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Managing in the AI Era:

A Systematic Literature Review on the Evolution of Managerial Roles and Competencies

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1 Introduction

The integration of Artificial Intelligence into business has become a strategic imperative for companies, with positive effects on efficiency, innovation and competitiveness (Oyekunle & Boohene, 2024). AI is today used in a broad spectrum of corporate functions, ranging from marketing (De Mauro et al., 2022) to human resource management (Afzal et al., 2023) and supply chain optimization (Younis et al., 2022). With advancing AI technologies, companies are increasingly adopting intelligent systems into both operational and planning workflows, revolutionizing conventional business models and reconfiguring industry dynamics. (Kolbjørnsrud, 2024).

Beyond technological advancements, AI adoption is posing major organisational issues. With increasing sophistication, these systems are likely to perform tasks that were hitherto done by humans, leading to potential job losses and organisational disruption. Although it must be acknowledged that job losses and organisational disruption concerns surround AI, it is also true that AI is generating new organisational roles and jobs (Faluyi, 2025). AI is able to handle repetitive work, which threatens jobs that involve manual labor or cognitive routine work. Yet, more automation creates more advanced and creative roles that it is difficult for machines to handle (Faluyi, 2025). Among these emerging roles, special attention is being accorded to roles that exclusively involve interaction between humans and AI, namely, algorithmic broker, algorithmic articulator, trust builder, and ethical ambassador, which are figures that can act as go-betweens for communication among technical and non-technical parties, orchestrate the adoption of AI solutions into organizational processes, build employee trust towards algorithmic systems, and ensure ethical usage (Lippert & Dresden, 2024). Recent estimates by the World Economic Forum further highlight that AI is going to considerably redefine the world's workforce, where most of today's jobs get automated by 2030. Although overall employment prospects look optimistic, disruption that is expected to be large-scale demands widespread upskilling and reskilling measures (Future of Jobs Report, 2025). Coordinating this transition from a managerial standpoint is going to be crucial to creating transformative changes in an organization that is not only sustainable but also inclusive, grounded in frameworks of collaboration between humans and machines, not just automation alone (Haesevoets et al., 2021).

In spite of this increasingly pressing subject, most of today's contributions to managerial skills and competencies is still bounded to pre-existent models and frameworks, constructed in organisational contexts that predated the large-scale diffusion of AI. Such traditional models, which have stressed transversal skills like leadership, communication, decision making, and problem-solving (Asumeng, 2014; Bolzan De Rezende & Blackwell, 2019; Hawi et al., 2015; Khoshouei et al., 2013), were designed in contexts that were not subject to the added complexity brought by Artificial Intelligence. Therefore, such skills and competencies require reinterpretation according to the changes brought by the integration of AI into companies and organisations, and also, new competencies must be created, as the diffusion of AI not only affects the existent skills, but also brings entirely new areas of expertise, especially in fields where data and algorithms prevail (Giraud et al., 2023). This gap in the literature has been highlighted by Bevilacqua *et al.*, who underline the lack of comprehensive and systematized frameworks able to grasp the changing set of competencies needed in AI-powered organisational environments (2025).

With reference to the above, this work aims to deepen the understanding of what is needed to manage in AI-saturated contexts, as well as what AI-enhanced or AI-enabled competencies are necessary in order to lead organizations effectively in these contexts. Specifically, in this study, it is examined which AI competencies are most important for managers and executives, what changes in the roles of managers occur in AI-driven organisational contexts, and what ethical and legal considerations need to be included in leadership competency frameworks. By leveraging a Systematic Literature Review approach integrated with LLM-assisted extraction techniques, this study provides a taxonomy that consolidates fragmented insights into a coherent framework. The resulting taxonomy is organized hierarchically: at the first level, four macro-competency families have been identified; each macro-family encompasses several specific sub-competencies, reflecting the multifaceted demands placed on contemporary managers by AI integration processes. We delve into this taxonomy extensively, considering whether and how these competencies relate to one another and address the arising issues and opportunities that result from pervasive AI adoption within organisational contexts.

The rest of the paper is organized as follows: Chapter 2 provides some theoretical background on the evolution of Artificial Intelligence, its applications and limitations, the evolution of managerial roles and the main traditional competency frameworks, including the formulation of research questions. Chapter 3 discusses the research methodology from a theoretical perspective, outlining the systematic literature review protocol, the content analysis techniques, and the integration of Large Language Models within a human-in-the-loop process. Chapter 4 illustrates the application of these methods, illustrating the process of article selection, data extraction through prompt engineering and data categorization. Chapter 5 delivers research findings, presenting an in-depth analysis of the proposed taxonomy of managerially relevant competencies, as well as reviewing sectoral distributions, methodological trends, fit scores, and other significant results arising from the systematic review. Finally, the last chapter provides conclusions of the research, and recognition of study limitations, together with suggestions for further research.

2 Theoretical Background

In the context of ongoing technological transformation, the analysis of Artificial Intelligence (AI) becomes increasingly central to understanding contemporary organizational and managerial dynamics. This introduction section aims to analyze the phenomenon by introducing an organized overview of its fundamental definitions, its technological and historical development, and its implications at both strategic and managerial levels. The discussion begins with a conceptual and definitional framing of AI, followed by an abridged reconstruction of its main technological milestones. This serves as a foundation for the analysis of its most significant current applications. In this context, specific attention is paid to Generative AI (GenAI), which is one of today's most prominent and revolutionary advances within the larger Artificial Intelligence field.

While the focus remains on AI technologies, this work places special emphasis on their implications for managerial competencies, highlighting how the emergence of AI challenges, reshapes, and redefines the knowledge, skills, and abilities required of managers in the digital era.

2.1 History of AI

Knowing out of past is key to understanding present trends and issues in AI. The following sections trace the evolution of AI from its earliest conceptual origins to the most relevant technological and methodological milestones that have shaped its trajectory. This overview includes the initial theoretical foundations of programmable computation and proceeds through the emergence of symbolic approaches, the rise of machine learning, and the recent advancements in deep learning and generative models, including Generative AI, which can be considered as the most recent discovery in this field.

2.1.1 The Origins of AI

The history of Artificial Intelligence (AI) is well over two centuries old, starting from seminal ideas in mechanical computation to current sophisticated generative systems and Large Language Models (LLMs). The intellectual origins of AI connect to Charles Babbage, who in 1822 conceptualized the Difference Engine, the very first mechanical device to perform mathematical computations based on finite differences (Grzybowski et al., 2024). This was succeeded by the Analytical Engine, an even more general-purpose design that incorporated programmability ideas based on punched cards, drawing inspiration from the Jacquard loom. His co-worker Ada Lovelace is also credited to have conceptualized the machine's capacity to process symbols and not just numbers, essentially being the world's first computer programmer. (Grzybowski et al., 2024).

