 61(4), 577–586

[68] Mosqueira-Rey, E., Hernández-Pereira, E., Alonso-Ríos, D., Bobes-Bascarán, J., Fernández-Leal, Á. (2022). Human-in-the-loop machine learning: a state of the art. Artificial Intelligence Review. 56. pp. 3020-3025

AI's current technical limitations help to strengthen this cooperative dynamic. Past data-derived algorithmic biases might affect valuation models or target M&A recommendations, hence demanding human oversight to preserve equity and strategic alignment. While for crisis management, the explainability gap, AI's inability to openly justify its recommendations, undermines the confidence of decision-makers, particularly in cases where safety is at risk. Practitioners emphasize that artificial intelligence should only be used to assist significant decisions and that people should still have last say over such decisions.

Future advances in privacy-preserving technology and domain-specific applications will enhance AI's involvement in exceptional activities. Target selection and due diligence in M&A will be more accurate with sector-specific AI technologies tailored to particular sectors and trained on proprietary data sets, according to the practitioners interviewed. Although its use calls for significant computational resource investment, safe Language Models could reduce data privacy issues by handling sensitive data inside company firewalls(Table 6, Appendix).

Strong early-warning systems can be developed for crisis management by training AI tools with defined governance frameworks, focusing their attention on specific KRIs and KPIs. Moreover, providing Language Models exact documentation bundles can help them generate crisis scenarios more, so improving the preparedness of companies.

Organizations would have to prioritize employee upskilling if they are willing to completely deploy artificial intelligence technologies. Training courses stressing data interpretation, prmpt engineering, and ethical artificial intelligence use will help to close the gap between technical skills and needs. Authorities should also develop consistent policies for AI governance that balance incentives for innovation with safeguards against misuse.

The integration of artificial intelligence into extraordinary corporate activities shows an important shift rather than only a technical development. Although artificial intelligence can increase analytical accuracy and efficiency in M&A, it cannot substitute the strategic intuition required for successful operations. Even if it often fails under unexpected situations or presents ethical issues, it offers unparalleled speed in resource allocation for crisis management and threat identification. Successful implementation in both domains is therefore based on the synergy between human knowledge and artificial intelligence capabilities.

Companies negotiating this evolving environment should resist the need to pursue total automation and instead focus on strategic augmentation, thereby employing artificial intelligence technologies to handle data-intensive, repetitive activities while preserving human knowledge for judgment-based decisions. Future successes will depend on investments in safe artificial intelligence infrastructures, the creation of hybrid competencies, and the encouragement of continous learning cultures. By following these ideas, companies should guarantee resilience in an increasingly complex and uncertain corporate environment, so maximizing the revolutionary power of artificial intelligence while minimizing its hazards.

CHAPTER 4

4.1 Introduction

Artificial intelligence provides formerly unreachable chances to increase production, accuracy, and continuous development as discussed in earlier chapters, but businesses still struggle with technical difficulties and continue to seek for competitive advantages in today's rapidly evolving industries. The use of artificial intelligence into daily operations has caused a fundamental shift in how companies approach strategic planning, operations management, and decisions making. This chapter investigates the several ways artificial intelligence is being applied in ordinary operations, considering both the theoretical background and practical uses transforming how companies run today.

Using artificial intelligence in ordinary operations refers to the application of artificial intelligence systems able to learn from data, identify trends, forecast outcomes, and adapt to evolving circumstances, tasks that previously required humans. In progressive firms, operational infrastructure has become vital as artificial intelligence has developed beyond experimental applications. A comprehensive report on artificial intelligence use shows that, indeed, AI is already part of companies' digital transformation projects offering tools for market research, decision-making assistance, and business model and process innovation.[69]

The integration of artificial intelligence into ordinary operations involves many functional areas. Indeed, AI applications go beyond simple automation to encompass supply chain efficiency, quality control, advanced analytics,

[69] Brock, J. K., & von Wangenheim, F. (2019). Demystifying AI: What Digital Transformation Leaders Can Teach You about Realistic Artificial Intelligence. *California Management Review, 61,* 110-134.

predictive maintenance, and enhanced customer service. These applications are complex, context-dependent, and require close consideration of corporate objectives and requirements.

Process improvement represents one of the most significant fields where artificial intelligence deployment could be helpful. A study on the use of artificial intelligence in the service industry reveals that companies might gain from higher production and quality by means of AI process improvement. AI-driven process improvements could also transform traditional operating methods by identifying inefficiencies, simplifying processes, and enabling data-driven decision-making. But many elements affect the level of automation; most notably, the first process's acceptance and the deployment of improvement tools.[70]

Integration of artificial intelligence has additionally greatly improved supply chain management operations. Especially in the field of risk assessment, the revolutionary advantages of artificial intelligence, machine learning models, and hybrid techniques are significantly raising supply chain accuracy. By forecasting potential interruptions, enhancing inventory levels, and proactively responding to changing market conditions, these technical developments would enable companies to raise organizational resilience.[71]

For many of the companies today, implementing artificial intelligence in operations is not just a technological development but also a strategic need since most of them are using cutting technologies or increasing their investment in AI systems. The increasing acceptance of artificial intelligence is a reflection of the increasing awareness of its capacity to create competitive advantages and solve operative issues. The speed of successful implementation differs greatly

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[70] Kocerova, S., Kalkis, H., Roja, Z. (2024). Process improvement with AI in service industry: case studies. In: Henrijs Kalkis and Zenija Roja (eds) Social and Occupational Ergonomics. AHFE (2024) International Conference.

[71] Jahin, M. A., Naife, S. A., Saha, A., & Mridha, M. F. (2023). AI in supply chain risk assessment: A systematic literature review and bibliometric analysis. arXiv

between sectors and company sizes when deciding whether or not to use artificial intelligence into business processes.

Despite its incredible potential, the use of artificial intelligence in operations has raised significant challenges in data security, model interpretability, and output quality. Moreover, the lack of knowledge on this subject causes a disparity between the theorical potential and the real use of artificial intelligence in corporate operations. Academic research underlines the need for safe data management, understandable artificial intelligence models, and robust data governance systems in order to overcome these constraints. In regulated industries, where the requirement to follow rules complicates AI implementation, these elements become particularly relevant.[72] Integrating artificial intelligence in operations is said to be most limited by proving financial value, a lack of infrastructure to enable use cases, and a dearth of qualified AI professionals. Thus, the effective incorporation of artificial intelligence into regular operations calls for not only technical infrastructure but also organizational readiness, suitable governance systems, and strategic goal alignment.

The AI systems' popularity in ordinary operations is expected to evolve along with companies' ability to develop complex implementation strategies and technological developments. Recent research indicates that artificial intelligence is always changing in tandem with technology developments and economic conditions. To further innovate industry-wide procedures and free up professionals to focus on more complex analyses and strategic decision-making, AI is generally integrated with other cutting-edge technologies like blockchain and robotic process automation. [73]

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[72] Brock, J. K., & von Wangenheim, F. (2019). Demystifying AI: What Digital Transformation Leaders Can Teach You about Realistic Artificial Intelligence. *California Management Review, 61,* 110-134

[73] Franca, O., Ayinla, B.S., Ndubuisi, N.L., Atadoga, A., Asuzu, O.F., Ugochukwu, C., & Adeleye, R.A. (2024). Enhancing accounting operations through cloud computing: A review and implementation guide. *World Journal of Advanced Research and Reviews*.

Later sections of this chapter will cover more specific aspects of artificial intelligence in ordinary operations as follows: Section 4.2 will examine applications in development, process improvement, and cost monitoring using comprehensive case studies and theoretical frameworks; Section 4.3 will investigate the possible benefits of adopting artificial intelligence, stressing efficiency, precision, and continuous improvement in operational environments; Section 4.4 will address the risks of using artificial intelligence as well as mitigating strategies such bias monitoring and business goal alignment. Finally, Section 4.5 will offer concluding comments on the application of artificial intelligence in ordinary operations and review the most significant results.

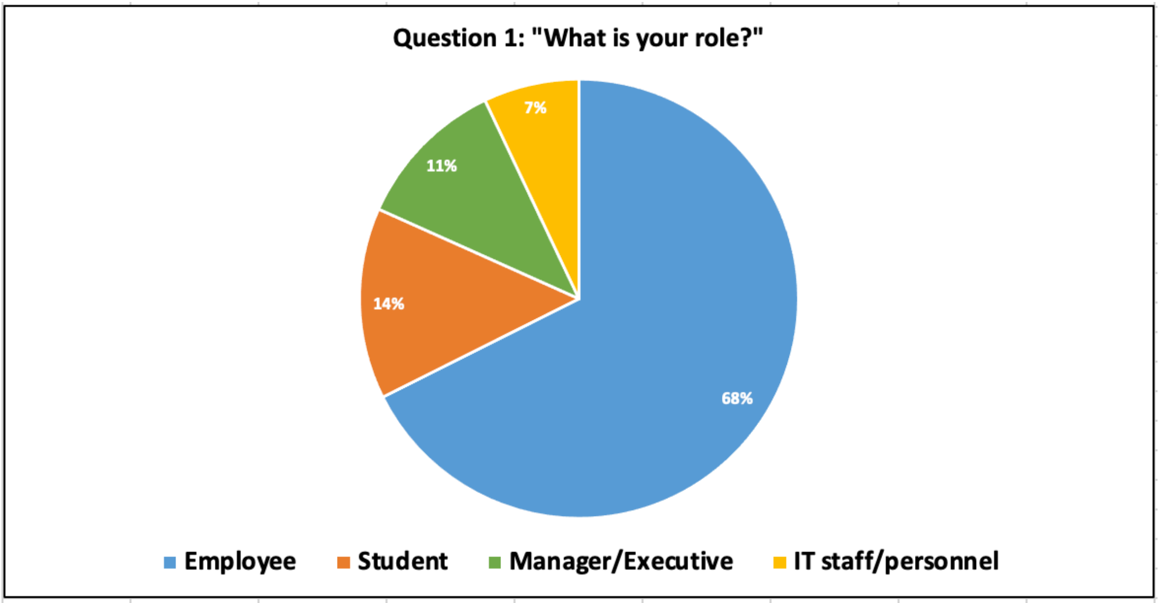
Empirical data from a quantitative survey provided to 71 practitioners and students from several sectors will support the theoretical findings presented in this chapter. The results of this study will provide interesting insights on how AI is currently being used, its perceived benefits, the common challenges experienced, and the future plans for AI in operations. This experimental component will improve the chapter’s contribution by highlighting realistic elements that may not be sufficiently addressed in the present research.

Ultimately, this chapter tries to provide a complete image of how AI is altering the ordinary operations processes and what companies can do to properly use its potential by combining theoretical ideas from academic research with practical evidence from survey data.

4.2 Current Role of AI in Ordinary Operations

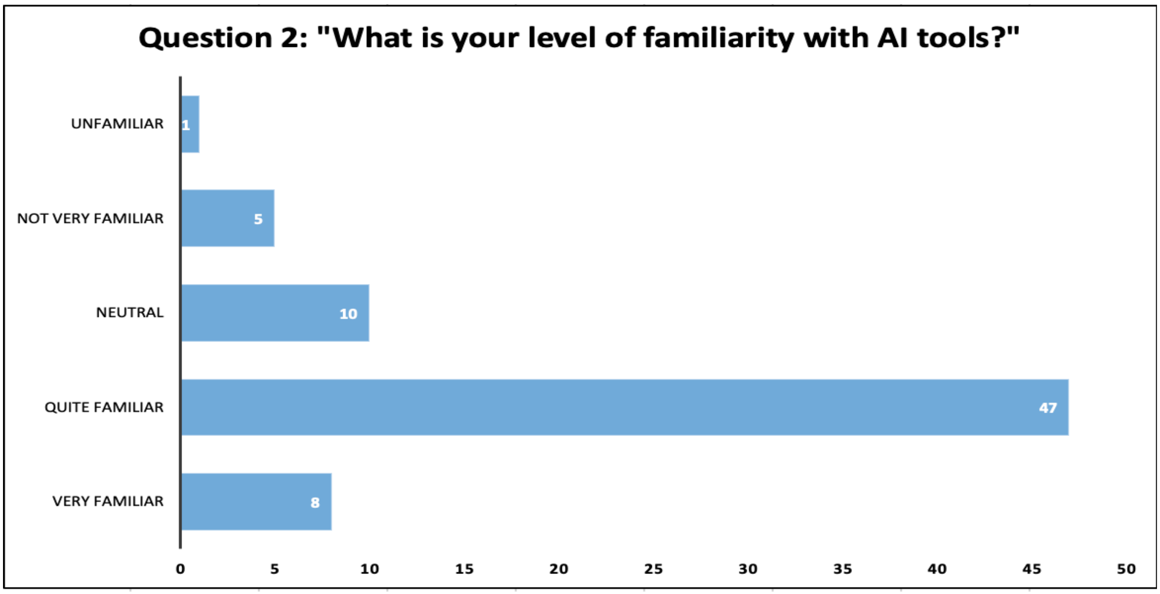
The integration of artificial intelligence into ordinary operations reflects a significant shift in how companies run their activities. This section investigates the actual implementation of AI systems in ordinary operations across several sectors using both theoretical frameworks from academic literature and empirical evidence from survey data. Examining the actual use of artificial intelligence in operations management will provide important insights on adoption patterns, implementation challenges, and the revolutionary potential of these technologies. Moreover, being focused on the uses of AI technologies in process automation, data analysis, customer service, inventory control, and decision-making processes, this section will offer a comprehensive understanding of the state of AI in ordinary operations.

To establish a foundational understanding of AI's current role in ordinary operations, it is essential to first consider the demographic context of survey respondents. The survey reveals a diverse cross-section of professional roles, with 68% identifying as employees, 14% as managers or executives, 11% as students, and 7% as IT staff or personnel (Question 1). Offering insights from various perspectives, this distribution gives a thorough picture of AI perception and use across several organizational levels.



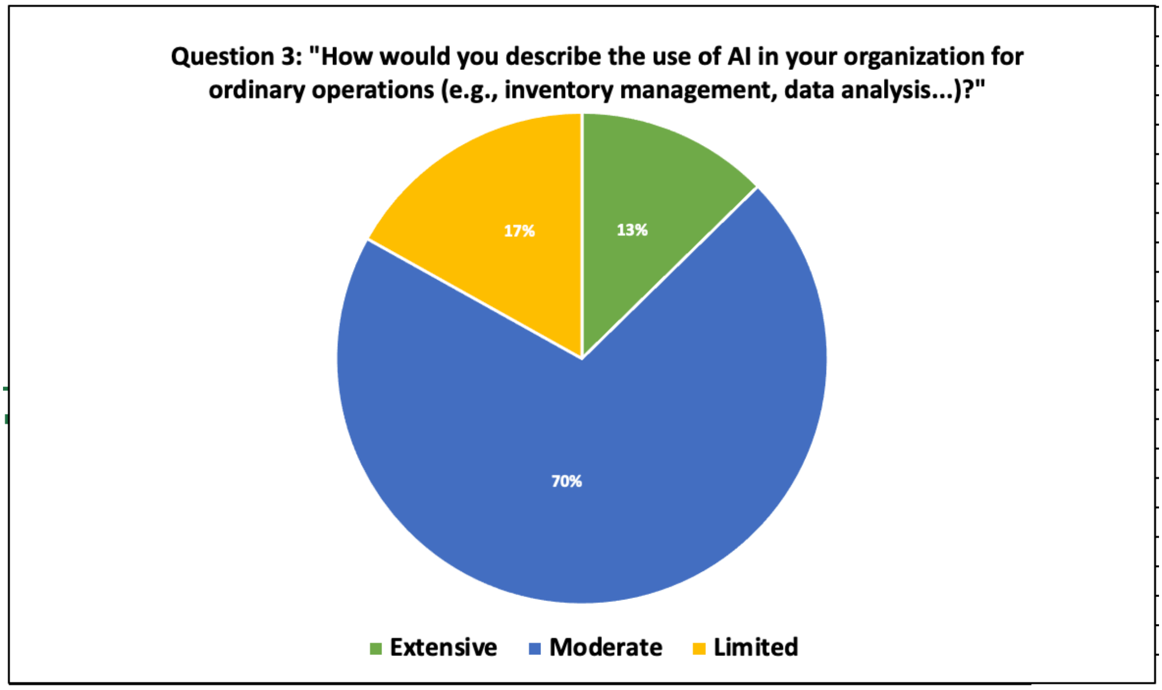
The survey further reveals interesting patterns regarding AI familiarity among participants. The majority of respondents (47) consider themselves Quite Familiar with AI tools, with smaller numbers reporting themselves as Very

Familiar (8), Neutral (10), Not Very Familiar (5), or Unfamiliar (1) (Question 2). This suggests that the survey participants exhibited a moderate level of artificial intelligence knowledge, which could affect their view on AI use in their organizations. As will be discussed in more depth, this personal knowledge does not necessarily translate into corporate adoption.