In the middle of the 20th century, Alan Turing gave the very first formal framework for considering machine intelligence. His 1950 paper "*Computing Machinery and Intelligence"* propounded the well-known Turing Test as a behavioral measure of machine intelligence and predicted that learning and reasoning could, in theory, be computationally simulative (Grzybowski et al., 2024; Haenlein & Kaplan, 2019). Albeit these achievements, AI as an area of research took its birth in 1956, as an official line of research, after the Dartmouth Summer Research Project on Artificial Intelligence, proposed by John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon in August 1955. Their proposal articulated the foundational conjecture of AI: *"that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it"* (Grzybowski et al., 2024; McCarthy et al., 2006). The project sought to investigate fundamental issues like language processing, abstraction, neural nets, self-improvement, and even randomness as an inspiration to creativity issues that remain significant today. In the 1970s, AI research began to center more on expert systems like MYCIN and DENDRAL, which employed rule-encoded knowledge by hand to simulate human decision-making in specific areas like medicine and chemistry (Grzybowski et al., 2024). Based on formal, logic-based representations of knowledge and inference, these systems were effective within narrow domains but inflexible in dealing with imprecise or unstructured data. This limitation was among the reasons that fueled mounting disillusionment within both the research community and funding agencies, ultimately leading to what is today known as the AI Winter, an era of decreased funding and diminished advances, especially within the United States and the United Kingdom (Haenlein & Kaplan, 2019).

In spite of this reverse, AI Winter also proved to be an inflection point for novel approaches to be born. Scientists started looking at data-driven and statistical approaches that could learn from data as opposed to fixed rules. Increased availability of computational power, together with digitized data, and improvements in neural network topologies, provided the foundation for movement toward machine learning and, ultimately, deep learning (Grzybowski et al., 2024). The watershed moment in this development was when IBM's Deep Blue beat world chess champion Garry Kasparov in 1997; it was an exercise in computational brute force and domain-specific optimization as opposed to adaptive intelligence (Haenlein & Kaplan, 2019). Unlike previous systems that were designed to mimic human reasoning, Deep Blue used gigantic parallel computation and domain-specific optimization, analyzing virtually 200 million chess positions every second using custom-built chips to boost move generation, position evaluation, and alpha-beta search (Hsu & Feng-hsiung, 1999).

Real advances towards flexible, adaptive AI began in the 2010s, when deep neural networks that were able to extract high-level features from raw data were developed. The breakthrough occurred with Google DeepMind's AlphaGo, which beat one of the world's best Go players by learning advanced strategies from large datasets using reinforcement learning and neural networks (Haenlein & Kaplan, 2019). According to Yu, Deep Blue uses brute-force computation, testing hundreds of millions of chess positions per second with defined rules and carefully built evaluation algorithms (2016). It could play at a world-class level, but it couldn't learn to improve on its own. AlphaGo, in contrast, employed a hybrid mode based on machine learning, mixing neural networks trained on games played by humans up to that moment with reinforcement learning based on self-play. This enabled the system not just to mimic expert strategies, but also to innovate novel ones superior to human intuition. The two systems were not just technologically different, but also from a cultural and symbolic standpoint. As Bory suggests, Deep Blue was perceived as a black-box machine whose unconventional moves were greeted with suspicion (2019). Kasparov himself wondered whether human involvement played a part in one of Deep Blue's most surprising moves, subsequently blamed on a software bug. AlphaGo's moment of creative insight came on move 37 of game two against Sedol, which commentators termed as "*beautiful*," "*surprising*," and "*unimaginable to a human player*". This move, instead of evoking fear, bred admiration and awe. The context shifted from confrontation to cooperation: AlphaGo was no longer an impenetrable adversary, but an instrument capable of inventiveness: an explorer of human knowledge in partnership. Together these two episodes signal not just technological change but also deeper change in that conceptualization and retelling of AI: from impenetrable foe to creative agent, from machine of determinism to self-enhancing system. These advances ushered in the current wave of AI, defined by application in natural language processing, machine vision, and autonomous systems. In recent years, AI entered yet another wave, as Large Language Models (LLMs) like GPT-3 and GPT-4, and high-impact tools like AlphaFold, predicted protein structure with hitherto unprecedented accuracy. These models pushed the limits further of what machines can generate, read, and forecast, bringing AI nearer than ever to the early dreams of the Dartmouth proposal, in particular to constructing machines that can learn, think in abstractions, and enhance themselves (Grzybowski et al., 2024; McCarthy et al., 2006).

While it is not possible or even desirable that researchers settle on one definition of intelligence, Wang suggests that even the term "artificial intelligence" rightfully requires more conceptual clarity than it has generally received (2019). The discipline, the author believes, is not one, but a collection of subdomains, each pursuing its own objectives, assumptions, and methods, all named "AI" largely for reasons of history. The risk is in lumping together radically different strategies under one rubric, which can bury important distinctions both in theory and application.

2.1.2 From Symbolic AI to Machine Learning

Early Artificial Intelligence, or expert systems, were based on symbolic representations of knowledge and explicitly defined rules of logic from human experts. According to Coats, these systems used fixed IF–THEN rules and were difficult to update or scale (1988). Although useful within narrowly defined domains like diagnosis or classification, it was not possible for them to flexibly manage uncertainty, adjust to novel inputs, or learn from experience. Such limitations were one of the reasons to shift to machine learning, a paradigm that allows systems to recognize patterns and make decisions based on data, not pre-defined logic. One of the most significant contributions to this movement was the adoption of artificial neural networks. Such models consist of layers of interconnected computational units and can learn to represent abstractions from high-dimensional data. They do not need to know about the problem domain in advance and construct internal mappings based on repeated learning processes (Prieto et al., 2016). In practical contexts, like medical diagnosis, this development has translated into real advantages. Ravuri *et al.* detail how data-driven models learned from electronic health records beat traditional expert systems both in terms of accuracy and flexibility

(2018). The models can update indefinitely, decreasing reliance on rule engineering by hand. Hybrid schemes in certain instances include where expert systems create training data to assist in boosting machine-learned model performance, highlighting an evolutionary convergence of symbolic reasoning and statistical learning.