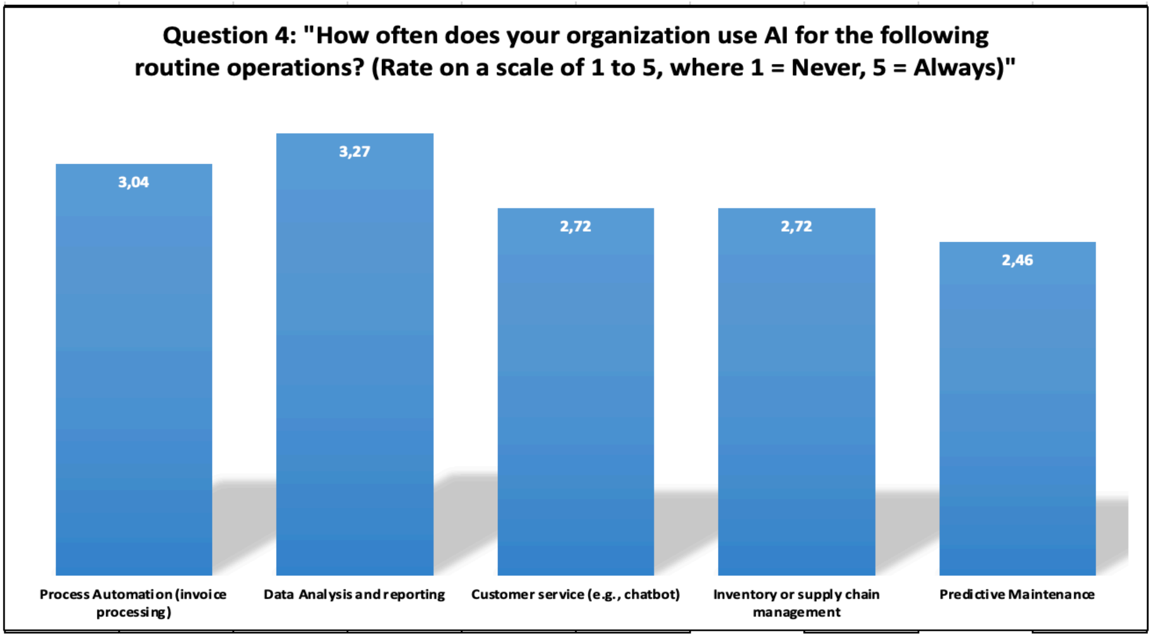


When asked about the extent of AI usage in their organizations for ordinary operations, 70% of respondents indicated Moderate use, while only 13% reported Extensive use and 17% answered Limited use (Question 3). This result confirms recent scientific studies suggesting that, despite the growing interest in artificial intelligence technologies, many companies' general operations are still in the early stages of widespread adoption, with pilot projects and isolated applications rather than a full-scale organizational implementation.[74] The difference between personal AI knowledge and business use suggests the presence of institutional barriers that could be limiting widespread adoption.

[74] Hansen, H.F., Lillesund, E., Mikalef, P. et al. (2024). Understanding Artificial Intelligence Diffusion through an AI Capability Maturity Model. Inf Syst Front 26, 2147–2163.



In terms of specific operative areas where AI is being applied, the survey indicates varying levels of adoption. On a scale of 1 (Never) to 5 (Always), respondents reported the following frequency of AI use: Data Analysis and Reporting (3.27), Process Automation (3.04), Customer service (2.72), Inventory or Supply Chain Management (2.72), and Predictive Maintenance (2.46) (Question 4). These findings imply that while more sophisticated tasks like predictive maintenance trail somewhat behind, process automation and data analysis are now the most common uses of AI in ordinary operations.



The predominance of process automation and data analysis as primary AI applications aligns with findings from recent research. According to a study on AI process automation, organizations are increasingly leveraging AI to automate repetitive, rule-based tasks, specifically in document processing and quality controls, recognizing an urgent need to move beyond simple automation and adopt AI-driven transformations at the core of their business processes. As the article notes, application domains including supply chain management, customer service, and predictive maintenance are typical of the contemporary employment of artificial intelligence systems within enterprises, despite the dominance of process automation and data analysis in the survey. The study further points out that AI-powered automation (including both processes and data analysis) is a major improvement over conventional automation techniques since it can learn, adapt, and make data-based judgments.[75]

Data analysis and reporting represent the most common application of AI in ordinary operations, with a frequency rating of 3.27 in the survey. Research emphasizes that Enterprise Cognitive Computing (ECC) involves embedding algorithms into applications that support organizational processes. ECC applications can automate repetitive, formulaic tasks and, in doing so, deliver orders-of-magnitude improvements in the speed of information analysis and in the reliability and accuracy of outputs. This highlights how AI-enhanced data analysis can significantly improve operational efficiency and accuracy.[76]

AI is being used in process automation to automate several routine activities. In the aforementioned research, it is further explained that by lowering the possibility of human error and manual intervention, AI-driven process automation can greatly streamline operations. AI-powered solutions can

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[75] Apu, K.U. (2025). AI-Driven Data Analytics and Automation: A Systematic Literature Review of Industry Applications. *Strategic Data Management and Innovation*.

[76] Tarafdar, M., Beath, C., & Ross, J. (2020). Using AI to enhance business operations. In How AI is transforming the organization.

automate repetitive processes like data entry, inventory control, and customer support, freeing up human resources to concentrate on more strategic initiatives.[77] This is consistent with the survey's conclusion that, among AI applications used in ordinary operations, process automation has one of the greatest acceptance rate (3.04 on a 5-point scale).

Customer service applications of AI, particularly chatbots and virtual assistants, received a moderate adoption rating of 2.72 in the survey. Academic research suggests that these AI-powered tools with natural language processing abilities can provide immediate responses with boundless availability, addressing limitations of traditional customer service channels that struggle with real-time support and high inquiry volumes. According to the report, humans can concentrate on more complex interactions since chatbots are qualified to manage repetitive tasks. Businesses would benefit from increased productivity, improved customer service, and happier customer service representatives. Nevertheless, these tools frequently fail to meet customer expectations, which makes end users less likely to express their needs to these technologies.[78] This finding indicates that while the potential benefits of AI in customer service are recognized, many organizations are still in relatively early stages of implementation due to the aforementioned limitations.

Inventory or supply chain management shows the same level of AI adoption as customer service (2.72), indicating moderate implementation. A study on AI solutions for supply chain management highlights several powerful ways AI can improve inventory management, including effortless demand forecasting and real-time inventory tracking. The study emphasizes that artificial intelligence systems excel at analyzing vast quantities of inventory data,

[77] Apu, K.U. (2025). AI-Driven Data Analytics and Automation: A Systematic Literature Review of Industry Applications. *Strategic Data Management and Innovation*.

[78] Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. Electronic Markets, 31(2), 427–445.

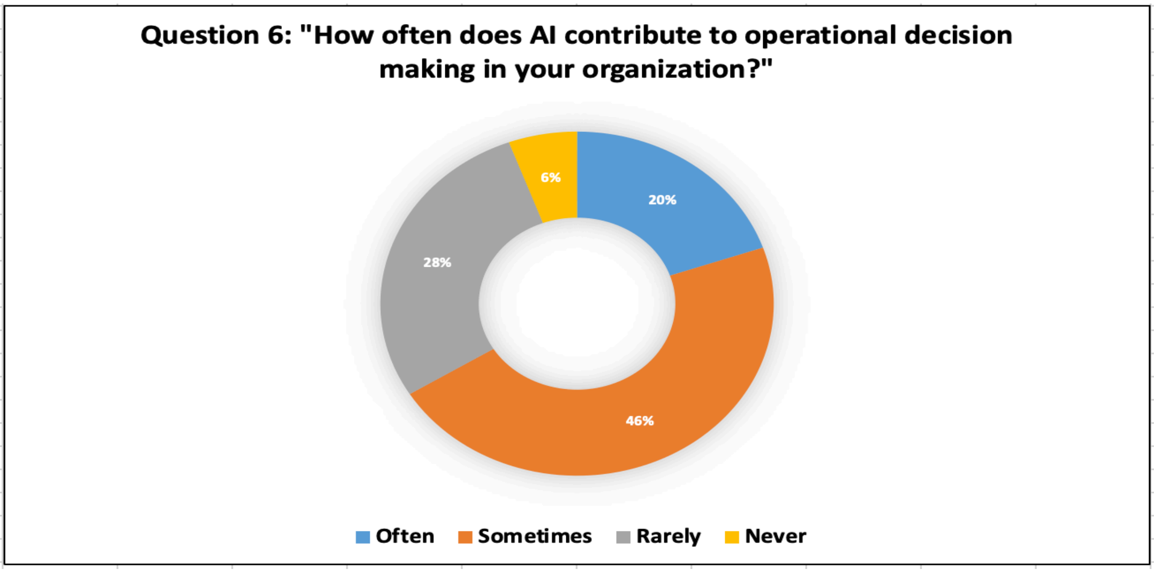
discerning patterns, and predicting incoming consumer demand forecasts with remarkable accuracy and that real-time inventory tracking plays a key role in the fast-paced world of retail and ecommerce.[79] However, the moderate adoption rate made clear by the survey results suggests that while these benefits are recognized, barriers like resistance to change or resource constraints may be limiting more widespread application and will be investigated deeply later on this chapter.

Predictive maintenance, with a score of 2.46, is the survey's least popular AI application. This finding is contrast with academic studies, which highlighted the presence of several possible benefits of AI-driven predictive maintenance. The study suggests that predictive maintenance success depends on technologies like machine learning and artificial intelligence, which enable companies to forecast potential failures and reduce downtimes.[80] Compared to more widespread applications like process automation or data analysis, the comparatively lower acceptance rate might be a reflection of the difficulty and specialized nature of applying AI for predictive maintenance. Moreover, certain companies could struggle with predictive maintenance since it usually calls for significant infrastructure investments in data collecting systems.

When it comes to AI's contribution to operational decision-making, the survey revealed a limited current role. The 74% of respondents indicated that AI Sometimes or Rarely contributes to operational decision-making in their organizations, while only the 20% reported that AI Often contributes, and just 6% answered that AI Never contributes to operational decisions (Question 6).

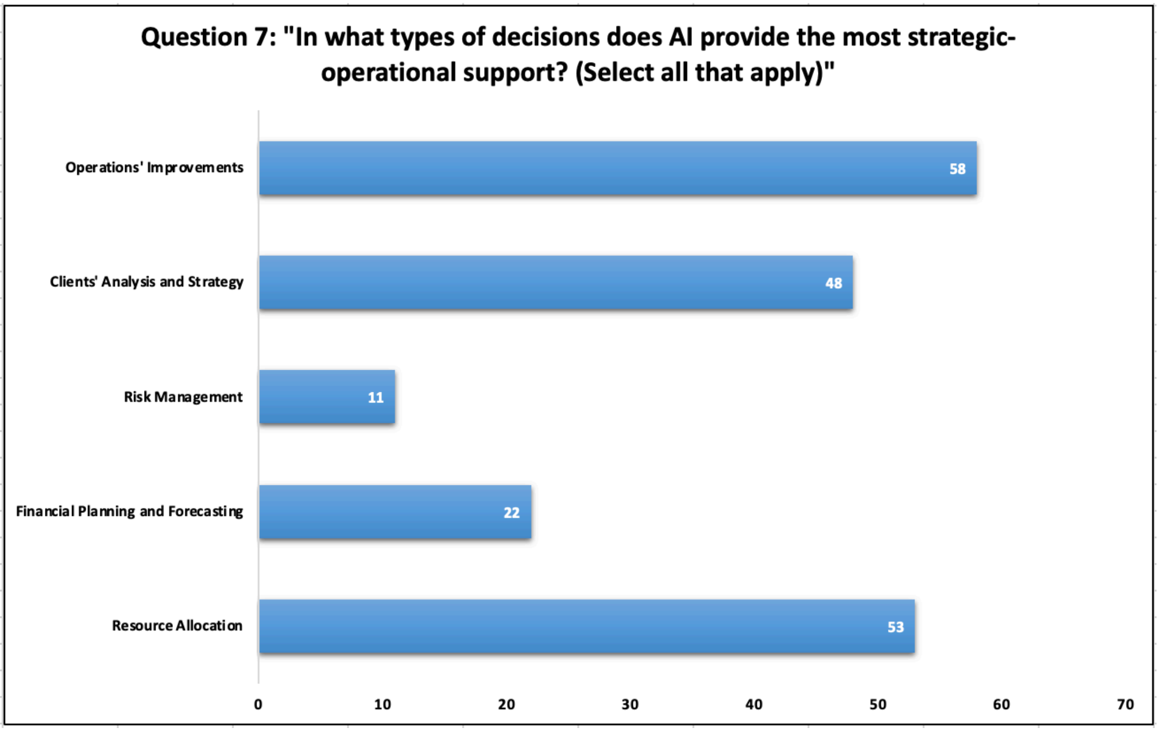
[79] Yenuganti, N. (2025). Transforming Supply Chain Efficiency: The Integration of Real-Time Inventory Tracking and AI-Powered Demand Forecasting. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*

[80] Uçar, A., Karakose, M., & Kırımça, N. (2024). Artificial intelligence for predictive maintenance applications: Key components, trustworthiness, and future trends. Applied Sciences, 14(2), 898.



These results highlighted a significant difference between the real use of artificial intelligence in companies and its theoretical promise for decision support. Moreover, organizational resistance, implementation challenges, or a lack of trust in AI-driven decision-making processes could contribute to this disparity between potential and practice. All of these topics will be discussed in more detail later in this chapter.

Despite the currently limited role of AI in operations' decision-making, the survey provided valuable insights into the specific decision domains where AI is making contributions. When asked about the types of decisions where AI provides the most strategic-operational support, respondents identified Operations' Improvements as the leading area with 58 responses, followed by Resource Allocation (53), Clients' Analysis and Strategy (48), Financial Planning and Forecasting (22), and Risk Management (11) (Question 7).



This distribution suggests that AI is being employed more for analyzing consumer behavior and optimizing present operations and less for financial planning and risk management decisions.

The prominence of operations improvements as an AI application area aligns with research findings. According to a study on AI-driven solutions, AI technologies can be used by companies to increase automation of corporate processes without direct interaction with customers, including applications that mean the use of AI in customer-facing services and products. The study further notes that process efficiency, insights generation, and transforming business processes in terms of actions, operational efficiency, financial efficiency, market efficiency are key impacts of AI implementation.[81]

Resource Allocation emerges as the second most common area for AI application in operational decisions, as indicated by the survey. This aligns with recent academic research demonstrating AI's capacity to optimize complex allocation challenges through advanced computational methods. Studies

[81] Tairov, I.; Stefanova, N.; Aleksandrova, A.; Aleksandrov, M. (2024) Review of AI-Driven Solutions in Business Value and Operational Efficiency. *Economics Ecology Socium 8*, 55-66.

utilizing deep reinforcement learning frameworks show AI-driven resource allocation achieving greater efficiency compared to traditional heuristic approaches in multi-process environments, particularly in inventory management and workforce distribution.[82] The strong survey response reflects growing recognition of AI's ability to balance competing priorities through real-time adaptive algorithms that consider operational constraints and dynamic demand patterns.

The increasing significance of customer-centric approaches in corporate operations is reflected in the third most popular application of AI in decision support: client analysis and strategy. According to research on AI in business operation, AI makes personalization easier by evaluating consumer data and customizing interactions according to each person's preferences and actions. By providing individualized experiences, this capability enables businesses to increase consumer happiness and foster loyalty.[83] Although broader adoption of AI in decision-making is still restricted, the substantial number of survey responses in this field demonstrates that firms are realizing the value of AI in creating deeper consumer insights.

Financial planning and forecasting received considerably fewer responses (22) in the survey, suggesting more limited current application of AI in this area compared to operations improvements, client analysis, and risk management.

Lastly, Risk Management appears to be the least common area for AI application in operational decisions, with only 11 survey responses despite theoretical recognition of AI's predictive capabilities. This implementation gap highlights ongoing difficulties in converting AI's analytical power into practical risk reduction plans, especially with respect to ethical frameworks and

[82] Dwivedi, S., Singh, C., Soni, K., Tripathi, S.K., & Garg, A.K. (2024). Dynamic Inventory Management In The Era Of Industry Harnessing Ai And Robotics For Agile Operations. *ShodhKosh: Journal of Visual and Performing Arts*

[83] Patil, D. (2024). Artificial intelligence for personalized marketing and consumer behaviour analysis: Enhancing engagement and conversion rates. SSRN

human-AI cooperation dynamics. Current studies highlight the need for explainable artificial intelligence systems to address this adoption gap in sensitive operational settings calling for transparency and stakeholder consensus.[84]

Survey data and academic literature showed a complex view of AI's present use in ordinary operations. Although survey participants seemed quite knowledgeable and comfortable with artificial intelligence technologies, their use in organizational settings still limited and moderate for the majority. This disparity between knowledge and execution highlights the difficult obstacles companies encounter in converting theoretical possibility into useful implementations.

With modest use of customer service, inventory control, and predictive maintenance applications, process automation and data analysis were identified as the main uses of artificial intelligence in ordinary operations. This trend implies that companies might be giving priority to solutions that enhance current capabilities and provide more direct operative advantages before implementing to more sophisticated applications.

The limited role of AI in operational decision-making reported by most respondents (74% indicating Rarely or Sometimes) contrasts with the significant theoretical potential highlighted in academic research. When AI is used for decision support, it most commonly applies to operations improvements, resource allocation, and clients' analysis, with less frequent application to financial planning and risk management.

The current state of AI in ordinary operations appears to be characterized by selective implementation in areas where benefits are most immediately

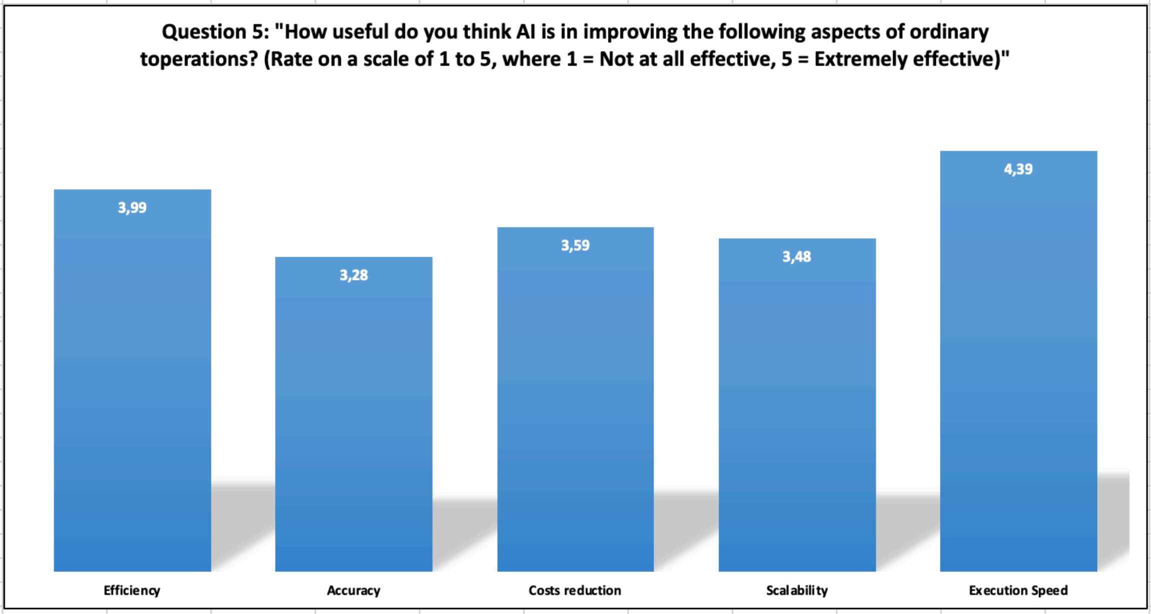
[84] Vijayabakar, S. (2024). Harnessing Generative AI for Risk Management and Fraud Detection in Fintech: A New Era of Human-Machine Collaboration. *International Journal of Scientific Research and Management (IJSRM).*

apparent and implementation challenges are more manageable. As technical capabilities advance, implementation expertise grows, and organizational readiness improves, flowing into higher expectations to see broader and deeper integration of AI across various operational domains. For companies willing to overcome the implementation obstacles and build the skills required to successfully integrate AI into their daily operations, there are still a lot of unrealized prospects, as seen by the significant discrepancy between theoretical potential and actual implementation.