Machine learning is more specifically defined as a set of computational methods that enable systems to become more proficient at an activity based on exposure to data, rather than being programmed explicitly for every situation. This represented a fundamental shift from the symbolically based AI paradigm, substituting rule-based reasoning with models that learn directly from data about patterns and regularities. As Arthur Samuel, one of the field's pioneers, famously stated, ML gives computers the capacity to "*learn without being explicitly programmed*" (Bell, 2014). The earliest machine learning implementations, like Samuel's self-learning program for playing checkers at IBM, were already embodying its fundamental idea of learning by experience to improve performance. But it was not until in the following decades, facilitated by advances in computational power and availability of large datasets, that ML became a mature, scalable method: this was strongly facilitated by the exponential increase in computational power, following what came to be known as Moore's Law. Firstly, this was an empirical observation by Gordon Moore in 1965 that transistors on chips doubled about every 12 months, leading to regular increases in processing power while reducing cost per computation (Moore, 2006). In 1975, Moore updated his estimate to every two years, based on design constraints. Notwithstanding this, industry experience in the 1980s and 1990s fell into an 18-month doubling time, especially concerning memory chips, as feature miniaturization and lithography advances pushed development ahead of Moore's projections (Mack, 2011). Such improvements enabled training more sophisticated machine learning algorithms and processing huge datasets, hitherto computationally impossible to undertake.

While, as defined by widely accepted terms of Tom M. Mitchell, a program is said to be learning if its task performance is improved by experience, as measured against an established performance criterion (Bell, 2014). This formalization has become standard in distinguishing ML from other methods of AI. From an historical perspective, ML is traced back as far as the later 1950s, when Frank Rosenblatt created the Perceptron, an inspiration of which was taken from the structure of the human brain which was also used in it as a precursor to recent work on neural networks. In the 1960s, work on machine learning in pattern recognition and control theory provided an enhancement to mathematization of these ideas. As described by Fradkov, these early prototypes were centered on optimization and function approximation from data, as it provided the theory upon which these current learning algorithms base their existence (2020).

Machine learning contains several fundamental paradigms, each well-suited to various problem structures and data availability scenarios. In accordance with Bell, supervised learning is most commonly used, where a model is trained on input-output pairs (2014). The system learns to relate input variables to target variables, aiming to generalize unseen data. Supervised learning is often applied in classification (e.g., assigning labels to texts) and regression (e.g., estimating numerical values based on observed features) tasks. Bell points out that the main task of supervised learning is to reduce the discrepancy between predictions of the model and actual target labels of training data. In contrast, in unsupervised learning, data lacks explicit labels. Following

Sarker's explanation, this type of learning is concerned with finding hidden structure, like clusters or associations, that are not directly observable (2021). Clustering algorithms and feature extraction methods remain typical instruments in this case. Although missing labels complicate model assessment, unsupervised learning is beneficial in exploratory data analysis as well as for cases where data labeling is not possible or practicable. Semi-supervised learning, which falls in between these two paradigms, applies to a small number of labeled data as well as to an ample number of unlabeled data. This method is viewed as being of particular utility where labeled data is time-consuming or expensive to obtain, like in speech recognition, bioinformatics, or fraud detection, while unlabeled data is plentiful. The model learns structure from unlabeled data and is informed by the limited number of labels (Sarker, 2021). A last and quite different paradigm is reinforcement learning, defined by Sarker as learning, in which an agent learns to act sequentially by directly communicating within an environment (2021). In contrast to being told correct answers, the agent is provided with evaluative feedback in terms of rewards or penalties, and it adapts actions to maximize cumulative gain. Reinforcement learning is particularly applicable to fields like robotics and autonomous driving, where decisions need to be dynamically adapted based on outcomes over time. For a better understanding of this domain, in Table 2.1 I have summarized the differences between the three types of learning, with the most used algorithms and common applications.

	Supervised Learning	**Semi-supervised Learning**	**Unsupervisded Learning**	**Reinforcement Learning**
Input data	Labeled data	Small amount of labeled + large unlabeled data	Unlabeled data	Environment interaction, reward signals only
Type of problem	Classification, regression	Classification (mainly) and regression	Clustering, pattern discovery	Sequential decision-making, optimization
Algorithms	Linear/logistic regression, decision trees, random forest, SVM, KNN, CNN, LSTM	Self-training, co-training, label propagation, semi-supervised GANs, graph-based methods	K-means, DBSCAN, hierarchical clustering, PCA, t-SNE, autoencoders	Q-learning, SARSA, Deep Q-Network (DQN), Policy Gradient, DDPG
Applications	Image classification, email filtering, stock price prediction	Speech recognition, fraud detection, bioinformatics	Market segmentation, anomaly detection, topic discovery, dimensionality reduction	Robotics, autonomous driving

Table 2.1: Summary of Supervised, Semi-supervised, Unsupervised and Reinforcement Learning

2.1.3 Deep Learning, Natural Language Processing and Generative Models

Among machine learning's many branches, deep learning has proven to be a very effective and versatile paradigm, making significant contributions to perception, language, and decision-making tasks. Deep learning models draw inspiration from the structure of the brain and consist of artificial neural networks with multiple layers of depth, hence the name used to describe them. Deep learning models can learn about data representations at multiple abstraction levels, automatically, without feature engineering as is needed in conventional machine learning (Lecun et al., 2015). The increasing availability of large datasets, as well as advances in computational power (like GPUs) and algorithms, has made it possible to train deep architectures well. According to Janiesch *et al.*, deep learning systems excel in image recognition, speech processing, and natural language interpretation, areas where inputs are high-dimensional and intricately structured (2021). Their ability to learn directly from raw data allows them to uncover patterns and correlations that may be hard or impossible to enumerate using explicit rules. Different deep learning architectures were created to solve various types of problems. For instance, convolutional neural networks (CNNs) find widespread application in image processing; recurrent neural networks (RNNs) are best used on time series or language data that occur sequentially; and autoencoders compress data and restore it, frequently used as building components in of recommendation systems or outlier identification (Xuedan et al., 2016). The backpropagation method is what is used to train these networks, adjusting internal parameters, one by one, to reduce errors in prediction. They also pose several issues despite their success. They tend to be "black boxes" due to the inability to explain internal reasoning. Additionally, they require large amounts of labeled data and significant computational resources upon which reliance raises issues of accessibility, fairness, and sustainability. Janiesch *et al.* also highlight risks of model drift, bias, and explainability, particularly in high-stakes domains like health or finance (2021). Yet deep learning continues to mold Artificial Intelligence's most advanced frontiers, making it possible to create generative systems, language systems, and autonomous agents. It has become a base technology for most of the recent AI breakouts, and one of the leading drivers of ongoing research and innovation.

In order to better understand the differences between Artificial Intelligence, Machine Learning and Deep Learning, figure 2.1 from Kuntz & Wilson (2022) offers a clear and concise visual representation of the hierarchical relationship between these three domains. As previously described, AI encompasses smart systems and machines capable of performing tasks that typically require human intelligence. Within this broad domain, ML refers to algorithms that can learn from data and make decisions based on observed patterns; at the most specialized level, DL, considered a subset of ML, relies on artificial neural networks to autonomously generate accurate outputs without the need for human involvement. This nested structure effectively illustrates the progressive levels of complexity within the broader field of Artificial Intelligence.

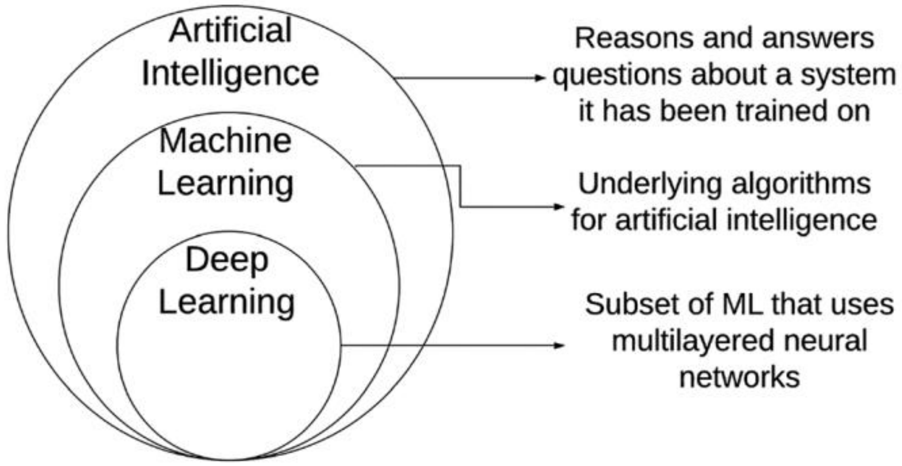

Figure 2.1: Venn diagram relationship between AI, ML and DL, from (Kuntz & Wilson, 2022)

One of the areas most visibly impacted by deep learning is Natural Language Processing (NLP), artificial intelligence's field of enabling computers to interpret, generate, and respond using human language. Once based on linguistics and rule-based systems, it has become an extremely dynamic area dominated by data and neural methods (Khurana et al., 2023). There are two primary processes of NLP: Natural Language Understanding, which is oriented towards understanding text or speech meaning, and Natural Language Generation, which is about generating text that is like natural language based on internal representations. They act at various linguistic levels: phonological, morphological, syntactic, semantic, and pragmatic, each enabling a system to comprehend and create coherent, context-sensitive language (Reshamwala et al., 2013). For instance, morphological analysis enables identification of root words and inflections, while semantic analysis sets word meaning based on context. Since the early 2000s, the discipline has seen considerable change, and neural networks have played an important role in expanding what is possible. Models at one time enabled systems to process sequential data like language better; subsequently, attention mechanisms and transformer architectures transformed the discipline to allow for long-range dependencies to be captured, leading to the proliferation of models like BERT and GPT, which support an extensive array of NLP use cases today (Khurana et al., 2023). The power of NLP is reflected in its wide range of real-world applications: machine translation, text classification, information extraction, sentiment analysis, and dialogue systems, to mention just a few. It also drives speech technologies like automatic speech recognition and text-to-speech systems, which are used in voice assistants and accessibility aids (Reshamwala et al., 2013). Specifically, transformer-based architectures have seen considerable gains in question answering and document summarization, providing richer contextualized understanding and more natural-sounding answers. Yet, even as these advances occur, fundamental challenges of NLP remain. Ambiguity of language is still at its center: one sentence can be resolved to multiple syntactic or semantic meanings based on context. Additionally, bias, lack of interpretability, and multilingual complexity remain leading topics of research today (Khurana et al., 2023).

And finally, the requirement for large annotated datasets and heavy computational resources is an obstacle to accessibility and to equity in development of NLP.

Finally, in recent years, advances in generative models have been one of the most important drivers of advances in artificial intelligence. They no longer just analyze or classify current data, but generate completely new content, from realistic images and movies to coherent text and even synthetic voices. In contrast to conventional methods based on explicit rules or statistical correlations, these models learn to represent the underlying structure of an entire dataset, enabling them to create brand-new examples that look like the original data (Harshvardhan et al., 2020). Originally designed in educational environments for image synthesis or data compression, today's generative models are at the core of sophisticated language models, such as used in current-day NLP. With their capacity to generate contextually relevant text, they become an indispensable feature of systems like virtual assistants, translation systems, and chatbots. With the capacity to not just comprehend, but create content like that of humans, generative models form the foundation of what is referred to as Generative AI today. This revolution is one that shifts what is being done in the field: from interpreting language to creating it, from processing data to creating new knowledge.

2.1.4 Generative AI

In the broad and diverse realm of AI, special consideration is accorded to Generative Artificial Intelligence (GenAI) owing to its pivotal role in current studies. At an academic level, Generative AI is defined as one of AI's unexplored areas that concentrates on producing novel, authentic content, like text, image, audio, or video, instead of just analyzing provided data. They gain support from generative models, which learn to know the data's underlying distribution and subsequently utilize this information to create novel instances that mimic training input data (Feuerriegel et al., 2024). In contrast to conventional discriminative AI systems that predict or classify, generative AI systems aim to mimic human creativity by creating novel content in various modalities. Generative AI has become possible due to advances in deep learning, especially in creating architectures like Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) and Transformers. Most importantly, transformer-based models like GPT-4 showed impressive fluency in generating language, making it possible to create tools like ChatGPT to converse like humans (Feuerriegel et al., 2024; Fui-Hoon Nah et al., 2023). Significantly, generative AI works on several layers. On the model level, it comprises base technologies such as GPT or Stable Diffusion. On the system level, these models become part of user interface-enabled applications like GitHub Copilot or Midjourney. Lastly, on the application level, generative AI tools become integrated into organisational processes to help generate content, develop software, diagnose health, and more (Feuerriegel et al., 2024).