4.3 Potential Benefits of AI Adoption in Ordinary Operations

This section will look at the possible benefits of artificial intelligence in enhancing ordinary corporate operations, stressing the possibilities of efficiency gains, precision enhancing, and continuous improvement. As they evolve and expand, artificial intelligence technologies in operations enable companies continuous growth by trying to simplify processes and acquire a competitive advantage. Through an in depth analysis of the various advantages of using artificial intelligence in ordinary operations, this section will provide an understanding of how these technologies might enhance organizational performance under several respects. The discussion will end by considering how artificial intelligence could help initiatives for continuous improvement after shifting from efficiency-related benefits to enhancements in accuracy.

Incorporating artificial intelligence technologies into ordinary operations has great promise for boosting efficiency across a variety of business processes. Of the many opportunities, efficiency gains represent the most tempting advantage of deploying artificial intelligence systems within businesses' structures. Survey results indicate that efficiency improvements are highly valued by organizations, with respondents rating AI's effectiveness in improving operational efficiency at 3.99 on a 5-point scale, where 5 represents extremely effective (Question 5). This relatively high rating suggests that practitioners recognize AI's capacity to streamline operations and reduce resource expenditure.



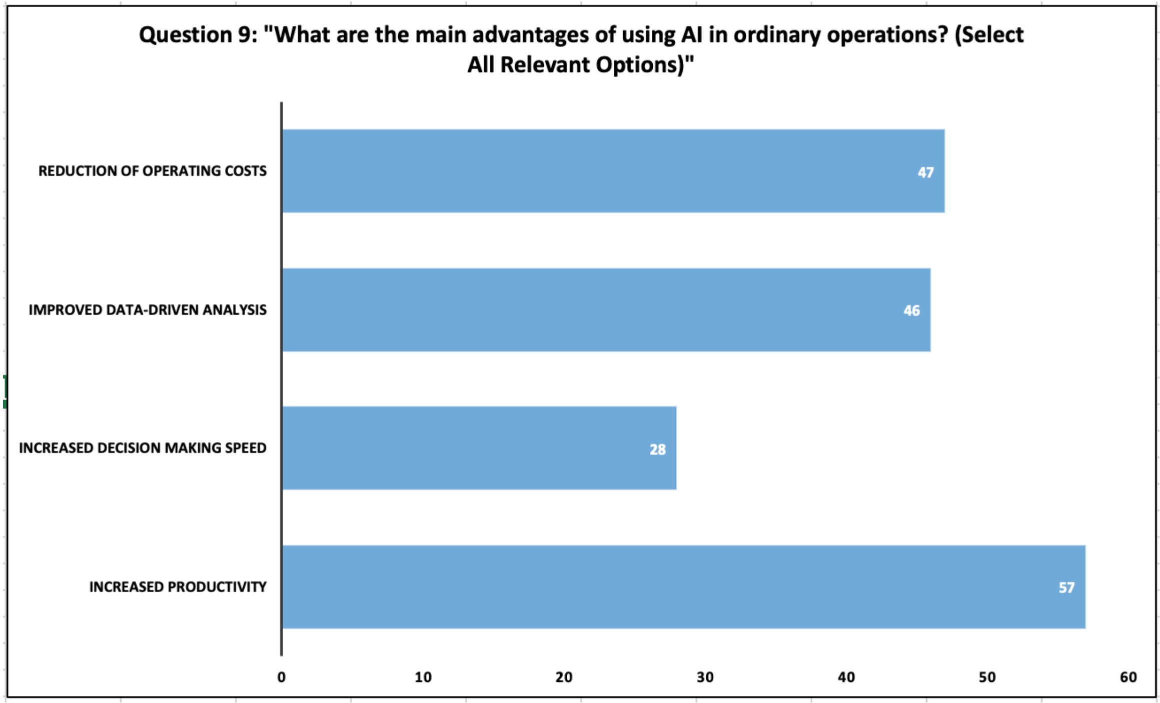
Recent academic studies support these views, emphasizing AI's revolutionary influence on operations' efficiency. Indeed, a comprehensive study of AI-driven solutions in operations' efficiency and commercial value gains revealed that artificial intelligence significantly enhances process efficiency by automating difficult procedures and enabling real-time data processing. This ability enables companies to swiftly respond to changing operative needs and effectively allocate resources.[85]

Another important aspect of efficiency where artificial intelligence shows extraordinary advantages is the execution speed of operations processes. Survey respondents rated AI's effectiveness in improving execution speed at 4.39 on a 5-point scale (Question 5), the highest rating among all operational aspects investigated. This finding suggests that the greatest way artificial

[85] Tairov, I., Stefanova, N., Aleksandrova, A., & Aleksandrov, M. (2024). Review of AI-Driven Solutions in Business Value and Operational Efficiency. *Economics Ecology Socium*

intelligence improves operations efficiency lies in its ability to understand data and quickly execute tasks.

Another major efficiency gain connected to the AI use in ordinary processes is cost cutting. Survey respondents rated AI's effectiveness in reducing operative costs at 3.59 on a 5-point scale (Question 5), indicating moderate to strong confidence in AI's cost-saving potential. The result that 47 respondents identified Reduction of Operating Costs as one of the key benefit of applying artificial intelligence in ordinary operations (Question 9) supports this view.



AI's efficiency advantages go beyond cost savings to involve higher productivity. When asked about the key benefits of applying artificial intelligence in ordinary tasks, 57 of the respondents highlighted increased productivity as a major advantage (Question 9). This outcome suggests that the most known advantage of using artificial intelligence is increased productivity. Studies on artificial intelligence operations' efficiency back this point of view demonstrating how, by automating ordinary tasks and simplifying processes, AI enables companies achieve more with their existing resources.[86]

[86] Chowdhury, R. H. (2024). AI-driven business analytics for operational efficiency. World Journal of Advanced Engineering Technology and Sciences, 12(2), 535–543

A particularly useful illustration of AI's efficiency advantages is the banking sector. To enhance operative dynamics with the aim of increasing efficiency, financial institutions have adopted artificial intelligence and machine learning technology. Academic literature on artificial intelligence use in the banking sector found that by means of advanced data processing and decision-making capabilities, these technologies can significantly boost production.[87] Although integration obstacles persist-including data security concerns, upfront investments, and lack of expertise, as widely covered in Chapter 3, the potential for operational transformation remains significant.

While efficiency gains mostly relate to resource optimization, advancements in accuracy and precision emphasize the quality of operations' results. Survey results indicate that respondents rated AI's effectiveness in improving accuracy at 3.28 on a 5-point scale (Question 5), suggesting moderate confidence in AI's capacity to enhance precision in operative contexts. Even though it got the lowest score of all those evaluated, this feature suggests that artificial intelligence can improve accuracy despite current standards.

Academic studies shed light on the ways in which artificial intelligence improves operational accuracy. AI systems with sophisticated machine learning algorithms can discover problems before they become more serious by spotting unmonitored irregularities that could be signs of poor quality or inefficient processes. This pattern recognition capacity promotes quality improvement and failure reduction, especially in industries that demand high accuracy. The accuracy advantage of AI comes from its capacity to analyze large datasets and spot patterns that human operators would miss, allowing for more reliable quality control and a decrease in errors.[88]

[87] Kristiana, I. (2024). Review of Improving Banking Operational Efficiency through AI and ML: Strategy, Implementation and Impact. *Jurnal Komunikasi, Sains dan Teknologi*.

[88] Shukla, M., Dubey, S., & Mishra, S. (2024). The impact of AI on improving the efficiency and accuracy of managerial decisions. International Journal for Research in Applied Science & Engineering Technology, 12(VII), 830–837

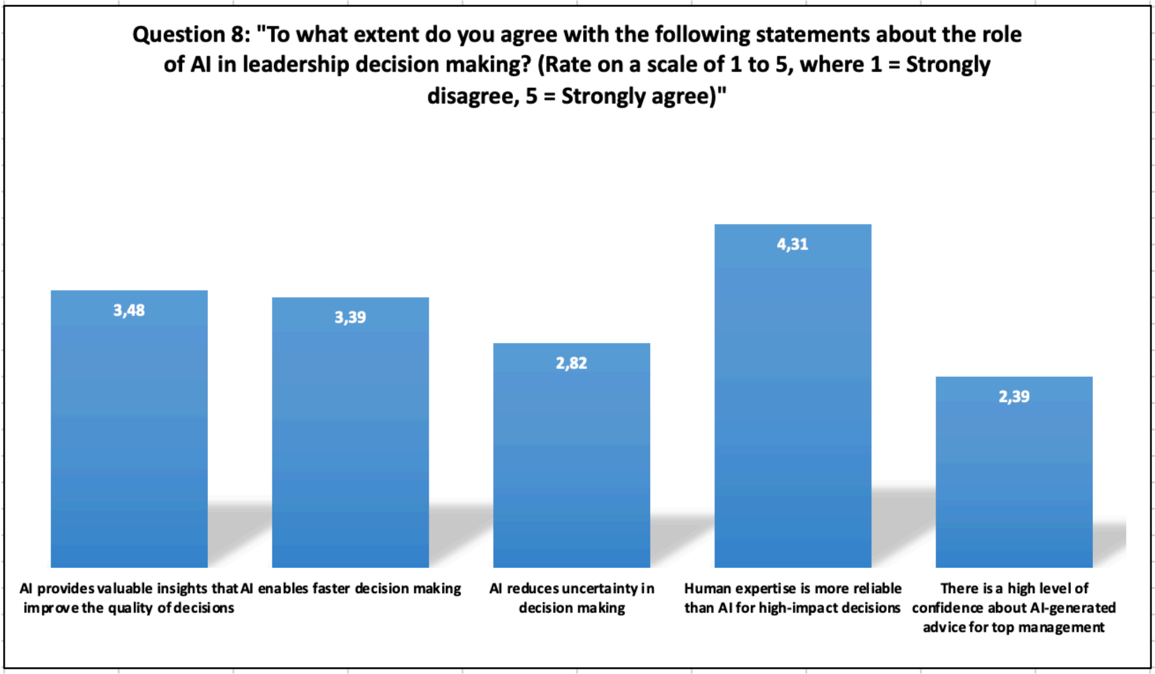
AI's ability to enhance data-driven analysis is directly related to its precision advantages. Survey results show that 46 respondents identified "improved data-driven analysis" as a main advantage of using AI in ordinary operations (Question 9), ranking it as the third most recognized benefit. According to this finding, businesses appreciate AI's analytical powers and its ability to help them make more accurate operational decisions.

AI and big data analytics are great prospects for increasing precision in supply chain management through better visibility, more accurate decision-making, and increased operational efficiency. According to research, artificial intelligence methods like machine learning, deep learning, and predictive analytics provide improved inventory control, more accurate demand forecasting, and more efficient logistics. These improvements in precision result in lower costs and better responsiveness to market swings, underscoring the usefulness of AI in intricate operational contexts that are unpredictable and variable.[89]

AI holds great promise for facilitating continuous operations improvement, going beyond imminent increases in efficiency and accuracy. The constant endeavor to improve goods, services, and procedures gradually over time is known as continuous improvement, and it is a fundamental of operational excellence. Through the provision of real-time monitoring capabilities, sophisticated analytical tools, and predictive insights, artificial intelligence solutions enable continuous improvement by empowering enterprises to proactively detect and address operational inefficiencies.[90] Survey results offer insight into AI's perceived role in supporting continuous improvement through enhanced decision-making. Respondents rated their agreement with the

[89] Abhulimen, A.O., & Ejike, O.G. (2024). Solving supply chain management issues with AI and Big Data analytics for future operational efficiency. *Computer Science & IT Research Journal*.
[90] Cisterna, D., Lauble, S., Haghsheno, S., & Wolber, J. (2022). Synergies Between Lean Construction and Artificial Intelligence: AI Driven Continuous Improvement Process. *Proc. 30th Annual Conference of the International Group for Lean Construction (IGLC)*.

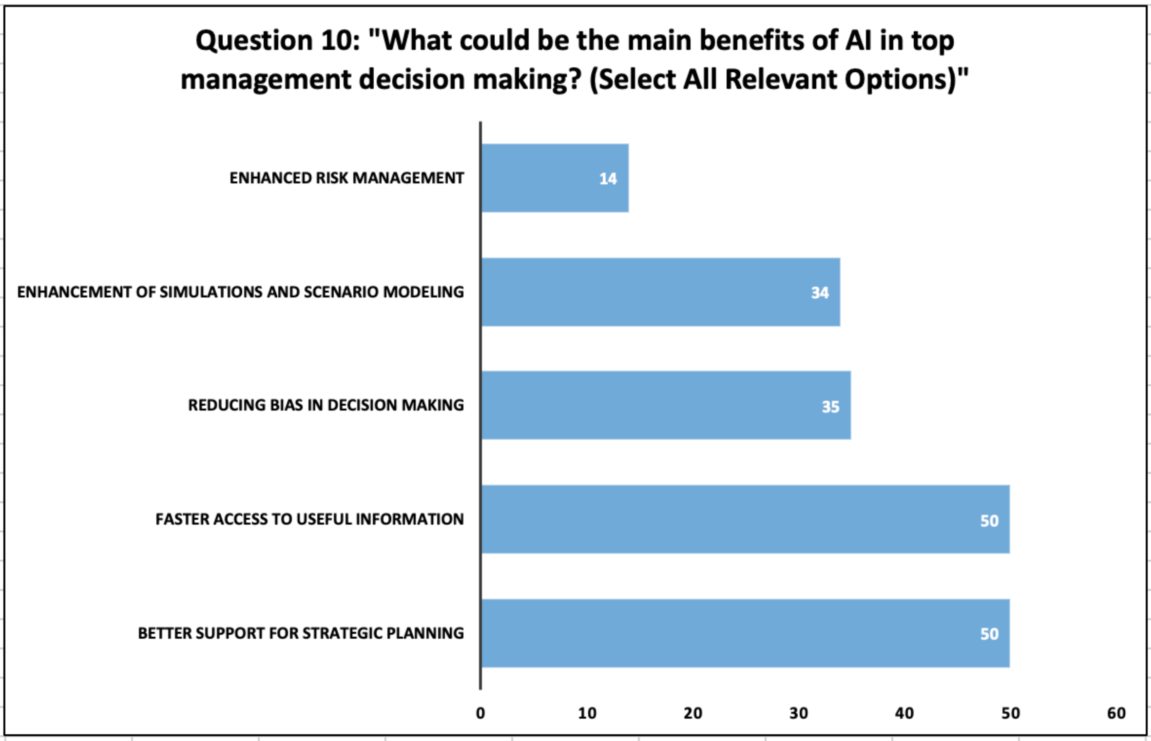
statement AI provides valuable insights that improve the quality of decisions at 3.48 on a 5-point scale (Question 8), indicating moderate to strong support for AI's contribution to decision quality. Similarly, respondents rated their agreement with the statement AI enables faster decision making at 3.39 (Question 8), suggesting recognition of AI's capacity to accelerate the decision-making processes that drive continuous improvement initiatives.



The benefits of AI integration for continuous improvement can be explained by academic research. AI does, in fact, strengthen the concepts of continuous improvement by automating ordinary tasks, anticipating future trends with previously unachievable precision, and offering more accurate data-based insights. The DMAIC Framework from Six Sigma is a real-world example of the close interaction between AI and continuous improvement approaches. Its application speeds up the implementation process and boosts the precision and quality of operational choices. Significant gains in productivity and creativity can be made by businesses that successfully integrate AI with well-known frameworks for continuous improvement, such as Six Sigma.[91]

[91] Sood, A., & Dhull, K. (2024). The future of Six Sigma-Integrating AI for continuous improvement. International Journal of Innovative Research in Engineering and Management, 11(5), Article 2.

Strategic planning support represents a key dimension of AI's continuous improvement benefits. When asked about the main benefits of AI in top management decision-making, 50 respondents identified better support for strategic planning as a primary advantage (Question 10), tying for the highest-ranked benefit.



According to this finding, companies value AI's ability to help them make long-term strategic choices that direct continuous improvement efforts. By generating insights that enable companies to continuously improve their operations and products, artificial intelligence (AI) supports the strategic planning processes that result in long-term operational development.

Scenario modeling and simulation capabilities constitute another significant continuous improvement benefit associated with AI. Survey results indicate that 34 respondents identified "enhancement of simulations and scenario modeling" as a main benefit of AI in top management decision-making (Question 10). This finding suggests recognition of AI's value in enabling organizations to evaluate potential process improvements before implementation, reducing risk and optimizing outcomes. Academic research on

AI in process control highlights how AI-enhanced simulation capabilities enable organizations to test process modifications virtually, predicting their impact on efficiency, quality, and cost metrics.[92] This capacity for advanced simulation supports more informed continuous improvement decisions and accelerates the identification of optimal operational enhancements.

Faster access to useful information represents a foundational continuous improvement benefit enabled by AI. Survey results show that 50 respondents identified this as a main benefit of AI in top management decision-making (Question 10). This result emphasizes how crucial fast access to information is for boosting continuous improvement. According to research, artificial intelligence greatly improves information accessibility, allowing businesses to extract useful insights from large datasets faster than they could in the past. AI helps businesses to find and fix operational inefficiencies faster by speeding up the information feedback loops that promote cycles of continuous improvement, increasing the speed and efficacy of improvement projects.[93]

Despite these benefits, survey results unveiled important limitations in perceptions of AI's continuous improvement capabilities. Respondents rated their agreement with the statement AI reduces uncertainty in decision making at only 2.82 on a 5-point scale (Question 8), indicating moderate skepticism regarding AI's capacity to mitigate decision-making ambiguity. Conversely, respondents expressed strong agreement (4.31) with the statement that Human expertise is more reliable than AI for high-impact decisions (Question 8), suggesting recognition of AI's current limitations in complex decision contexts. These results demonstrate how AI and human expertise should work together to promote continuous improvement, highlighting the fact that although AI

[92] Bitra, D. (2024). Artificial intelligence in business scenario analysis: A framework for enhanced decision-making through what-if simulations. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 10(1), 1149–1159.
[93] Chowdhury, R. H. (2024). AI-driven business analytics for operational efficiency. World Journal of Advanced Engineering Technology and Sciences, 12(2), 535–543.

offers useful analytical assistance, human judgment is still necessary for identifying and utilizing AI-generated insights.

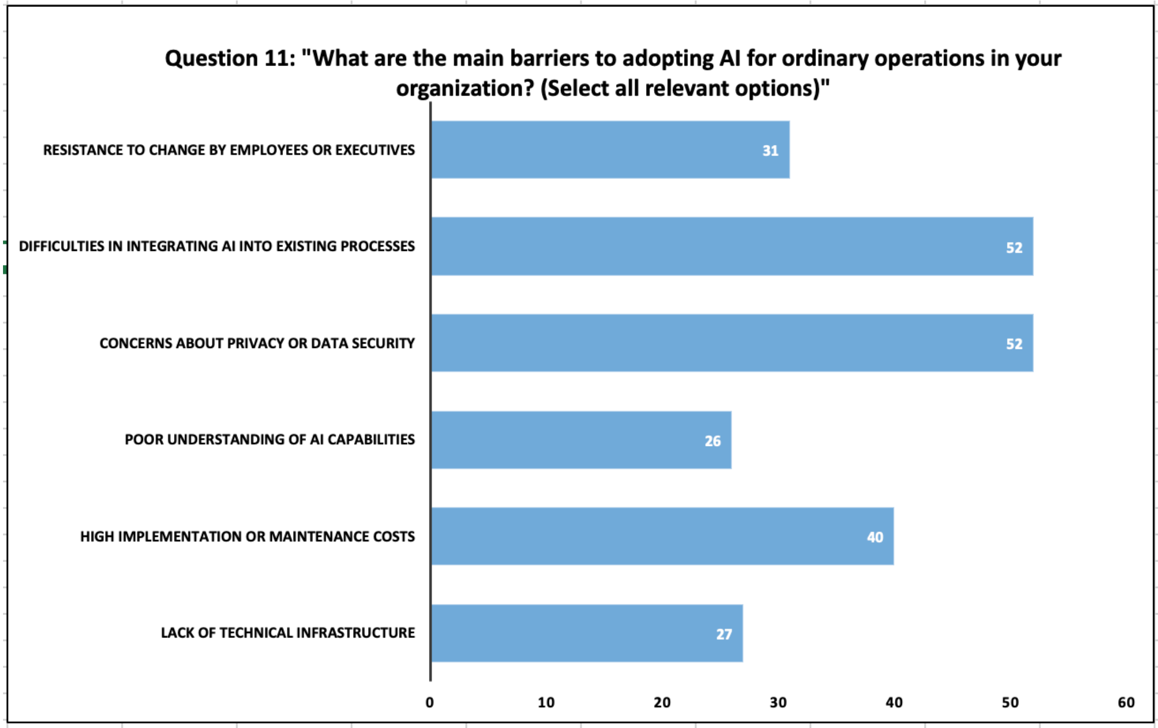
The relatively low confidence in AI-generated advice for top management (2.39) further underscores the perceived limitations of current AI technologies in supporting high-level decision-making. The finding implies that although artificial intelligence provides significant advantages for improving operations, businesses are reluctant to use it in strategic decision-making situations that direct larger projects. The perceived value of AI technology for strategic continuous improvement applications may increase as a result of addressing these limitations through increased transparency, explainability, and validation.

To conclude, the potential benefits of AI in ordinary operations span multiple dimensions, encompassing efficiency enhancements, precision improvements, and continuous advancement capabilities. Survey results indicate that execution speed and productivity gains represent the most widely recognized advantages of AI implementation, with cost reduction and data-driven analysis capabilities also receiving substantial recognition. Academic research provides theoretical context for these benefits, highlighting the mechanisms through which AI transforms operational performance. While perceptions of AI's accuracy benefits appear more moderate, evidence suggests significant potential for precision enhancements in quality control and error reduction. In the domain of continuous improvement, AI offers valuable support for strategic planning and scenario modeling, though limitations regarding uncertainty reduction and high-impact decision-making persist. Together, these results imply that AI offers significant potential for improving operations, especially when used in combination with human knowledge and tried-and-true improvement techniques. The potential benefits of AI deployment will probably become more apparent as businesses continue to improve their methods, which will lead to even more advancements in their operations' development.

4.4 Current Challenges and Future Expectations

While earlier sections have examined the expected benefits along with current uses of artificial intelligence in ordinary operations, this section explores the challenges businesses face when putting AI solutions into practice along with their future implementation trajectory. Developing successful implementation techniques that optimize AI's capabilities while avoiding disruption requires a clear understanding of these obstacles. Analyzing expectations for the future also reveals how businesses believe AI will change their business practices in the years to come. Blending survey data and recent research, this section provides a thorough study of the changing AI landscape in everyday operations, looking at both the barriers to adoption and the developments anticipated to encourage future adoption.

When trying to incorporate AI into their operating procedures, organizations encounter many challenges. These obstacles involve organizational, technological, financial, and human aspects, resulting in a challenging implementation environment that needs to be carefully managed. According to survey results, the biggest obstacles for businesses implementing AI technologies are integration issues and data-related concerns.
Indeed, according to the survey results, the primary barriers to adopting AI for ordinary operations include difficulties in integrating AI into existing processes with 52 answers tied with concerns about privacy or data security (52), high implementation or maintenance costs (40), resistance to change by employees or executives (31), lack of technical infrastructure (27), and poor understanding of AI capabilities (26)(Question 11).



These results are consistent with recent literature that found resource limitations, organizational resistance, and technical complexity to be the main barriers to the adoption of AI.

Indeed, for businesses, integrating AI into current procedures is a particularly difficult stage. The intricate nature of integrating AI solutions with current technology infrastructures frequently calls for extensive system and process modification. This difficulty is made even worse by the speed at which AI technologies are developing, which has the potential to soon make current integration strategies outdated. Furthermore, technical compatibility as well as complexity and adoption success rates for AI applications show a close link, thus stressing the vital need of addressing integration problems.[94]

Privacy and data security issues also impede AI adoption in certain sectors. Concerns about data privacy, legal compliance, and possible security flaws are natural considering AI systems often need access to large amounts of business data. Since restrictive data privacy regulations and comparable systems have

[94] Kapoor, A. (2024). Big Data Infrastructure: Integrating Legacy Systems with AI-Driven Platforms. *Computer Science, Engineering and Information Technology*.

been applied worldwide, these issues have grown. Studies done recently show that one of the main obstacles to AI acceptance is privacy issues. Companies have to give data governance and ethical artificial intelligence ideas top priority if they are to alleviate these worries.[95]

High implementation and maintenance expenses drive many companies away from using artificial intelligence solutions, thus the financial impacts of AI deployment is another major obstacle. Apart from the direct expense of artificial intelligence technologies, these costs cover the indirect expenses of process reengineering, personnel training, and infrastructure improvements.

Human factors, such as executives' and employees' resistance to change, make implementing AI more challenging. Changing workplace dynamics and personal skills becoming obsolete are the main reasons from which this reluctance arises. Recent research indicates that in many business settings, employees opposition and insufficient leadership support have significantly slowed the adoption of artificial intelligence. Moreover, comprehensive management techniques that foster trust and highlight AI's role in enhancing rather than replacing human talents are necessary to address these human factors.[96]

Lastly, infrastructure limitations and a lack of knowledge about AI's capabilities complete the list of the survey's main obstacles. Many companies lack the technological basis required for successful AI implementation, which includes sufficient computational power, data management systems, and infrastructures. Insufficient experience with artificial intelligence have also been highlighted as a significant obstacle in every stage of AI deployment.[97]

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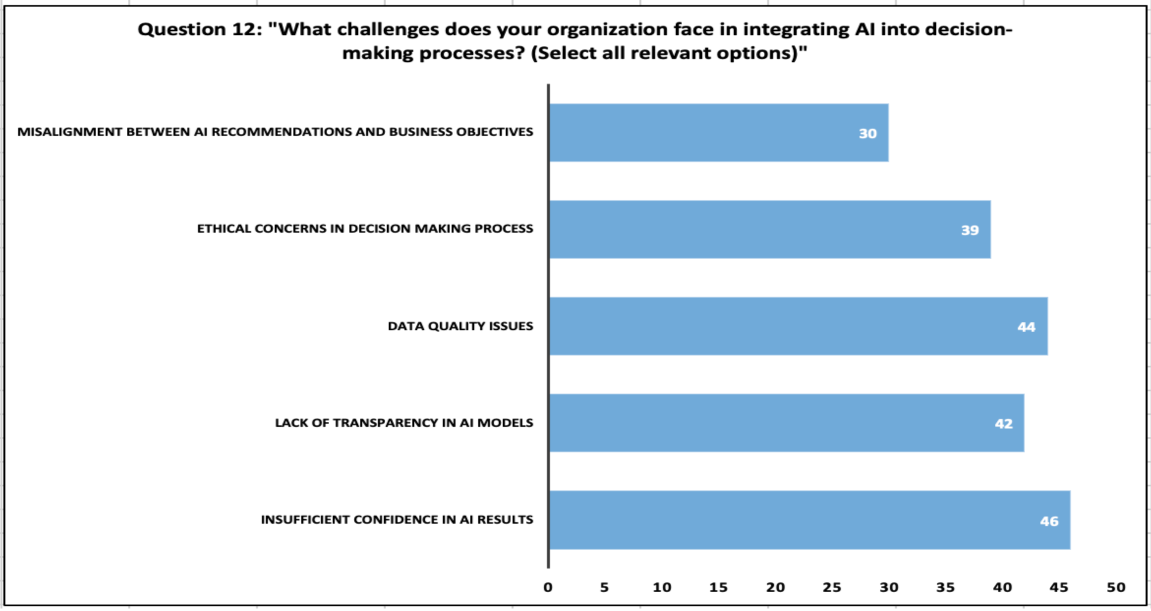
[95] Mbah, G.O. (2024). Data privacy in the era of AI: Navigating regulatory landscapes for global businesses. *International Journal of Science and Research Archive*.

[96] Golgeci, I., Ritala, P., Arslan, A., McKenna, B., & Ali, I. (2025). Confronting and alleviating AI resistance in the workplace: An integrative review and a process framework. Human Resource Management Review, 35(2), Article 101075

[97] Gruenbichler, R. (2023). Implementation Barriers of Artificial Intelligence in Companies. In *Proceedings of FEB Zagreb 14th International Odyssey: Conference on Economics and Business* (1 ed., Vol. 5, pp. 193-203). University of Zagreb

Apart from the more general obstacles to AI adoption such as those described above, companies face specific issues as well when trying to include artificial intelligence into decision-making processes. These difficulties are brought on by ethical issues, models' opacity, data integrity, and conflicts with corporate goals. Survey research indicates that these factors significantly affect how effectively artificial intelligence enables decision-making in organizations.

According to Question 12, the main challenges organizations face in integrating AI into decision-making processes include insufficient confidence in AI results (46), data quality issues (44), lack of transparency in AI models (42), ethical concerns in the decision-making process (39), and misalignment between AI recommendations and business objectives (30).



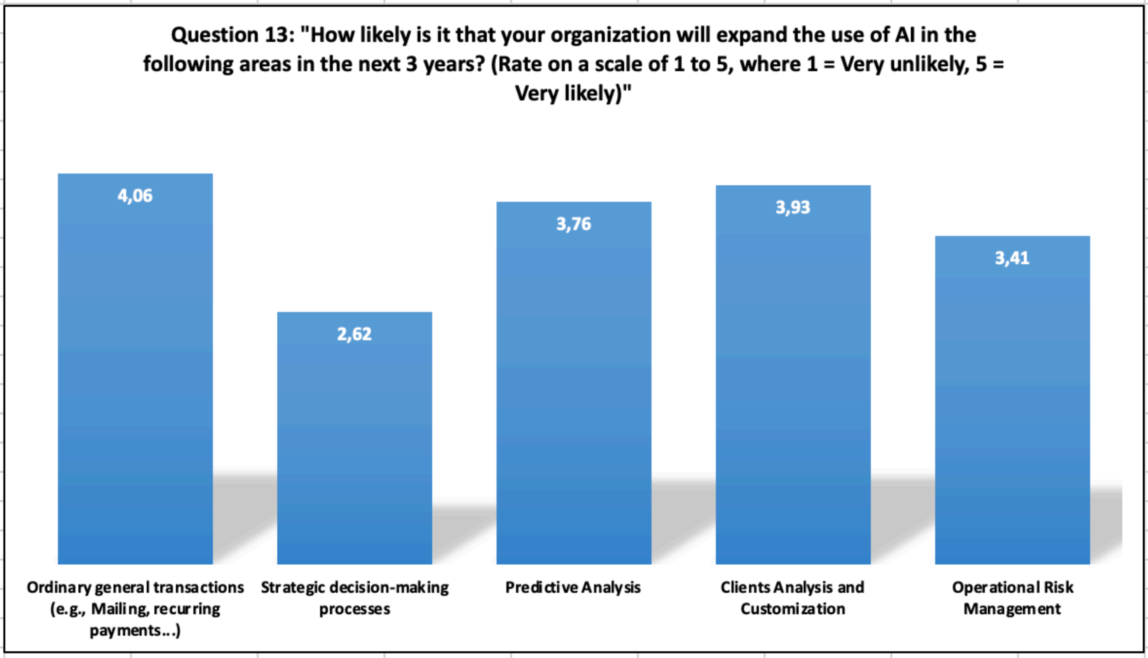
Successful decision-making integration depends first on trust in artificial intelligence tools' results. Nearly 65% of survey's participants cited this as the primary obstacle to incorporating AI into decision-making processes. Decision-makers are inevitably reluctant to include AI-generated insights into their processes if they can't trust them, hence ignoring their possible value. Often, this lack of confidence results from the black box nature of many artificial intelligence systems generating recommendations via complex processes

which become difficult for people to understand. The difficulty of gaining users' trust in AI systems is highlighted by recent research showing that, although explainable AI can improve users' performance on decision tasks, the benefit of explanations as opposed to just AI forecasts is frequently small.[98]
Issues with data quality further impede AI's capacity to assist in decision-making. AI systems depend on the training data's completeness, quality, and accuracy. AI results could be wrong when this data presents general mistakes or biases, thus preventing organizations from their use. Data quality is therefore quite important in deciding the outcome of artificial intelligence deployment since it highlights the need of strong data governance systems and validation techniques.[99]
Ethical concerns in AI-supported decision-making have attracted increased notice as AI applications have widened into sensitive domains with significant human impact. Companies must deal with challenging ethical issues including potential prejudices in artificial intelligence systems, responsibility, fairness, and privacy. Recent research indicates that ethical artificial intelligence frameworks are becoming more important as companies understood the need of governance systems to ensure the responsible use of artificial intelligence. These ethical concerns are clearly visible in those sectors that exert great impact on individuals, thereby requiring rigorous commitment to the principles of fairness, responsibility, and transparency.[100]

Despite the challenges highlighted above, companies appear hopeful about increasing the application of artificial intelligence in several operative areas in

[98] De Brito Duarte, R., Correia, F., Arriaga, P., & Paiva, A. (2023). AI Trust: Can Explainable AI Enhance Warranted Trust? *Human Behavior and Emerging Technologies*
[99] Chukwurah, N., Ige, A. B., Adebayo, V. I., & Eyieyien, O. G. (2024). Frameworks for effective data governance: Best practices, challenges, and implementation strategies across industries. Computer Science & IT Research Journal, 5(7), 1666–1679.
[100] Osasona, F., Amoo, O.O., Atadoga, A., Abrahams, T.O., Farayola, O.A., & Ayinla, B.S. (2024). Reviewing The Ethical Implications Of Ai In Decision Making Processes. *International Journal of Management & Entrepreneurship Research*

the next years. Survey findings indicate that, with an emphasis on transactional operations, predictive analytics, and customer-focused applications, AI will probably gain field across several disciplines. According to Question 13, organizations report varying likelihoods of expanding AI use across different operational areas in the next three years. The highest one is reported for ordinary general transactions (4.06 on a 5-point scale), followed by client analysis and customization (3.93), predictive analysis (3.76), operational risk management (3.41), and strategic decision-making processes (2.62).



These findings suggest that organizations' AI implementation will have the greatest near-term impact on routine operational processes and customer-focused applications, with more gradual adoption in strategic decision domains. The strong expectation for AI expansion in general ordinary transactions reflects the significant efficiency and accuracy improvements AI can deliver in routine operational processes.