Statista estimates that globally, the Generative AI market will be valued at US$66.89 billion in 2025[1]. The industry is estimated to expand at a staggering Compound Annual Growth Rate (CAGR) of 36.99% from 2025 to 2031, to achieve an overall market value of about US$442.07 billion by 2031. In comparison to the rest of the world, the largest individual market is the United States, which is predicted to contribute alone to US$21.65 billion in 2025. Demand is being fueled by mounting interest in AI-generated content like image, video, music, and text within media, entertainment, and marketing industries. Aside from its economic significance, burgeoning public interest in Generative AI is also reflected in online search trends. Figure 2.2 shows that, according to Google Trends data of April 11, 2025, global searches on the term "Generative AI" jumped considerably from late 2022, peaking in early 2024. All values are normalized on a scale of 0 to 100, which is based on maximum popularity within the chosen time period, while 50 is half of that interest level. A value of 0 means not enough data about the term on a specific date is available. Although there was slight stabilization thereafter, search volumes remained considerably higher than before 2023, showing an ongoing and high level of public interest.

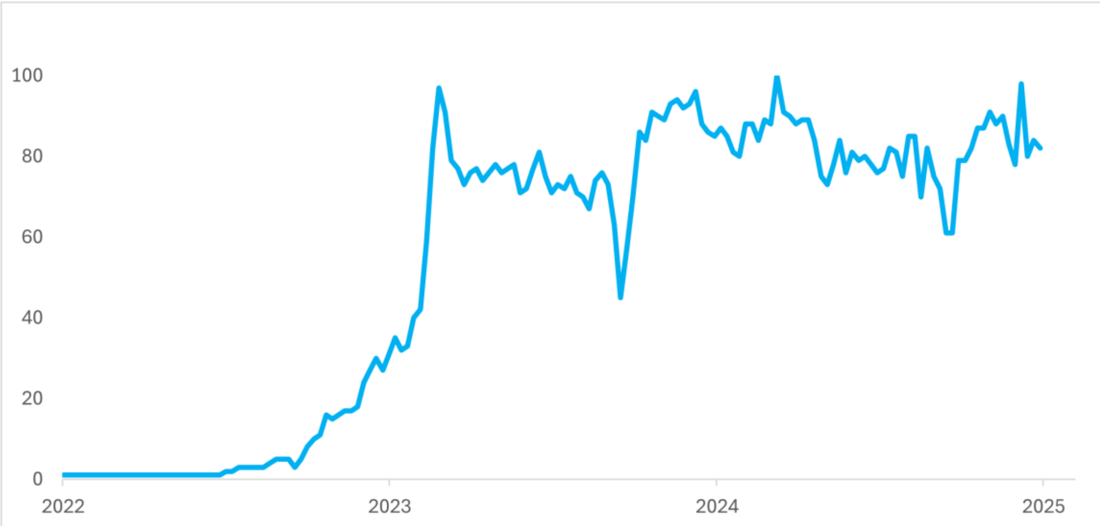

Figure 2.2: Global search interest for "Generative AI" (Google Trends data, April 2025).

The burgeoning significance of Generative AI is not only reflected in public discussion and commercial use, but also in academic output. An extensive bibliometric study by Dwivedi & Elluri scanned more than 10,000 peer-reviewed papers on generative AI published from 2013 to early 2024 (2024). With strong evidence, it confirms an accelerating growth in research output, from an average of merely 53 articles published each year between 2013 and 2018, to an astronomical growth to 1726 articles per year from 2019 and beyond. This is reflective of not only both GANs and LLMs maturing as base technologies, but also of near-universal interest from researchers, institutions, and funding organizations from multiple disciplines. Especially from 2018

[1] Statista: Artificial intelligence (AI) worldwide - statistics & facts. Published by Bergur Thormundsson, Mar 18, 2025

onwards, the field experienced vigorous growth into applied areas such as medicine, earth sciences, cybersecurity, and education, as well as rising interest in social, ethical, and organisational implications.

To further comprehend the various GenAI tools that exist today, recent advances resulted in an explosion of large-scale models, each with distinct architectures and use cases. ChatGPT, for instance, by OpenAI, continues to predominate in general-purpose conversation as well as content creation, while DeepSeek targets structured problem-solving and scientific computing using a Mixture-of-Experts framework. Grok AI aggregates real-time social media data to analyze trends, Gemini by Google DeepMind provides multimodal functionality within text, image, and video, and Manus AI is enterprise workflow automation-specific (D.R & Smiju I.S, 2025). This extensive, heterogenic catalog showcases just how Generative AI has expanded beyond task-independent creative endeavors to enable technical accuracy, enterprise decision-making, and real-time analysis, as it stands as an unmistakable shift from previous systems that were either symbolic or pattern-matching based.

2.2 AI Applications in Business Contexts

In recent decades, Artificial Intelligence has moved from being an idealized discipline to becoming a force of transformation within organizations. Drawing upon technological advances covered in the earlier section, AI is today extensively used in various spheres of business, from supply chain to customer interactions and employee management. The next section offers an overview of AI's most applicable uses in today's business environment, with an aim to ascertain where its organizational influence is strongest to date. With an understanding of these uses, it is possible to position the evolving expectations placed on managers and organizations, which is covered in the following chapters.

2.2.1 AI Applications in Marketing

Artificial Intelligence has become an essential element in modern marketing, transitioning from an emerging technology to a strategic enabler of personalized, efficient, and data-driven customer engagement. A structured contribution in this field is provided by De Mauro *et al.*, who developed a taxonomy of machine learning applications in marketing based on a content analysis of 40 real-life business cases (2022). The authors map these applications into four strategic areas: shopper fundamentals (e.g., personalized offers or personalized recommendations), consumption experience (e.g., product or experience improvement), improve decision making (e.g., consumer sensing and market understanding), and financial impact (e.g., dynamic pricing). The first two applications are classified as consumer-facing applications, meaning they are designed to directly enhance the consumer experience, by increasing personalization, reducing friction in the buyer journey, or improving perceived service value; in contrast, the third and the last one are classified as business-facing applications, which are instead aimed at internal optimization or managerial support. While business-facing applications operate behind the scenes, consumer-facing ones are visible to the end user and tend to be directly related to customer loyalty and satisfaction. According to George *et al.*, AI is an adjunctive instrument but an integral element of marketing plans, moving performances and sparking innovation (2024). One of the most interesting contributions of AI is its power to leverage data-driven decision-making more effectively. AI technologies, especially machine learning, predictive analytics, and natural language processing, enable marketers to derive actionable insights from huge amounts of customer data. This enables dynamic segmenting of audiences, real-time tracking of performances, and continuous optimization of marketing tactics in accordance with behavioural trends (V. Kumar et al., 2024). The transition from intuitive decisions to algorithmically informed decisions is a structural transformation in marketing planning among firms. Another key area of influence is that of personalization. AI facilitates hyper-personalized experiences by considering consumer preferences, past behaviors, and context-driven variables. According to Masnita *et al.*, recommendation engines, dynamic pricing algorithms, and personalized content delivery systems significantly improve user satisfaction and loyalty (2024). Basha emphasizes how AI supports scalable, one-to-one communication that would be unmanageable with traditional human-led approaches (2023). Anticipating consumer needs and presenting them in turn with appropriate content, firms are capable of constructing deeper, more qualitative relations with constituencies. Apart from strategic intelligence and personalization, AI also aids in operational efficiency. It automates routine, time-consuming work in terms of email targets, lead scoring, campaign launches, and customer service using chatbots. Not just cost, but also marketing teams' agility is enhanced (George et al., 2024). Amazon, Spotify, and Starbucks are mentioned as prominent examples of the same in using AI to streamline operations while, at the same time, optimizing customer-end processes as well. The literature also mentions AI helping to aid strategic agility, as also future readiness. With marketing environments becoming increasingly dynamic and digital, AI assists companies in staying ahead of the game as it allows for real-time adjustment in campaigns as well as predictive future-scenario planning. George *et al.* discuss emerging trends such as voice-activated search, augmented and virtual reality, and blockchain-based transparency as new frontiers where AI is destined to expand its scope (2024).