Another area of expected AI growth is customer analysis and customization, which reflects the technology's significant personalization, segmentation, and behavior prediction capabilities. With sentiment analysis, chatbot automation, and text summarization emerging as important applications across industries, academic research shows that AI tools can revolutionize how businesses analyze text data, automate responses, and improve search relevance. Businesses are realizing more and more that these skills are essential differentiators in markets with high customer expectations and a wide range of options.[101]

Applications of predictive analysis also exhibit high growth expectations as businesses look to use AI's pattern recognition and forecasting powers to foresee market trends, operational difficulties, and new opportunities. Recent studies on predictive analytics and AI show how businesses can use these technologies to identify opportunities and enhance forecasting precision. It is anticipated that predictive models' incorporation into routine operations will speed up as they become more advanced and widely available.[102]

Given the complexity and higher stakes of these applications, there is comparatively little expectation that AI will become more prevalent in strategic decision-making processes. Higher barriers to AI adoption and integration are caused by the fact that strategic decisions usually involve a large number of variables, a great deal of uncertainty, and significant organizational ramifications. This trend is supported by recent studies on explainable AI in business decision-making, which show that although AI can improve decision-making, adoption is slower in fields that call for sophisticated judgment and tacit knowledge.[103] However, it seems likely that AI will gradually expand into strategic domains as its capabilities improve and organizational comfort with the technology increases.

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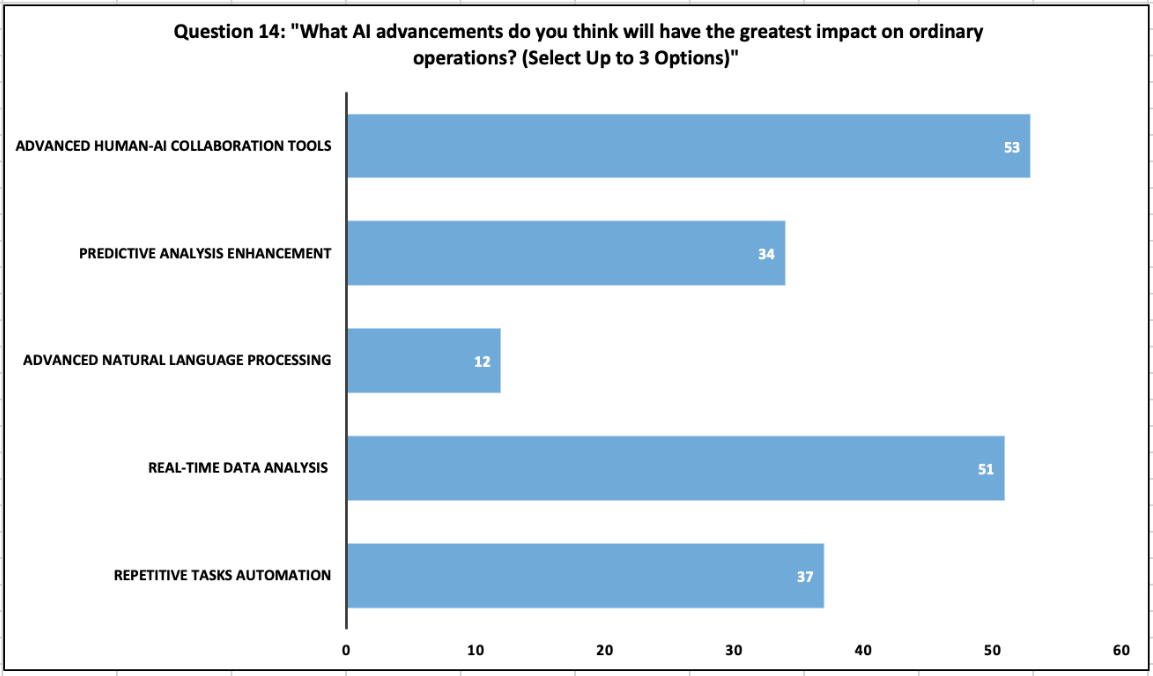
[101] Delgado, S., Villamarin, A., & Insuasti, J. (2025). AI-Powered Chatbots in Organizations: A Systematic Literature Review. *Journal of Information Systems Engineering and Management*

[102] Ajiga, D.I., Ndubuisi, N.L., Asuzu, O.F., Owolabi, O.R., Tubokirifuruar, T.S., & Adeleye, R.A. (2024). AI-Driven Predictive Analytics In Retail: A Review Of Emerging Trends And Customer Engagement Strategies. *International Journal of Management & Entrepreneurship Research*

[103] Rogha, M. (2023). Explain to decide: A human-centric review on the role of explainable artificial intelligence in AI-assisted decision making. arXiv.

Beyond broad adoption patterns, businesses define particular AI developments that are anticipated to have the biggest effects on daily operations and managerial choices. These expected developments are a reflection of shifting priorities for AI governance, integration, and functionality.

According to Question 14, the AI advancements expected to have the greatest impact on ordinary operations include advanced human-AI collaboration tools, leading with 53 answers, followed by real-time data analysis (51), repetitive tasks automation (37), predictive analysis enhancement (34), and advanced natural language processing (12).



These expectations underscore the ongoing significance of data analysis and automation functionalities, as well as the growing emphasis on collaborative AI approaches that enhance rather than replace human capabilities.

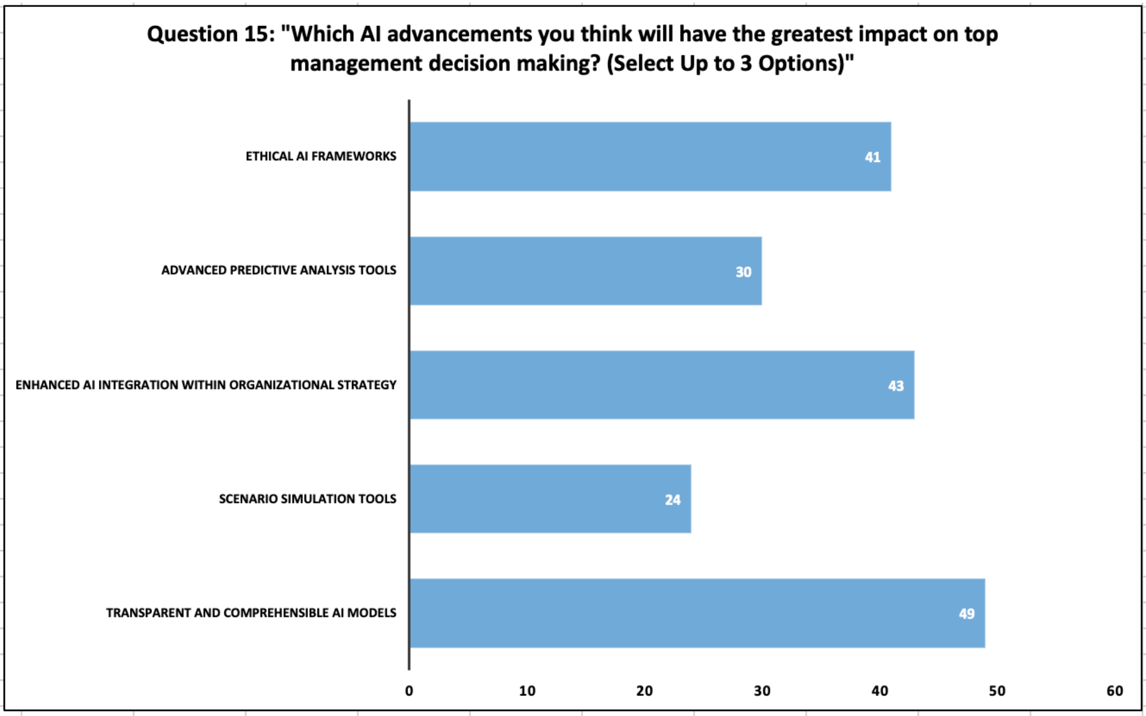
A major shift in the philosophy of AI implementation from replacement to augmentation and complementarity is reflected in the strong emphasis on sophisticated human-AI collaboration tools. The development of assessment frameworks that evaluate the efficacy of collaborative systems across AI-centric, human-centric, and symbiotic modes of interaction is highlighted by recent research on human-AI collaboration (HAIC).[104] Businesses are realizing more and more that integrating AI's computational power and pattern recognition skills with human creativity, judgment, and contextual awareness frequently yields the best results.

Similarly, real-time data analysis capabilities are a high-priority development, reflecting the increased speed of corporate operations and the increasing significance of rapid decision-making. Recent academic research explores the integration of artificial intelligence with stream processing technologies to facilitate decision support, allowing organizations to analyze data in real-time and improve response times in dynamic environments.[105] These capabilities can enhance operational responsiveness and agility across multiple domains, from supply chain management to customer service to risk monitoring.

Lastly, Question 15 results assessed which AI advancements will have the greatest impact on top management decision-making practices. These include transparent and comprehensible AI models (49), advanced predictive analysis tools (43), ethical AI frameworks (41), enhanced AI integration within organizational strategy (30), and scenario simulation tools (24).

[104] Fragiadakis, G., Diou, C., Kousiouris, G., & Nikolaidou, M. (2024). Evaluating human-AI collaboration: A review and methodological framework. arXiv

[105] Boppiniti, S. (2021). Real-Time Data Analytics with AI: Leveraging Stream Processing for Dynamic Decision Support. International Journal of Management Education for Sustainable Development, 4(4). Retrieved from https://ijsdcs.com/index.php/IJMESD/article/view/589/227



These expectations highlight the particular importance of explainability, ethics, and strategic alignment in management-level AI applications.

The emphasis on transparent and comprehensible AI models for management decision-making aligns with research on explainable artificial intelligence in decision support systems mentioned above.

The high rating for enhanced AI integration within organizational strategy reflects the recognition that AI must be strategically embedded within organizational processes rather than implemented as standalone tools. Recent research emphasizes that this integration needs organizational culture, ethical concerns, and data privacy to be addressed through the development of a comprehensive framework. Furthermore, it is acknowledged that the strategic integration of AI, if properly implemented, extends beyond operational efficiency, offering opportunities for competitive advantage through enhanced decision quality.[106]

[106] Abuzaid, A.N. (2024). Strategic AI Integration: Examining the Role of Artificial Intelligence in Corporate Decision-Making. *2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS), 1*, 1-6

Despite receiving the fewest votes, scenario simulation tools represent a significant frontier in AI-assisted strategic planning. Recent research highlights that artificially intelligent tools can now generate an abundant number of differentiated scenarios on seemingly any topic, at essentially zero cost. This capability could dramatically transform how top management engages with future planning, yet survey respondents seem less convinced of its immediate impact compared to other AI advancements.

The relatively lower ranking of scenario simulation tools may reflect current limitations identified in the same research, aligning with the survey's results which emphasize transparency and comprehensibility in AI models, suggesting that decision-makers must prioritize understanding AI's reasoning over simply receiving its outputs. As researchers further note, scenario tools must be able to retrieve the appropriate raw material from the artificially intelligent bot, hence requiring significant human oversight and interpretation.

The survey results and academic analysis together suggest that while scenario simulation tools offer tremendous potential for expanding strategic thinking, their effective implementation requires integration with other highly ranked AI advancements, particularly transparent models and organizational strategy alignment, to truly impact top management decision making.[107]

There are many opportunities and challenges associated with integrating AI into organizational operations. Even though there are organizational, technical, and human implementation barriers, organizations are still hopeful about AI's growing operational role. Adoption is expected to progress unevenly, with routine transactions and customer applications advancing more rapidly than strategic decision-making functions. Success requires holistic implementation roadmaps that address not only technological considerations but also

[107] Spaniol, M.J., & Rowland, N.J. (2023). AI-assisted scenario generation for strategic planning. *Futures & Foresight Science*.

organizational culture, skills development, change management, stakeholder engagement, and ethical governance. By effectively navigating these dimensions, organizations can overcome current barriers and leverage AI's operational benefits.

4.5 Conclusion

To conclude, the integration of artificial intelligence into routine business processes is a revolutionary development that has significant effects on organizational effectiveness, strategic flexibility, and decision-making. Based on survey data from 71 professionals and students in a variety of industries, this chapter's empirical investigation offered important insights into the adoption of AI as it is today, as well as its perceived advantages, enduring difficulties, and projected future directions. The survey was a crucial instrument for connecting theoretical frameworks with real-world applications, exposing a complex environment where hope for AI's future coexists with major implementation obstacles and unsolved constraints.

The findings demonstrated that, despite moderate adoption rates across industries, process automation and data analysis are the main functions of AI in ordinary operations. AI has the potential to improve operational performance, accelerate processes and facilitate data-driven decision-making, but organizations find it challenging to implement these advantages due to organizational, technical, and human factors. The intricate relationship between technological capabilities and organizational readiness is reflected in the difficulties encountered, which include integrating AI into previous systems, protecting data privacy and security, and overcoming resistance to change. Moreover, there's an ongoing gap between AI's theoretical and its actual use, particularly in fields where human judgment is still crucial and its expertise is still dominant.

Data from the survey demonstrated AI's dual function both as a disruptor and as an enabler. On the one hand, respondents highlighted how AI's advanced analytics and predictive powers can revolutionize productivity, cost reduction, and continuous improvement. However, persistent problems that necessitate interdisciplinary solutions were exposed by model transparency limitations, ethical issues, and misalignment with strategic objectives. Notably, the survey revealed a cautious optimism regarding AI's future, with expectations focused on real-time data processing, improved human-AI collaboration, and ethical frameworks that match advances in technology with organizational values.

Most importantly, the survey offered empirical support for academic discussions, confirming that the development of AI in ordinary operations is both a social and a technical phenomenon that calls for comprehensive approaches. According to the data, in order to fully utilize AI's potential, organizations must give explainable AI systems, strong data governance, and workforce upskilling top priority. The findings warn against ignoring the investments needed in infrastructure, trust-building, and strategic alignment as industries look forward to increased AI adoption in customer-centric applications and predictive analytics.

This chapter showed how AI's place in ordinary operations is set to undergo a substantial evolution, but how it develops will rely on how the obstacles that have been identified will be resolved. Lastly, to fully realize AI's potential as a catalyst for operational excellence, theoretical frameworks and empirical data must continue to interact.

CHAPTER 5

5.1 AI Integration in Ordinary and Extraordinary Operations

By examining its uses, obstacles, and possibilities in both ordinary and extraordinary operations, this thesis has investigated the several ways in which artificial intelligence can be integrated into management processes. The study tried to address several important issues about how artificial intelligence could improve decision-making processes, what operational and ethical issues occur during its deployment, and which techniques companies can use to maximize advantages while reducing dangers. Particular emphasis has been placed on finding the best balance between human judgement and artificial intelligence that would generate the most efficient decision-making results. This final chapter offers last thoughts on the present condition and future path of artificial intelligence in management by means of a synthesis of the main results and implications from the other chapters.

The research carried out for this thesis has uncovered a unique trend in how companies now use artificial intelligence in certain operative settings. AI systems showed great efficiency in ordinary operations marked by repetitive, rule-based tasks by means of process optimization and predictive maintenance capabilities. These systems generate closed-loop feedback mechanisms that automatically change workflows depending on performance criteria, therefore matching with transaction cost economics by reducing coordination costs through automated inventory restocking, quality control, and demand forecasting, as shown in Chapter 2.[108]

[108] Tariq, M. U., Poulin, M., Abonamah, A. (2021). Achieving Operational Excellence Through Artificial Intelligence: Driving Forces and Barriers. Frontiers in Psychology. 12

The study, however, showed significant drawbacks in static artificial intelligence systems, which usually find it difficult to fit with contexts' changes. These difficulties call for hybrid systems such human-in-the-loop theory that include human supervision for operations management, hence maintaining operational continuity during disruptions.[109] This result supports a key idea running throughout the thesis: despite recognized developments, AI systems in ordinary operations need careful balancing between automation and human oversight.

The study showed more complex implementation patterns when looking at extraordinary operations as mergers and acquisitions and crisis management are. AI applications in M&A procedures proved to be specifically useful in data-intensive tasks such target screening, due diligence analysis, and comparable business identification. Interviews with industry professionals from financial institutions showed that artificial intelligence technologies provide major benefits in pre-due diligence stages, stressing that AI has greatly assisted in all areas from scouting to origination and evaluation studies (Table 3, 4 and 5, Appendix). These findings align with results from recent academic studies showing that AI-driven target identification examines elements including financial health, market positioning, and growth potential to help businesses create a strong M&A pipeline.[110]

The study, however, showed significant M&A implementation hurdles, especially with regard to data protection and ownership rights. Grasso underlined that uploading sensitive or proprietary data to public domain tools, in order to get syntheses or reports, removes the information uploaded ownership and there is no intention of doing so because that sort of information

[109] Mosqueira-Rey, E., Hernández-Pereira, E., Alonso-Ríos, D., Bobes-Bascarán, J., Fernández-Leal, Á. (2022). Human-in-the-loop machine learning: a state of the art. Artificial Intelligence Review. 56. pp. 3020-3025.

[110] Rashid, M. M., Ullah, N., Uddin, M., Rahman, M. (2025). Artificial Intelligence on Merger and Acquisition Processes: Observation from The Target Identification and Due Diligence Perspective. International Journal of Innovative Research in Multidisciplinary Education. 4. 21-27

is usually sold (Table 1, Appendix). This point of view emphasizes the tension between ownership of proprietary information and artificial intelligence systems that maybe include training data into more general models, therefore posing a major obstacle to adoption.

In crisis management settings, artificial intelligence also shows useful features despite some constraints. The study found different ways in which artificial intelligence might improve real-time information processing, scenario creation, and early warning systems during crisis situations. According to one crisis management specialist interviewed, the use of generative artificial intelligence technologies can be seen as vitally vital during the preparation for a crisis. The concept is that a massive pool of data and knowledge can be generated, from which scenario simulations can then be produced, thus marking an amazing technological advancement. By means of this capacity, one may more intelligently prepare contingencies by means of identification of possible scenarios that could otherwise go unconsidered in conventional planning methods (Table 7, Appendix).

5.2 Policy Requirements for Ethical Implementation

The studies have repeatedly underlined that strong policy frameworks on algorithmic bias, openness, and responsibility are what enable good AI integration. Chapter 2 underlined how algorithmic bias can strengthen and emphasize cultural prejudices, therefore producing what researchers called the bias in, bias out phenomenon, a negative cycle whereby historical inequalities in training datasets are algorithmically processed and projected into future choices.[111] Processed algorithmically and projected into future decisions, this phenomenon could create a self-reinforcing cycle of discrimination that poses

[111] Mayson, S.G., Bias In, Bias Out (September 28, 2018). 128 Yale Law Journal 2218 (2019),, University of Georgia School of Law Legal Studies Research Paper No. 2018-35

especially severe problems in corporate environments where hiring policies, development opportunities, and resource allocation must follow fairness and equitable values.

The investigation revealed the EMMA framework as a viable option for companies trying to foster an ethical AI adoption. Rating AI projects by their possibility for self-learning and human influence, this approach connects ethical ideals with leadership decisions at strategic, tactical, and operational levels. Organizations could use this approach to manage difficult trade-offs and reduce operative, legal, and reputational risks by adding ethics into the decision-making process and balancing innovation and societal values.[112]

Notably, the study found developing legislative frameworks that formalize human supervision standards for high-risk AI applications, including Article 14 of the European Union's AI Act, which will take effect by August 2026.[113] Including design, this law mandates AI system providers to include human monitoring measures at all levels of the system lifetime. While stressing that there's still a major difficulty in translating legal obligations into efficient monitoring systems, the study underlined that the form, substance, and breadth of AI governance are shaped by the involvement of individuals in the AI decision-making process.

The analyses also found a number of feasible ways to solve ethical issues in AI-supported decision-making, such as building more objective datasets by reconfiguring disorganized data, using multiple data centers to provide more accurate results, and carefully deleting data points reflecting past biases. Another interesting approach is to combine small and large data to boost accuracy and precision; while small data provides, user-specific information

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[112] Brendel, A. B., Mirbabaie, M., Lembcke, T.-B., & Hofeditz, L. (2021). Ethical Management of Artificial Intelligence. *Sustainability*, *13*(4), 1974

[113] European Union (Official journal version of 13 June 2024). Artificial Intelligence Act (Regulation (EU) 2024/1689) – Article 14. Interinstitutional File: 2021/0106 (COD).

that helps to prevent errors in causality, big data analysis stresses correlations, so creating a more complicated basis for decision-making.[114]

5.3 Human-AI Collaboration Possibilities

A key result of this study is that efficient AI deployment depends on well-crafted human-AI cooperation models using the complimentary abilities of both sides. The data showed again that companies use artificial intelligence as a supporting tool to enhance human capacity instead of as an independent decision-maker, so matching what researchers have called augmented intelligence in artificial intelligence deployment.[115]

The study found that in M&A situations, the main advantage of human-AI cooperation is the significant speed increases of preliminary analyses' phases, hence enabling analysts to concentrate on higher-value tasks needing human judgement and knowledge. Salimbeni offered a specific illustration in this respect: "A list of 151 players, we're mapping rivals who install stairlifts and lifts. We gave it to OpenAI to map whether they sell platforms... as well as lifts and whether they sell only stairlifts. The mapping was quite fast since it performed the work of an analyst in half a day" (Table 3, Appendix). Although the result needed human validation, time savings were significant.

Human-AI cooperation in crisis management provides unique advantages focused on fast information processing and objectivity. AI systems' emotional neutrality offers a useful counterpoint to human decision-makers, who may be affected by stress, fear, or other emotions during crises. Parboni observed that emotionality and impulsiveness are the main issues for people in crisis situations. From this perspective, artificial intelligence offers a benefit by

[114] Chen, Z. Ethics and discrimination in artificial intelligence-enabled recruitment practices. *Humanit Soc Sci Commun* 10, 567 (2023)

[115] Sadiku, M. N. O., Ashaolu, T. J., Ajayi-Majebi, A., & Musa, S. M. (2021). Augmented intelligence. International Journal of Scientific Advances, 2(5), 772–776

eliminating all those emotional elements that surround people and prevent them from thinking with a clear mind (Table 7, Appendix).

The complementarity of human and artificial intelligence capabilities produces what researchers called collaborative intelligence, whereby each party adds unique strengths to the alliance.[116] While artificial intelligence systems give computational capacity, pattern recognition, and consistency, humans provide contextual knowledge, ethical judgement, and interpersonal skills. Grasso showed this complementarity by talking about developments in due diligence: "The auditing firm sends two interns to flip through pay stubs for four days to check, say, the pay stubs of 1,000 employees to see if they were accurately accounted for. But nowadays tools can scan it, input it, and the artificial intelligence will do it easily" (Table 1, Appendix).

The study, however, highlighted major obstacles to efficient human-AI cooperation: inadequate accuracy of present AI systems managing complicated or ambiguous tasks; data security and privacy issues; economic obstacles to advanced AI deployment; and basic limits in AI's capacity to manage qualitative, interpersonal aspects of both M&A and crisis management. These issues call for thoughtful analysis of implementation plans and suitable governance structures to guarantee that human-AI cooperation optimizes advantages while reducing risks.

5.4 Future Research Directions and Final Reflections

The findings of this thesis revealed several important topics for future research that would increase knowledge of AI integration in management settings. Dynamic ethical frameworks are first needed due to the fluidity of machine

[116] Wilson, H., & Daugherty, P.R. (2018). Collaborative intelligence: Humans and AI are joining forces to solve business problems and create value together. Harvard Business Review, 96(4), 114–123

learning algorithms. Governance models should grow natural adaptation mechanisms to preserve value alignment as artificial intelligence systems improve via ongoing data collecting and retraining cycles. Research should emphasize creating frameworks that guarantee ethical principles' compliance even as they fit these evolutionary traits.

Moreover, future studies should look at cross-cultural validity in AI deployment. The creation of training data and the codification of normative decision rules frequently produce biases in current AI systems, as underlined all through the study. These biases can undermine their efficacy in operational settings all around. Research on how artificial intelligence systems operate in various cultural settings might provide insightful analysis for companies worldwide.

Creating validation protocols for generative artificial intelligence in high-risk operations industries is third on the list of urgent research topics. Robust validation methods guaranteeing correctness while maintaining efficiency improvements are urgently needed in vital services such financial due diligence, where multi-layered verification systems are required because of the technology's tendency for factual inaccuracies.

Furthermore, as several industry professionals contacted for this thesis pointed out, there is great promise for creating safe artificial intelligence systems that can handle sensitive information without sacrificing data ownership or confidentiality. Research on synthetic data creation and Privacy Enhancing Techniques (PETs), as underlined by the CEDPO Institution, provides interesting possibilities for handling these issues.[117]

At last, studies should investigate how AI implementation affects organizational structure, culture, and workforce development over time. The financial analysts interviewed said, "The analyst does many low-value-added

[117] CEDPO AI Working Group. (2023, October 16). Generative AI: The data protection implications. Confederation of European Data Protection Organisations

things. Still, it would be wonderful if there were a technology that enables us to use our time more effectively" (Table 2 and 5, Appendix). Companies willing to control this change will need to grasp how artificial intelligence integration changes professional responsibilities and growth routes.

This thesis has shown that for modern management the combination of artificial and human intelligences is both a major prospect and a problem. The results imply that ethical artificial intelligence integration relies on symbiotic human-machine ecosystems balancing algorithmic efficiency with human judgement and ethical control. Organizations can reduce risks while maximizing advantages by anchoring artificial intelligence development to prospect theory's psychological realism, ecological rationality's adaptive pragmatism, and bounded rationality's cognitive humility.

The study repeatedly underlined that technical optimization by itself is inadequate; artificial and human intelligences must cooperate to provide efficient, fair, and evolutionarily strong decision-making. Approaching artificial intelligence not as a substitute for human management but as a complementing force that improves human capacities while demanding careful governance and deliberate execution will help organizations still negotiate this difficult terrain.

All things considered, this thesis tried to contribute to the growing corpus of studies on artificial intelligence in management by providing a thorough examination of its applications, challenges, and possible remedies. By answering the study questions presented at the beginning, it offers a basis for knowing how companies may efficiently include artificial intelligence into their decision-making systems while preserving necessary human control and ethical governance. The theories and insights created in this study will be useful tools for both academics and practitioners aiming to maximize the promise of artificial intelligence even as AI technology develops, hence reducing its risks.

APPENDIX

Table 1)

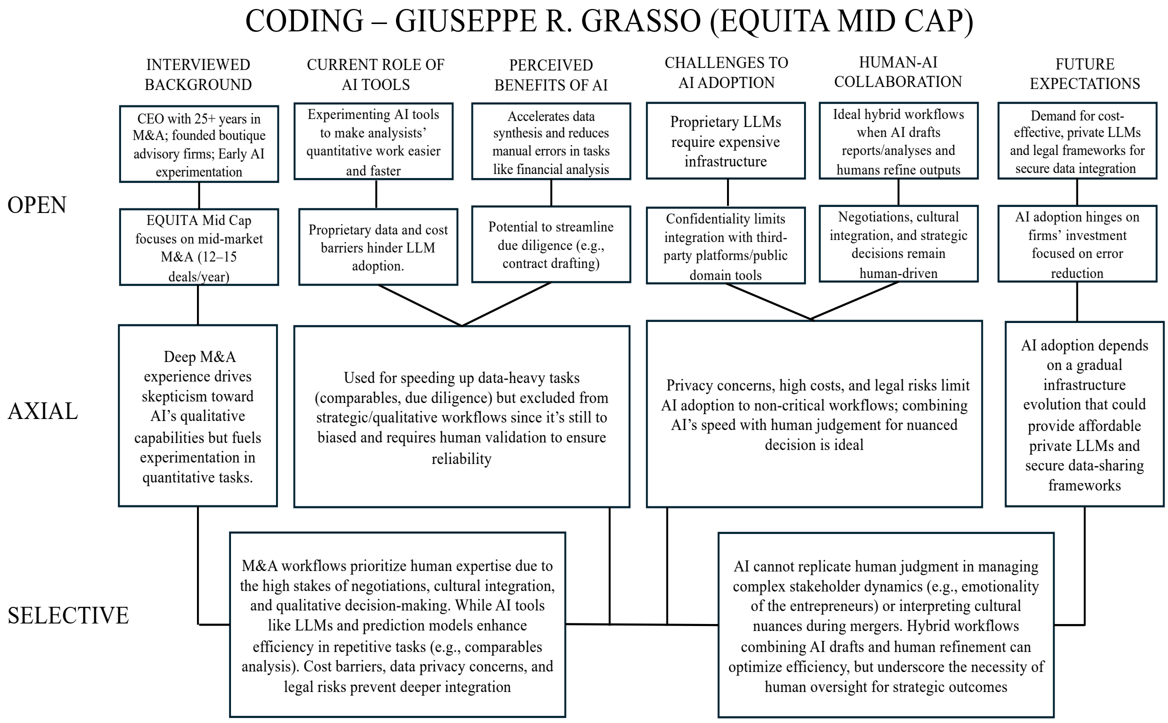


Table 2)

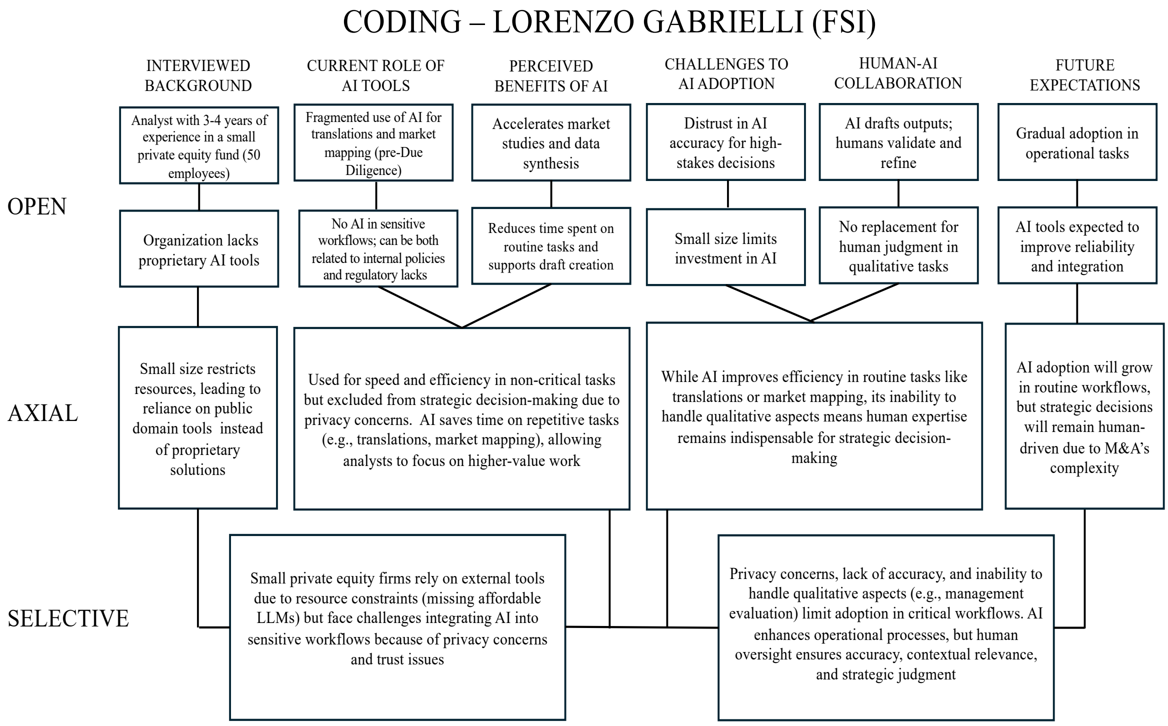


Table 3)

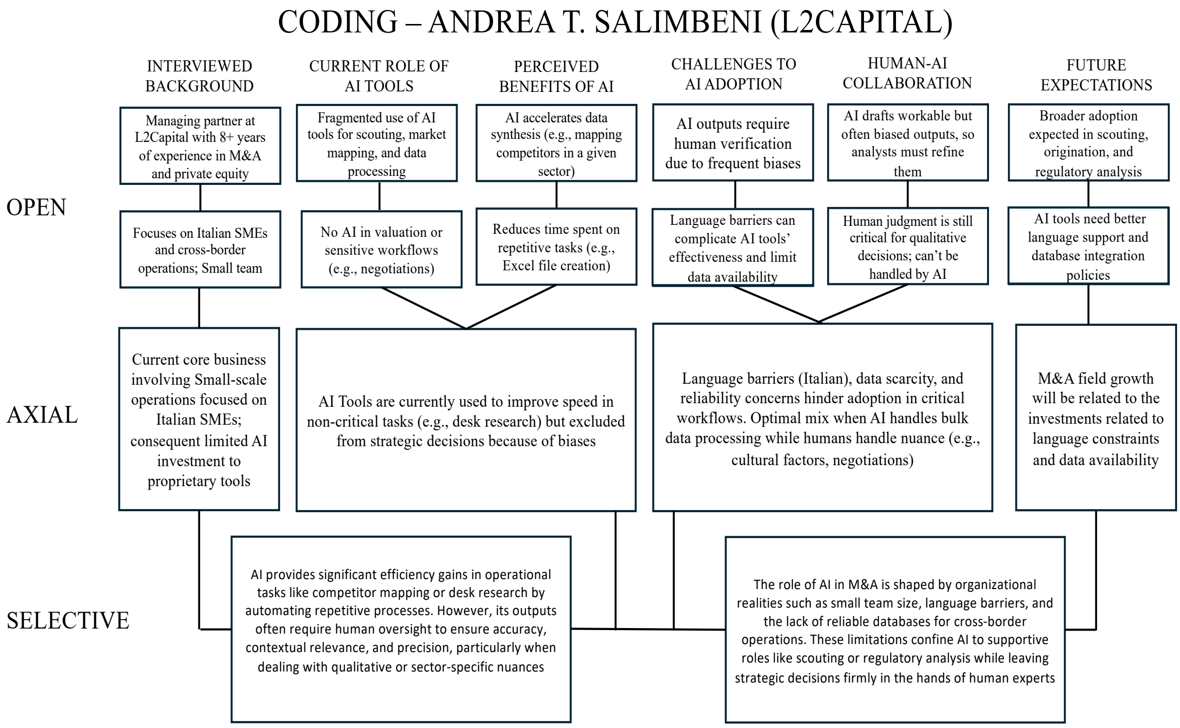


Table 4)

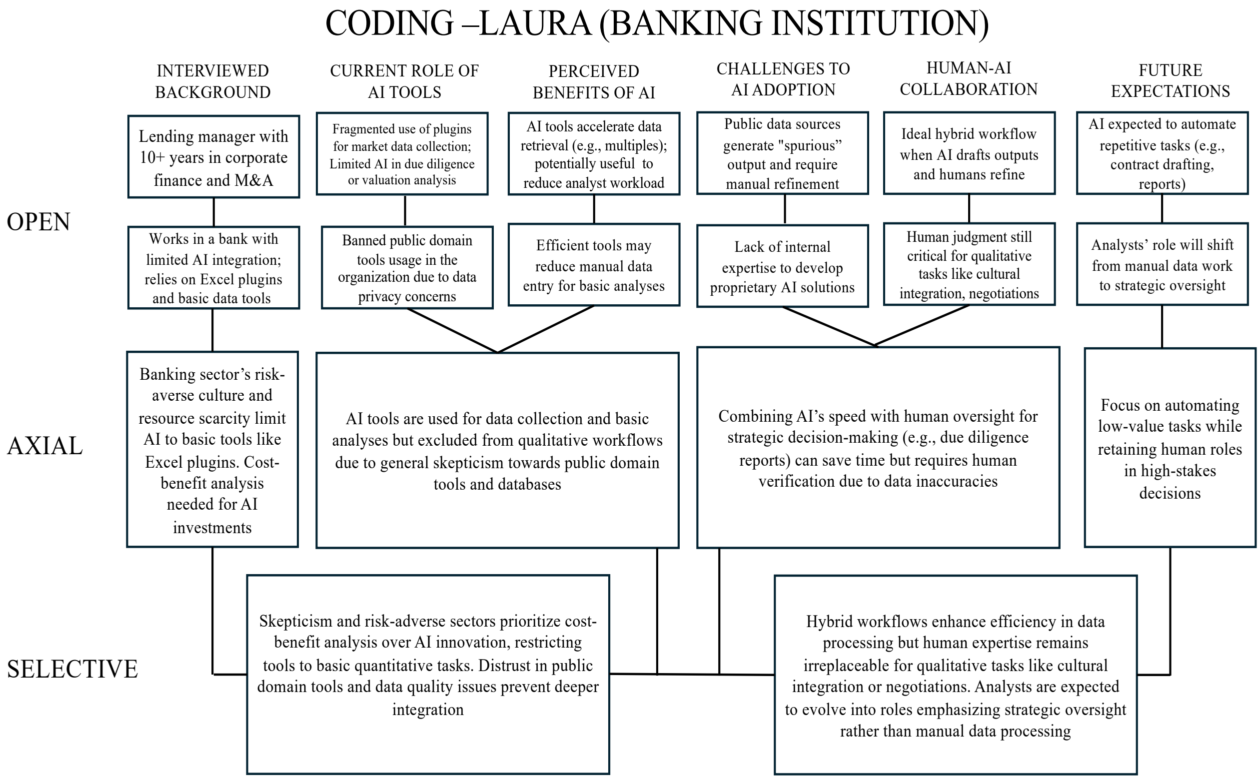


Table 5)