In sum, integration of analytical capabilities, automation, and individualization characterizes AI's revolutionary role in marketing. AI does not displace marketers but strengthens them to act more accurately, quickly, and contextually. In line with the literature, AI's full marketing potential depends not only on technological development but also on strategic co-alignment and ethical use within businesses.

2.2.2 AI Applications in Human Resources

The adoption of Artificial Intelligence in Human Resource Management (HRM) is radically transforming organizations' approaches to talent attraction, talent handling, and retention of talent. AI, paired with HR analytics, allows for sharper and data-driven decisions that span various HR activities like talent attraction, training, and employee retention. One of its most notable influences in HR is its impact on talent attraction. Smart tools now process traditionally time-consuming and subjective work like resume screening, candidate prioritization, and preliminary interviewing faster and more fairly. As highlighted by Jia *et al.*, AI systems like

Leap.ai can analyze technical skills as well as cultural fit, enhancing candidate choice quality (2018). In addition, AI-powered hiring processes minimize bias and create improved working conditions by providing real-time candidate tracking and onboarding reminders (Arora et al., 2021). Such abilities help to minimize dropout risks and enhance candidate interest throughout the recruitment pipeline. Apart from recruitment, AI also plays an important role in training and development. With AI-powered platforms and Intelligent Tutoring Systems, organizations can provide adaptable learning experiences based on the specific affiliation of individual users. Such systems scan employee behavior and skills deficiencies and suggest individualized training pathways (Afzal et al., 2023). Arora *et al*. add that AI tools can even forecast whether upskilling or outside hiring is cheaper to address skill deficiencies, hence optimizing staff planning (2021). AI and HR analytics also play critical roles in employees' retention. Predictive analytics can recognize warning signs of employee disaffection or turnover based on behavioral metrics, pattern changes, and historical data. Such insights allow for HR managers to respond to it using customized incentives or leadership changes (Afzal et al., 2023; Arora et al., 2021). In addition, advanced analytics can connect training enrollment to employee tenure plus work output, enabling decisions on strategic learning and development spending. Performance management-wise, AI-powered systems enhance the accuracy of performance reviews by collating and integrating multiple data sources that cover objective metrics. Performance reviews traditionally suffer from subjectivity and bias, while AI allows for more detailed analysis based on behavioral data and commercial outcomes (Jia et al., 2018).

Still, despite these innovations, issues persist. Resistance to change, inadequate digital skills among HR professionals, as well as fear of job replacement, continue to hold back adoption (Arora et al., 2021). Ensuring ethical use of data and safeguarding employee privacy are also critical to achieving trust in such innovative systems. In summary, AI and HR analytics hold significant promise to augment HRM by making it possible to leverage personalized, predictive, and objective methods of managing people. Their adoption is likely to result in enhanced operational efficiency, cost savings, and employee experience, putting HR in the position of being an organizational growth partner.

2.2.3 AI Applications in Supply Chain Management

The application of Artificial Intelligence to Supply Chain Management (SCM) has been a revolutionary force, boosting strategic as well as operational aspects of business logistics. Across the reviewed literature, AI is viewed not as just an automation vehicle but as an agent of agility, responsiveness, and competitive leverage. A key first contribution of AI to SCM is in terms of forecasting customer demands and optimizing inventories. As pointed out by Dash *et al.*, AI-powered platforms can accurately forecast customer demands based on analyzing hundreds of dynamic parameters like weather, market trends, and consumption habits (2019). Such systems enable businesses to pre-empt needs, decrease levels of inventory, and avoid waste. For instance, businesses like Otto were able to streamline levels of stock to such an extent that it depends completely upon AI to pre-empt purchasing decisions without any human interaction. AI also finds crucial application in manufacturing and operation, especially in terms of automation and preventive maintenance. AI-powered intelligent robots, integrated with machine learning, are becoming indispensable in warehouses, manufacturing facilities, and last-mile logistics. Not only do they detect patterns and anomalies in real time, but also adjust manufacturing cycles to uphold high efficiency and quality standards; this is precisely what is observed in industries like semiconductor, retail, where AI has enhanced cost containment and product quality (Dash et al., 2019). In addition, machine learning has proven effective in resolving sophisticated supply chain issues like alleviating the bullwhip effect, managing risks, and forecasting delay or disruption risks. Younis *et al.* stress that although AI and ML remain nascent in many industries, use has already been proven to deliver measurable supply chain efficiency and responsiveness gains (2022). Their systematic review mentions AI's expanding role in every SCOR model cycle: planning, sourcing, making, delivering, and returning goods. A more recent paper by Mohsen reaffirms that AI not only enhances supply chain efficiency, but also expands supply chain agility, responsiveness, as well as customer satisfaction (2023). Such applications as smart planning, dynamic transport optimisation, and automated warehousing are generating tangible outcomes in terms of cost reductions as well as enhanced service levels. But extending these technologies also raises demands for novel managerial skills, as regards managing data flows, ethical risks, as well as collaboration of humans and machines.

2.3 Limitations and Risks of Artificial Intelligence

While Artificial Intelligence brings considerable value in fields like Marketing, Human Resources, and Supply Chain Management, various limitations and risks have arisen over time. One of them is that of algorithmic bias, which can result in discriminatory or unfair decisions when AI systems learn from unbalanced data. The other is that of the phenomenon of "hallucinations," particularly in case of generative models, where results seem plausible but turn out to be factually wrong. Moreover, the non-explainability of many AI systems is creating issues related to transparency and accountability. All these risks highlight that AI needs to be adopted responsibly, taking into consideration data quality, ethical issues, and interpretable models in business environments. The following sections discuss these issues in more detail, whose significance has become central in today's environment.

2.3.1 The Challenge of Explainabilty

As AI systems become further integrated into business decision-making, their lack of explainability has become of pressing concern. Doran *et al.* classify three distinct types of AI models based of explainability (2017). Firstly, opaque models are "black box" systems that reveal nothing about what drives them and can be viewed as *"oracles that make predictions over an input, without indicating how and why predictions are made"*, whereby it is virtually impossible to backtrace exactly how particular outputs are created. Secondly, interpretable models enable users to track back mathematically from inputs to outputs; standard examples include linear regression or decision trees, where meaning is carried by structure in the model itself. Thirdly, comprehensible models push it one further, and create output enriched with symbolic representations as to enable users to build up an idea of what is decided. But, as the authors note, even this requires heavy dependence on the user to create an explanation. Based on this, further recent work proposed an understood-tiered theory of explainability. Explainable AI has been classified in various types based on methodology: pre-modeling (e.g., bias mitigation and data curation), interpretable modeling (e.g., selecting inherently transparent algorithms), and post-modeling techniques that attempt to retroactively explain complex models (Minh et al., 2022). Although these tools are an improvement, explainability is often at the expense of performance, producing an infamous trade-off.

This trade-off has been empirically examined by Assis *et al.*, who compared transparent algorithms like Decision Trees and Logistic Regression with opaque ones like Random Forests and Support Vector Machines (2023). Their findings confirm that opaque models tend to be superior in terms of accuracy but report worse interpretability and higher latency, whereas transparent ones are more interpretable and quicker, but poorer in accuracy. In reality, this translates to model choice needing to be matched to priorities of specific business contexts: when regulation or end-user trust is of great importance, explainability is to be prioritized, and when prediction accuracy is paramount, opaque models can be used, as long as supporting explanation tools are used as well. Significantly, explainability is closely related to the larger notion of accountability. As highlighted by Raja & Zhou, accountability is influenced by an intricate mix of influencing factors such as explainability, fairness, transparency, empathy, and uncertainty (2023). Among these, explainability is especially critical: it allows stakeholders to follow and comprehend decisions, assess their fairness, and question them where needed. Without explanations that matter, AI systems become impenetrable and unaccountable, particularly in high-stakes contexts where ethical and legal consequences are most dire. Ensuring an appropriate level of explainability is thus not merely an issue of technical optimization, but is an enabling condition for developing secure and responsible AI ecosystems.

2.3.2 The Problem of Biases in Artificial Intelligence

AI systems become increasingly used in high-stakes decision-making, but remain susceptible to an extensive range of algorithmic biases that compromise fairness, accuracy, and trustworthiness. Roselli *et al.* identify three main sources of biases (2019). Firstly, goal specification bias emerges when objectives defined by humans get imperfectly transferred to the logic of algorithms, typically by means of proxy variables or optimization objectives which do not represent what is actually meant to be attained. Secondly, data bias stems from unbalanced, partial, or unrepresentative training datasets that perpetuate prevailing societal or organisational imbalances. Thirdly, sample bias is at the level of individual points, where labelling inconsistencies or outliers create biased learning impulses. Ferrara extends this framework by introducing what he calls the butterfly effect of AI systems: small, perhaps innocuous design decisions, like model structure or data preprocessing, having disproportionately large and inevitably unforeseen implications (2024). This systemic paradigm emphasizes that bias is more than an isolable defect, but a dynamic process that infects the AI pipeline as a whole. Mitigation, as such, is not merely about statistical corrections, but requires more of a structural solution that engages socio-technical consciousness, organisational governance, and stakeholder engagement.

There are various real-life instances of such tangible implications of these biasing artefacts. The COMPAS algorithm, employed within the U.S. criminal justice spectrum to predict recidivism risk, has been demonstrated to generate considerably higher false positive scores for Black rather than white defendants (Kawamleh, 2024). Although race as such was not an explicit feature within the model, historical prejudices within the training data resulted in disparately punishing outcomes for specific demographic groups. In the same vein, Amazon's AI recruiting assistant was adopted, following revelations that the agent deliberately downgraded résumés that mentioned the term "womens" as it was trained predominantly upon male-majority hiring data (Gupta et al., 2021). Such instances highlight that even though algorithms might be proclaimed to be formalistic, in fact, they can perpetuate and exaggerate structural imbalances, unless audited and contextualized in proper time. Combined, these observations illustrate that reducing algorithmic biases is not simply a technical endeavour, but one of ethical responsibility and organisational accountability. Without proper safeguards, AI systems can become agents of social injustice instead of promoting advances.

2.3.3 Hallucinations in Generative AI

In spite of the impressive abilities of Large Language Models (LLMs), they are susceptible to hallucination, which refers to text that is coherent yet factually inaccurate or logially inconsistent, representing an important limitation for real-world deployments. As noted by Huang *et al.*, hallucination is not exclusive to conventional tasks such as abstractive summarization or machine translation; it is something of an added burden in open-ended, user-initiated interactions characteristic of LLMs (2025). The prevailing research on this subject separates two broad categories of hallucination: factuality hallucinations, where outputs deviate from provable facts (e.g., made-up historical facts or misquoted statements), and faithfulness hallucinations, created by deviation from prompt, logic, or consistency with supplied context (Huang et al., 2025). Such delineations are important in grasping the nuance of the phenomenon, particularly in environments where LLMs serve as decision support systems. The cause of such hallucination is nuanced. Huang *et al.* break down such hallucination into three broad phases: data, where disinformation or biased content is imprinted in pre-training; training, where alignment of models by means of supervisory fine-tuning could compel models to generate self-assured-sounding answers beyond their scope of knowledge; and inference, where decoding methods (e.g., high temperature sampling) or structural constraints (e.g., softmax bottleneck) lead to errors (2025). Perković *et al.* further emphasize the difficulty of hallucination brought about by inconsistency of instructions or logic errors, errors that pose an exceptionally critical threat to professional environments like legal or medical counsel (2024). Hallucination is not just an attack on the technical reliability of AI systems, but also on AI's trustworthiness in enterprise, legal, and educational environments. Finding solutions to it, therefore, demands an integrative strategy that goes beyond engineering, to include governance, user training, and transparancy of model constraints.