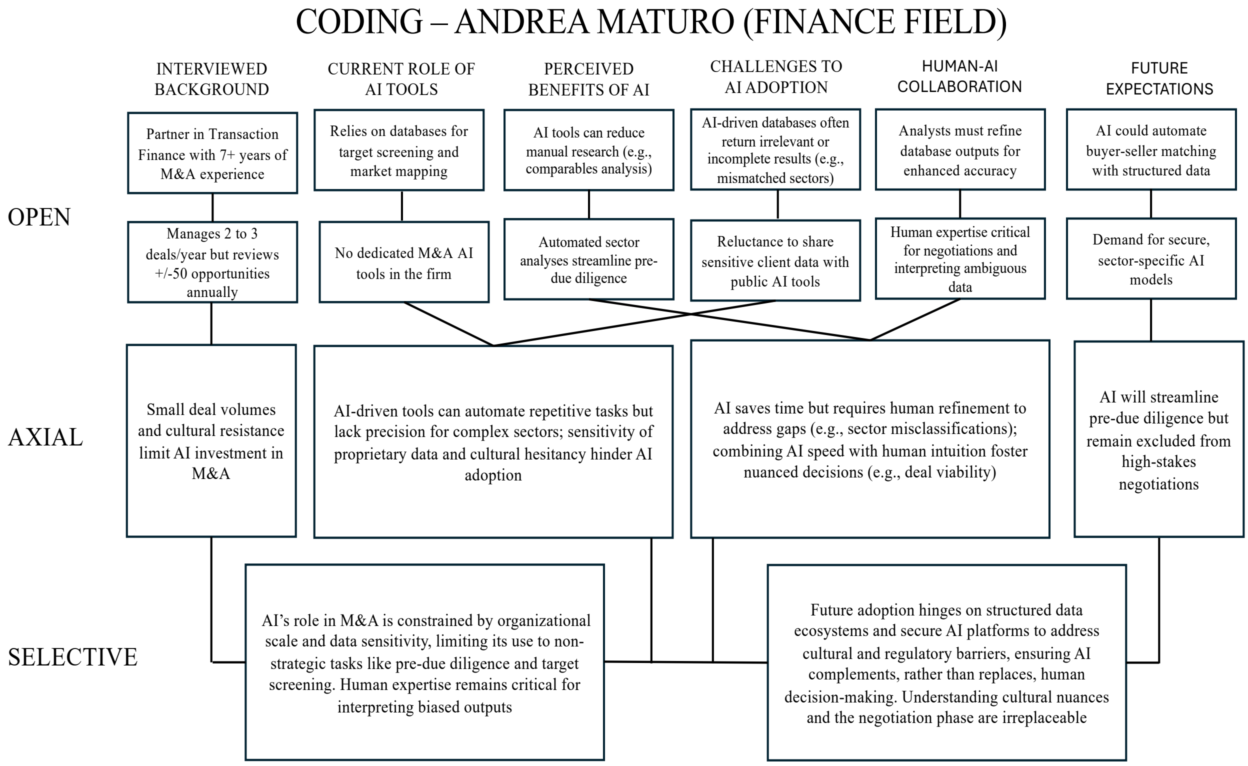


Table 6)

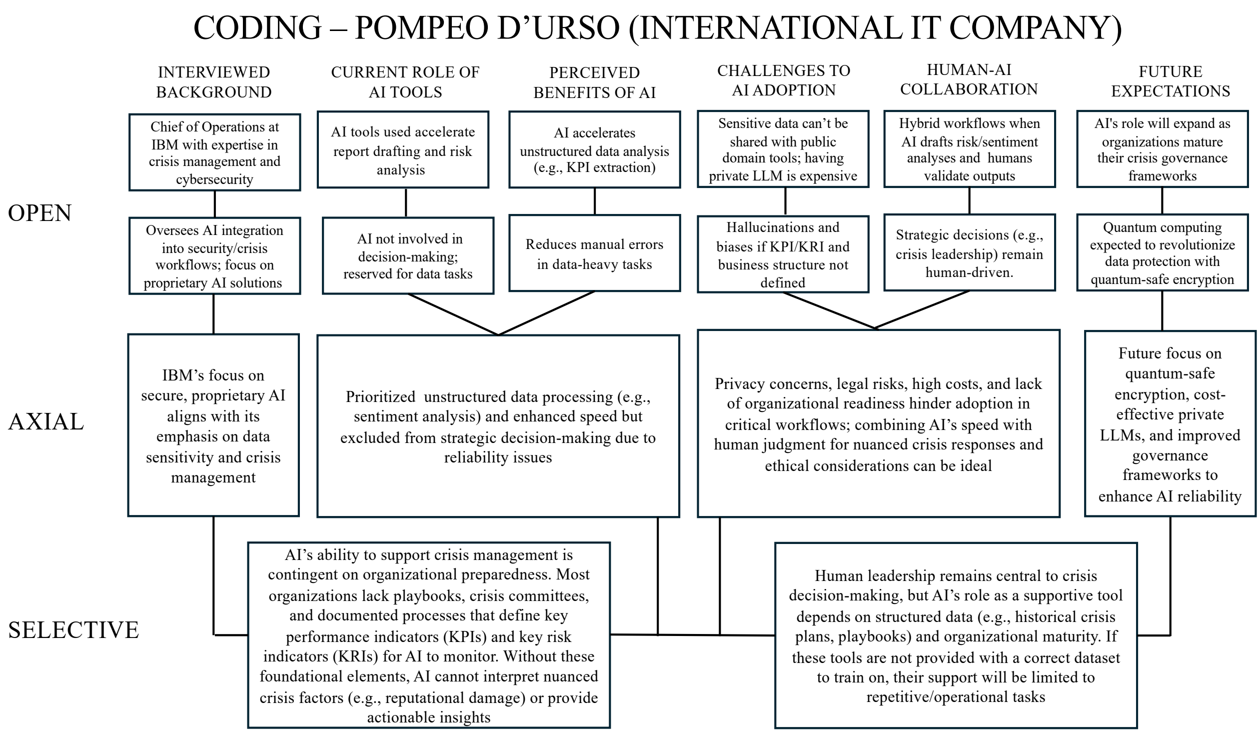
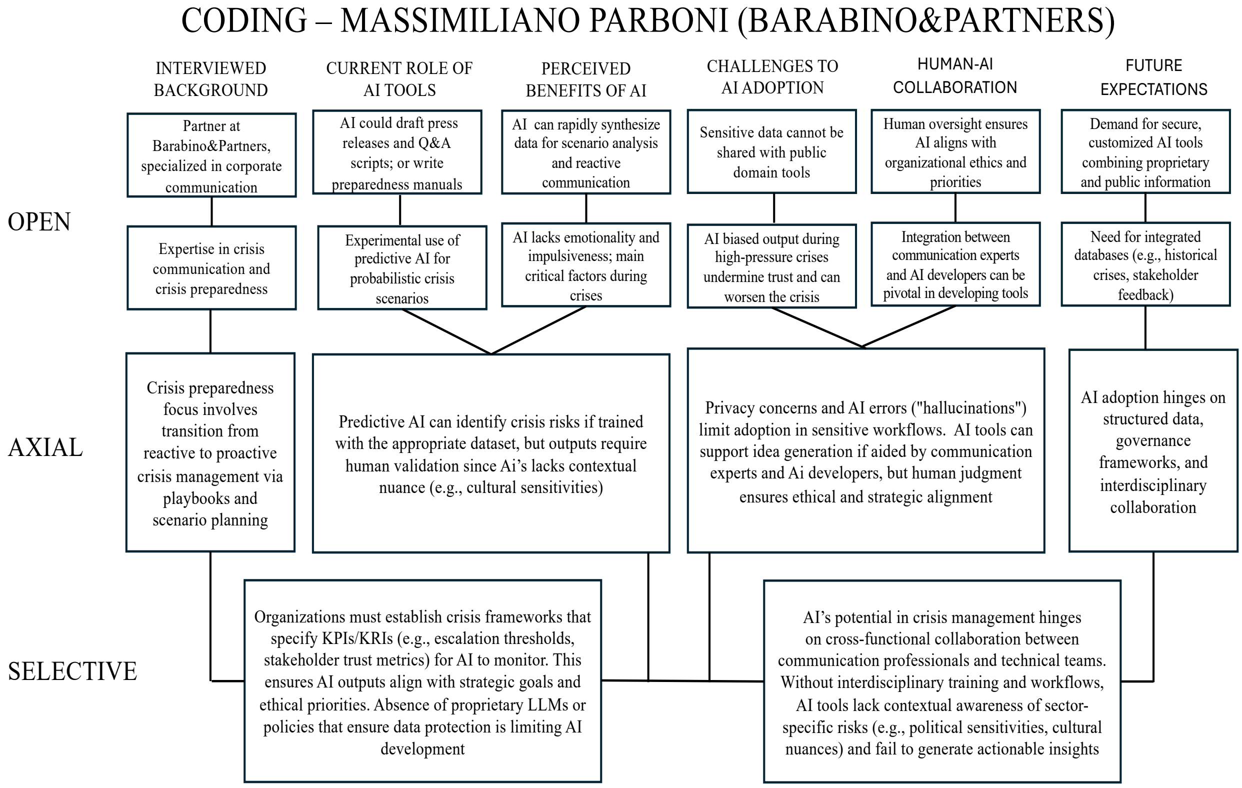


Table 7)



CODING – MASSIMILIANO PARBONI (BARABINO&PARTNERS)
INTERVIEWED BACKGROUND
CURRENT ROLE OF AI TOOLS
PERCEIVED BENEFITS OF AI
CHALLENGES TO AI ADOPTION
HUMAN-AI COLLABORATION
FUTURE EXPECTATIONS
OPEN
Partner at Barabino&Partners, specialized in corporate communication
AI could draft press releases and Q&A scripts; or write preparedness manuals
AI can rapidly synthesize data for scenario analysis and reactive communication
Sensitive data cannot be shared with public domain tools
Human oversight ensures AI aligns with organizational ethics and priorities
Demand for secure, customized AI tools combining proprietary and public information
Expertise in crisis communication and crisis preparedness
Experimental use of predictive AI for probabilistic crisis scenarios
AI lacks emotionality and impulsiveness; main critical factors during crises
AI biased output during high-pressure crises undermine trust and can worsen the crisis
Integration between communication experts and AI developers can be pivotal in developing tools
Need for integrated databases (e.g., historical crises, stakeholder feedback)
AXIAL
Crisis preparedness focus involves transition from reactive to proactive crisis management via playbooks and scenario planning
Predictive AI can identify crisis risks if trained with the appropriate dataset, but outputs require human validation since Ai's lacks contextual nuance (e.g., cultural sensitivities)
Privacy concerns and AI errors ("hallucinations") limit adoption in sensitive workflows. AI tools can support idea generation if aided by communication experts and Ai developers, but human judgment ensures ethical and strategic alignment
AI adoption hinges on structured data, governance frameworks, and interdisciplinary collaboration
SELECTIVE
Organizations must establish crisis frameworks that specify KPIs/KRIs (e.g., escalation thresholds, stakeholder trust metrics) for AI to monitor. This ensures AI outputs align with strategic goals and ethical priorities. Absence of proprietary LLMs or policies that ensure data protection is limiting AI development
AI's potential in crisis management hinges on cross-functional collaboration between communication professionals and technical teams. Without interdisciplinary training and workflows, AI tools lack contextual awareness of sector-specific risks (e.g., political sensitivities, cultural nuances) and fail to generate actionable insights

REFERENCES

- Abhulimen, A.O., & Ejike, O.G. (2024). Solving supply chain management issues with AI and Big Data analytics for future operational efficiency. *Computer Science & IT Research Journal*. DOI:10.51594/csitrj.v5i8.1396
- Abuzaid, A.N. (2024). Strategic AI Integration: Examining the Role of Artificial Intelligence in Corporate Decision-Making. *2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS), 1*, 1-6. DOI:10.1109/ICKECS61492.2024.10616871
- Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. Electronic Markets, 31(2), 427–445. https://doi.org/10.1007/s12525-020-00414-7.
- Ajiga, D.I., Ndubuisi, N.L., Asuzu, O.F., Owolabi, O.R., Tubokirifuruar, T.S., & Adeleye, R.A. (2024). AI-Driven Predictive Analytics In Retail: A Review Of Emerging Trends And Customer Engagement Strategies. *International Journal of Management & Entrepreneurship Research*. https://doi.org/10.51594/ijmer.v6i2.772
- Almaiman, S. (2024). The impact of AI on maintenance performance and predictions. SSRN. https://doi.org/10.2139/ssrn.4797461
- Apu, K.U. (2025). AI-Driven Data Analytics and Automation: A Systematic Literature Review of Industry Applications. Strategic Data Management and Innovation.
- Aquino, S. R., Kilag, O. K., & Valle, J. (2023). From Preparedness to Action: Effective Real-time Crisis Management. *Excellencia: International Multi-Disciplinary Journal of Education (2994-9521)*, *1*(5), 372-384. https://multijournals.org/index.php/excellencia-imje/article/view/137
- Artificial Intelligence Act (Regulation (EU) 2024/1689), Official Journal version of 13 June 2024 *Interinstitutional File: 2021/0106(COD)*
- Artificial Intelligence Act (Regulation (EU) 2024/1689), Official Journal version of 13 June 2024. (Art. 2) *Interinstitutional File: 2021/0106(COD). https://artificialintelligenceact.eu/article/2/*
- Bain & Company. (2024). Global M&A Report 2024: Gaining an edge in a market reset. Bain & Company. Pp.18-29 https://www.bain.com/insights/topics/global-ma-report/
- Bajwa, A. (March, 2025). AI-based emergency response systems: A systematic literature review on smart infrastructure safety. American Journal of Advanced Technology and Engineering Solutions. Pp.*174-200.* https://doi.org/10.2139/ssrn.5171521
- Banasik, A., & Pikiewicz, P. (2023). Application of AI in crisis management [Unpublished manuscript]. Silesian University of Technology, RMS2. https://managementpapers.polsl.pl/wp-content/uploads/2024/02/186-Banasik-Pikieiwcz-1.pdf
- Bitra, D. (2024). Artificial intelligence in business scenario analysis: A framework for enhanced decision-making through what-if simulations. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 10(1), 1149–1159. https://doi.org/10.32628/CSEIT241061155

- Boppiniti, S. (2021). Real-Time Data Analytics with AI: Leveraging Stream Processing for Dynamic Decision Support. International Journal of Management Education for Sustainable Development, 4(4). Retrieved from https://ijsdcs.com/index.php/IJMESD/article/view/589/227
- Brendel, A. B., Mirbabaie, M., Lembcke, T.-B., & Hofeditz, L. (2021). Ethical Management of Artificial Intelligence. *Sustainability*, *13*(4), 1974. https://doi.org/10.3390/su13041974
- Brock, J. K., & von Wangenheim, F. (2019). Demystifying AI: What Digital Transformation Leaders Can Teach You about Realistic Artificial Intelligence. *California Management Review, 61,* 110-134. https://doi.org/10.1177/1536504219865226
- CEDPO AI Working Group. (2023, October 16). Generative AI: The data protection implications. Confederation of European Data Protection Organisations. https://cedpo.eu/wp-content/uploads/generative-ai-the-data-protection-implications-16-10-2023.pdf
- Chen, Z. Ethics and discrimination in artificial intelligence-enabled recruitment practices. *Humanit Soc Sci Commun* 10, 567 (2023). https://doi.org/10.1057/s41599-023-02079-x
- Chowdhury, R. H. (2024). AI-driven business analytics for operational efficiency. World Journal of Advanced Engineering Technology and Sciences, 12(2), 535–543. https://doi.org/10.30574/wjaets.2024.12.2.0329
- Chukwurah, N., Ige, A. B., Adebayo, V. I., & Eyieyien, O. G. (2024). Frameworks for effective data governance: Best practices, challenges, and implementation strategies across industries. Computer Science & IT Research Journal, 5(7), 1666–1679. https://doi.org/10.51594/csitrj.v5i7.1351
- Cisterna, D., Lauble, S., Haghsheno, S., & Wolber, J. (2022). Synergies Between Lean Construction and Artificial Intelligence: AI Driven Continuous Improvement Process. *Proc. 30th Annual Conference of the International Group for Lean Construction (IGLC)*. DOI:10.24928/2022/012
- Coccia, M. (2020). Critical decisions in crisis management (Working Paper CocciaLab No. 45/2020). CNR – National Research Council of Italy. SSRN. https://doi.org/10.2139/ssrn.3541580
- Coombs, W.. (2007). Protecting Organization Reputations During a Crisis: The Development and Application of Situational Crisis Communication Theory. Corporate Reputation Review. 10. 163-176. 10.1057/palgrave.crr.1550049.
- Cristofaro, Matteo. (2017). Herbert Simon's bounded rationality: Its historical evolution in management and cross-fertilizing contribution. Journal of Management History. 23. 170-190. 10.1108/JMH-11-2016-0060.
- Csaszar, Felipe A. and Ketkar, Harsh and Kim, Hyunjin, Artificial Intelligence and Strategic Decision-Making: Evidence from Entrepreneurs and Investors (September 12, 2024). http://dx.doi.org/10.2139/ssrn.4913363
- De Brito Duarte, R., Correia, F., Arriaga, P., & Paiva, A. (2023). AI Trust: Can Explainable AI Enhance Warranted Trust? Human Behavior and Emerging Technologies. DOI:10.1155/2023/4637678
- Delgado, S., Villamarin, A., & Insuasti, J. (2025). AI-Powered Chatbots in Organizations: A Systematic Literature Review. Journal of Information Systems Engineering and Management. DOI:10.52783/jisem.v10i22s.3542

- Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. Management Science, 64(3), 1155–1170. DOI: 10.1287/mnsc.2016.2643
- Dogru, A. K., & Keskin, B. B. (2020). AI in operations management: Applications, challenges, and opportunities. *Journal of Data, Information and Management*, 2(2), 75–94. https://doi.org/10.1007/s42488-020-00023-1
- Dwivedi, S., Singh, C., Soni, K., Tripathi, S.K., & Garg, A.K. (2024). Dynamic Inventory Management In The Era Of Industry Harnessing Ai And Robotics For Agile Operations. ShodhKosh: Journal of Visual and Performing Arts. https://api.semanticscholar.org/CorpusID:275488355
- El Moujahid, O., Murtinu, S., & Sekerci, N. (2023). Artificial intelligence and firm resilience (pp. 6–24). SSRN. https://doi.org/10.2139/ssrn.4544691
- Emmi, P. A. (2025). The impact of artificial intelligence on M&A deals—Part I. The Journal of Robotics, Artificial Intelligence & Law, 8 (2), 125–146. https://www.reedsmith.com/en/perspectives/2025/03/impact-of-artificial-intelligence-ma-deals-part-i
- Engelbrecht, W., Canon, J., Dilger, E., McKenzie, S., & Dasharath, S. (June, 2024). Artificial intelligence and mergers and acquisitions: Observations from the frontlines and how to prepare for the coming shift. Deloitte Development LLC https://www2.deloitte.com/content/dam/Deloitte/us/Documents/mergers-acqisitions/us-artificial-intelligence-and-mergers-and-acquisitions.pdf
- European Union (Official journal version of 13 June 2024). Artificial Intelligence Act (Regulation (EU) 2024/1689) – Article 14. Interinstitutional File: 2021/0106 (COD). https://artificialintelligenceact.eu/article/14/
- Filippucci, F., Gal, P., Jona-Lasinio, C., Leandro, A., & Nicoletti, G. (2024). The impact of artificial intelligence on productivity, distribution and growth: Key mechanisms, initial evidence and policy challenges (OECD Artificial Intelligence Papers No. 15). OECD Publishing https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/04/the-impact-of-artificial-intelligence-on-productivity-distribution-and-growth_d54e2842/8d900037-en.pdf
- Foss, N. J. (2002). *Bounded Rationality and Tacit Knowledge in the Organizational Capabilities Approach: An Assessment and a Reevaluation*. The Link Program. LINK Working Paper No. 2002-18
- Fragiadakis, G., Diou, C., Kousiouris, G., & Nikolaidou, M. (2024). Evaluating human-AI collaboration: A review and methodological framework. arXiv. https://doi.org/10.48550/arXiv.2407.19098
- Franca, O., Ayinla, B.S., Ndubuisi, N.L., Atadoga, A., Asuzu, O.F., Ugochukwu, C., & Adeleye, R.A. (2024). Enhancing accounting operations through cloud computing: A review and implementation guide. *World Journal of Advanced Research and Reviews*. DOI:10.30574/wjarr.2024.21.2.0441
- Frey, C., & Osborne, M. (2017). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

- Fu, R., Huang, Y., & Singh, P. V. (2020). AI and algorithmic bias: Source, detection, mitigation and implications. SSRN. https://doi.org/10.2139/ssrn.3681517
- Gavade, D. (2023). AI-driven process automation in manufacturing business administration: Efficiency and cost-efficiency analysis. Presented at the 7th IET International Smart Cities Symposium, Bahrain. DOI: 10.1049/icp.2024.1038
- Ghaffarian, S., & Taghikhah, F. (April, 2023). Explainable artificial intelligence in disaster risk management: Achievements and prospective futures. SSRN. https://doi.org/10.2139/ssrn.4421109
- Goldstein, D. G., & Gigerenzer, G. (2002). Models of ecological rationality: The recognition heuristic. *Psychological Review,109*(1),75–90. https://doi.org/10.1037/0033-295X.109.1.75
- Golgeci, I., Ritala, P., Arslan, A., McKenna, B., & Ali, I. (2025). Confronting and alleviating AI resistance in the workplace: An integrative review and a process framework. Human Resource Management Review, 35(2), Article 101075. https://doi.org/10.1016/j.hrmr.2024.101075
- Gruenbichler, R. (2023). Implementation Barriers of Artificial Intelligence in Companies. In Proceedings of FEB Zagreb 14th International Odyssey: Conference on Economics and Business (1 ed., Vol. 5, pp. 193-203). University of Zagreb. https://doi.org/10.22598/odyssey/2023.5
- Hammerstein, P., & Stevens, J. (2012). Six reasons for invoking evolution in decision theory. *In P. Hammerstein & J. Stevens (Eds.), Evolution and the mechanisms of decision making* (pp. 1–16). MIT Press. https://doi.org/10.7551/mitpress/9780262018081.003.0001
- Han, M., Shen, H., Wu, J., & Zhang, X. (Michael). (2023). Artificial intelligence and firm resilience: Evidence from firm performance under natural disaster shocks (pp. 3–25). Forthcoming in Information Systems Research. SSRN. https://doi.org/10.2139/ssrn.5095227
- Hansen, H.F., Lillesund, E., Mikalef, P. et al. (2024). Understanding Artificial Intelligence Diffusion through an AI Capability Maturity Model. Inf Syst Front 26, 2147–2163. https://doi.org/10.1007/s10796-024-10528-4
- Huang, A. H., & You, H. (2022). Artificial intelligence in financial decision making. Handbook of Financial Decision Making (Forthcoming). HKUST Business School Research Paper No. 2022-082. Available at SSRN: https://ssrn.com/abstract=4235511
- Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service: A customer service revolution. Journal of Service Research, 21(2), 155–172. DOI 10.1177/1094670517752459
- Hunkenschroer, A., & Kriebitz, A. (2022). Is AI recruiting (un)ethical? A human rights perspective on the use of AI for hiring. *AI and Ethics, 3*, Article 166. https://doi.org/10.1007/s43681-022-00166-4
- Jahin, M. A., Naife, S. A., Saha, A., & Mridha, M. F. (2023). AI in supply chain risk assessment: A systematic literature review and bibliometric analysis. arXiv. https://doi.org/10.48550/arXiv.2401.10895
- Jarrahi, M.H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision-making. Business Horizons, 61(4), 577–586
- Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, *47*(2), 263–291. https://doi.org/10.2307/1914185

- Kapoor, A. (2024). Big Data Infrastructure: Integrating Legacy Systems with AI-Driven Platforms. *Computer Science, Engineering and Information Technology*. DOI:10.5121/csit.2024.141913
- Karikatti, M., Kalkoti, N., & Mogare, H. (June, 2024). A systematic review on augmented intelligence: A relation between human intelligence and artificial intelligence. International Journal of Research Publication and Reviews, Vol (5), Issue (6), June (2024), Page – 5448-5454. https://ijrpr.com/uploads/V5ISSUE6/IJRPR30435.pdf
- Kenrick, D. T., Griskevicius, V., Sundie, J. M., Li, N. P., Li, Y. J., & Neuberg, S. L. (2009). Deep rationality: The evolutionary economics of decision making. *Social Cognition, 27*(5), 764-785. https://api.semanticscholar.org/CorpusID:2528536
- Khattar, A., & Quadri, S. M. K. (March, 2020). Emerging role of artificial intelligence for disaster management based on microblogged communication. Proceedings of the International Conference on Innovative Computing & Communications (ICICC) 2020. SSRN. https://doi.org/10.2139/ssrn.3562973
- Knight, G., & Smallman, C. (2014). Crisis response: Aligning scripts and actors. SSRN. https://doi.org/10.2139/ssrn.2461981
- Kocerova, S., Kalkis, H., Roja, Z. (2024). Process improvement with AI in service industry: case studies. In: Henrijs Kalkis and Zenija Roja (eds) Social and Occupational Ergonomics. AHFE (2024) International Conference. AHFE Open Access, vol 152. AHFE International, USA. http://doi.org/10.54941/ahfe1005323
- Kristiana, I. (2024). Review of Improving Banking Operational Efficiency through AI and ML: Strategy, Implementation and Impact. *Jurnal Komunikasi, Sains dan Teknologi*. DOI:10.61098/jkst.v3i1.125
- Kvam, Peter & Cesario, Joseph & Schossau, Jory & Eisthen, Heather & Hintze, Arend. (2015). Computational evolution of decision-making strategies. https://adamilab.msu.edu/wp-content/uploads/paper0216-1.pdf
- Łabędzki, R. (October 12, 2024). Hybrid Multi-Agent Systems as a subject of scientific research in the field of management. http://dx.doi.org/10.2139/ssrn.4985522
- Mayson, S.G., Bias In, Bias Out (September 28, 2018). 128 Yale Law Journal 2218 (2019),, University of Georgia School of Law Legal Studies Research Paper No. 2018-35, Available at SSRN: https://ssrn.com/abstract=3257004
- Mbah, G.O. (2024). Data privacy in the era of AI: Navigating regulatory landscapes for global businesses. *International Journal of Science and Research Archive*. https://doi.org/10.30574/ijsra.2024.13.2.2396
- Mirzayev, E., Vanneste, B., Testoni, M. (January 31, 2025) Artificial Agents and the Evaluation of M&As. http://dx.doi.org/10.2139/ssrn.5119314
- Mittelstadt, B., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. Big Data & Society. https://doi.org/10.1177/2053951716679679

- Mosqueira-Rey, E., Hernández-Pereira, E., Alonso-Ríos, D., Bobes-Bascarán, J., Fernández-Leal, Á. (2022). Human-in-the-loop machine learning: a state of the art. Artificial Intelligence Review. 56. pp. 3020-3025. 10.1007/s10462-022-10246-w.
- Nah, S., Luo, J., & Joo, J. (2023). Rethinking Artificial Intelligence: Algorithmic Bias and Ethical Issues| Mapping Scholarship on Algorithmic Bias: Conceptualization, Empirical Results, and Ethical Concerns. *International Journal Of Communication, 18*, 22. Retrieved from https://ijoc.org/index.php/ijoc/article/view/20805
- Nassar, A., & Kamal, M. (2021). Ethical Dilemmas in AI-Powered Decision-Making: A Deep Dive into Big Data-Driven Ethical Considerations. International Journal of Responsible Artificial Intelligence, 11(8), 1–11. Retrieved from https://neuralslate.com/index.php/Journal-of-Responsible-AI/article/view/43
- Nima N. (18 September, 2023) Transforming the M&A Process: The Current and Future Role of Artificial Intelligence. IMAA Institute. https://imaa-institute.org/blog/the-future-role-of-artificial-intelligence-in-mergers-and-acquisitions/#banner
- Osasona, F., Amoo, O., Atadoga, A., Abrahams, T., Farayola, O., Ayinla, B. (2024). Reviewing the ethical implications of ai in decision making processes. International Journal of Management & Entrepreneurship Research. 6. 322-335. 10.51594/ijmer.v6i2.773.
- Osasona, F., Amoo, O.O., Atadoga, A., Abrahams, T.O., Farayola, O.A., & Ayinla, B.S. (2024). Reviewing The Ethical Implications Of Ai In Decision Making Processes. International Journal of Management & Entrepreneurship Research. https://doi.org/10.51594/ijmer.v6i2.773
- Patil, D. (2024). Artificial intelligence for personalized marketing and consumer behaviour analysis: Enhancing engagement and conversion rates. SSRN. https://ssrn.com/abstract=5057436
- Pieretti, C., Papanastasiou, D. (2025, January 29). Moody's GenAI-powered Research Assistant drives significant efficiency gains for financial services industry. Moody's. https://www.moodys.com/web/en/us/site-assets/genai-research-assistant-financial-services.pdf
- Rainer, K., Kundratitz, V., Hagendorn, M., Neubauer, G., Ignjatović, D., Kutalek, R., & Sturm, N. (2024). Artificial intelligence in crisis management: Potential solutions and challenges. IDIMT-2024. https://doi.org/10.35011/IDIMT-2024-13
- Rashid, M. M., Ullah, N., Uddin, M., Rahman, M. (2025). Artificial Intelligence on Merger and Acquisition Processes: Observation from The Target Identification and Due Diligence Perspective. International Journal of Innovative Research in Multidisciplinary Education. 4. 21-27. 10.58806/ijirme.2025.v4i1n03.
- Rashid, M. M., Ullah, N., Uddin, M., Rahman, M. (2025). Artificial Intelligence on Merger and Acquisition Processes: Observation from The Target Identification and Due Diligence Perspective. International Journal of Innovative Research in Multidisciplinary Education. 4. 21-27. 10.58806/ijirme.2025.v4i1n03. (già citato nel 2.3)
- Raso, F., Hilligoss, H., Krishnamurthy, V., Bavitz, C., Kim, L. Y. Artificial Intelligence & Human Rights: Opportunities & Risks (September 25, 2018). Berkman Klein Center Research Publication No. 2018-6, Available at SSRN: https://ssrn.com/abstract=3259344 or http://dx.doi.org/10.2139/ssrn.3259344

- Rogha, M. (2023). Explain to decide: A human-centric review on the role of explainable artificial intelligence in AI-assisted decision making. arXiv. https://arxiv.org/abs/2312.11507

- S. Ransbotham, D. Kiron, P. Gerbert, and M. Reeves, "Reshaping Business With Artificial Intelligence," MIT Sloan Management Review and The Boston Consulting Group, September 2017.https://web-assets.bcg.com/img-src/Reshaping%20Business%20with%20Artificial%20Intelligence_tcm9-177882.pdf
- Sadiku, M. N. O., Ashaolu, T. J., Ajayi-Majebi, A., & Musa, S. M. (2021). Augmented intelligence. International Journal of Scientific Advances, 2(5), 772–776. https://doi.org/10.51542/ijscia.v2i5.17
- Shukla, M., Dubey, S., & Mishra, S. (2024). The impact of AI on improving the efficiency and accuracy of managerial decisions. International Journal for Research in Applied Science & Engineering Technology, 12(VII), 830–837. https://doi.org/10.22214/ijraset.2024.63652
- Sood, A., & Dhull, K. (2024). The future of Six Sigma-Integrating AI for continuous improvement. International Journal of Innovative Research in Engineering and Management, 11(5), Article 2. https://doi.org/10.55524/ijirem.2024.11.5.2
- Spaniol, M.J., & Rowland, N.J. (2023). AI-assisted scenario generation for strategic planning. *Futures & Foresight Science*. DOI:10.1002/ffo2.148
- Sterz, Sarah & Baum, Kevin & Biewer, Sebastian & Hermanns, Holger & Lauber-Rönsberg, Anne & Meinel, Philip & Langer, Markus. (2024). On the Quest for Effectiveness in Human Oversight: Interdisciplinary Perspectives. 2495-2507. https://doi.org/10.48550/arXiv.2404.04059
- Tairov, I.; Stefanova, N.; Aleksandrova, A.; Aleksandrov, M. (2024) Review of AI-Driven Solutions in Business Value and Operational Efficiency. *Economics Ecology Socium* *8*, 55-66. https://doi.org/10.61954/2616-7107/2024.8.3-5
- Tarafdar, M., Beath, C., & Ross, J. (2020). Using AI to enhance business operations. In How AI is transforming the organization (https://doi.org/10.7551/mitpress/12588.003.0015)
- Tariq, M. U., Poulin, M., Abonamah, A. (2021). Achieving Operational Excellence Through Artificial Intelligence: Driving Forces and Barriers. Frontiers in Psychology. 12. 10.3389/fpsyg.2021.686624.
- Uçar, A., Karakose, M., & Kırımça, N. (2024). Artificial intelligence for predictive maintenance applications: Key components, trustworthiness, and future trends. Applied Sciences, 14(2), 898. https://doi.org/10.3390/app14020898
- Vijayabakar, S. (2024). Harnessing Generative AI for Risk Management and Fraud Detection in Fintech: A New Era of Human-Machine Collaboration. International Journal of Scientific Research and Management (IJSRM). DOI:10.18535/ijsrm/v8i04.ec01
- Wang, H. & Zhou, Y. (2023). Combination of Artificial Intelligence with Mergers and Acquisitions. BCP Business & Management. 39. 235-241. 10.54691/bcpbm.v39i.4069.
- Wasil, A., Smith, E., Katzke, C., Reed, T., & Bullock, J. (July, 2024). AI Emergency Preparedness: Examining the UK government's ability to detect and respond to AI-related national security threats. SSRN. https://doi.org/10.2139/ssrn.4896801
- Wilson, H., & Daugherty, P.R. (2018). Collaborative intelligence: Humans and AI are joining forces to solve business problems and create value together. Harvard Business Review, 96(4), 114–123

- Yenuganti, N. (2025). Transforming Supply Chain Efficiency: The Integration of Real-Time Inventory Tracking and AI-Powered Demand Forecasting. International Journal of Scientific Research in Computer Science, Engineering and Information Technology.
- Zhang, H., Pu, Y. ., Zheng, S. ., & Li, L. . (2024). AI-Driven M&A Target Selection and Synergy Prediction: A Machine Learning-Based Approach. *Journal of Artificial Intelligence General Science (JAIGS) ISSN:3006-4023*, *6*(1), 359–377. https://doi.org/10.60087/jaigs.v6i1.260
- Zhishuo, H. (December 27, 2024) Does AI Adoption in M&A Teams Improve Deal Performance? pp.17-21. https://ssrn.com/abstract=5128530