2.4 From Technological Transformation to Managerial Transformation

The use of Artificial Intelligence in critical business functions not only brings about new technological capabilities, but also induces deep organisational transformation. Although earlier sections identified not only the benefits, but also the limitations of AI systems, it is increasingly apparent that effective and ethical integration of these technologies is based upon more than algorithms and hardware. Organisations, and their managers, need to change in the way that they lead, govern, and adjust to AI-enabled processes. This section sets out to address organisational and managerial implications of AI adoption, as an introduction to further examination of skills and competencies needed to address this change.

2.4.1 AI as a Transformational Force in Organizations

Artificial Intelligence is increasingly understood not just as a technological development, but also as a general-purpose, transformative power that reconfigures organizations, as well as the ways in which organizations compete and create value. Far beyond automation, it requires traditional management practices to be challenged and reconfigured, as well as changes in organizational architectures, decision-making, and worker skills. In this sense, it is a force for change at every level: strategic, operation, and cultural. Researchers pinpointed that AI transformational power largely rests in the notion of AI readiness, which is an organization's readiness to initiate and maintain AI adoption. According to Jöhnk *et al.*, AI readiness is not an endpoint, but an emerging, multidimensional state that adapts to evolving organization ambitions and application scenarios (2021). AI readiness covers five domains: strategic alignment, resources, knowledge, culture, and data, each comprising specific determinants of an organization, such as top management support, process standardization, data quality, collaboration, and employee upskilling. Accordingly, AI also needs to be perceived as an organization development (OD) driver that can shape all four traditional OD fields: techno-structural design, human resources, human processes, and strategic change (S. Park et al., 2024). In this respect, AI adoption never is successful as merely technical interventions alone. Organizations, rather, need to align AI to strategic objectives, support it with suitable leadership and change practices, and embed it in organizations' learning culture. That is, successful AI transformation is not merely about implementing systems, but about rethinking roles, values, and capabilities. The literature also points out that readiness and adoption are mutually reinforcing. As stressed by Tehrani *et al.*, AI readiness is leading to effective and sustained adoption, while real-life examples of adoption are creating organizational learning and maturity (2024). Furthermore, Bankin *et al.* suggest that this transformation is multilevel: it not only influences organization processes, but also group dynamics (e.g., collaboration with algorithms) and individual perceptions (e.g., attitudes toward AI, perceived fairness, skill obsolescence) (2024). Such an influence shows that AI adoption is as much socio-organizational as it is technological.

Here, organizations need to address AI not only as an instrument but as an agent of transformation, having the potential to unleash novel business models, refashion managerial roles, and shape long-term competitive advantage. But it is dependent on the capability of an organization to measure and continue to build its AI readiness to ensure that technological potential is converted into real value creation.

2.4.2 Redefining Managerial Roles in the Evolving Landscape

As Artificial Intelligence permeates organisational processes, its influence on managerial work is increasingly apparent, leading to redefinition of roles, accountability, and decision-making dynamics. On one hand, according to McKinsey 2025 report, while employees are leveraging generative AI tools for most of what they do, up to three times more than what leaders perceive, and organisations continue to invest in AI, with more than 90% of them planning to increase expenditure within three years, though just 1% report to be fully mature. The primary gap is not technological: close to half of executives refer to lack of skills and leadership alignment as an impediment to effective AI adoption. Of note, millennial managers experience higher levels of awareness of AI tools, setting up as unofficial catalysts of adoption within teams (Mayer et al., 2025).

Hence, mass adoption of Artificial Intelligence is revolutionising the global labour force. Based on the World Economic Forum's Future of Jobs Report 2025, only about one-third of work activities in 2030 will be comprised of work done by humans alone, down from 47% in 2025. Despite this transition, the anticipated net employment scenario is still optimistic: as it estimates that about 170 million new jobs globally will be created by 2030, while an estimated 92 million jobs are expected to be lost, leading to an overall of 78 million added posts, which is equivalent to a 7% addition to total global employment. In terms of skills, companies project that 39% of core skills currently in demand will be rendered obsolete or extensively transformed by 2030. This looming “skill disruption” emanates from an urgent need for mass-scale upskilling: more than half of the global working population is predicted to need retraining or upskilling in upcoming years, while 85% of companies intend to invest in worker development programmes to resolve emerging skills gaps. From a managerial standpoint, seamless orchestration of this process is going to be pivotal. The World Economic Forum endorses an approach to human–machine collaboration, where technological advances complement and augment as well as support human labor, rather than displacing it. Simultaneously, businesses are rethinking their strategic visions: 47% of companies questioned plan to rethink their business models as a result of AI uptake, while 40% predict reductions of workers in roles that can be automated. These insights highlight the need for proactive stewardship to drive reskilling and intra-company mobility initiatives to enable a sustained and fair transformation of professional roles (Future of Jobs Report, 2025).

In addition to aggregate labor projections, an evolving body of research is looking closer at how AI adoption modifies the nature of managerial decision-making specifically. Empirical research conducted by Haesevoets *et al*. illustrate managers' perceptions of integrating Artificial Intelligence into decision-making (2021). Drawing on five experiments entailing more than 1,000 managerial experts, findings indicate decisive support for collaborative decision-making approaches in which humans wield significant control (around 70%), complemented by AI systems that add an equivalent of 30% decision weight. Notably, raising the share of the human component beyond this ratio does not pay off perceptibly in terms of acceptance. The study further delineates various manager profiles, varying from full AI rejection to a minority favoring enhanced machine freedom of action. The findings confirm expectations that delegated decision-making, not complete automation, is best suited to managerial expectations and organisational acceptance, highlighting the crucial task of crafting hybrid governance systems balancing intuitive human judgment and machine support. Wilson & Daugherty more explicitly stipulate the strategic value of collaborative intelligence: as opposed to automated attempts to supplant managers, superior companies in leading industries redesign processes to harness synergic relationships of human judgment and algorithmic capabilities (2018). Their cross-industry analysis shows that companies experience best-performing results by taking up configurations in which humans and AI complement one another: humans deliver creativity, empathy, and contextual sense, while machines provide speed, exactness, and scalability. Authors also propose three future roles: trainers, who educate AI systems to execute functions, explainers, who explain algorithmic logic to parties, and sustainers, who ensure AI operates ethically and responsibly. The roles demonstrate an emerging appreciation that manager success in an AI environment rests not upon displacing, but upon creating new jobs and roles.

Building upon these foundations, Lippert constructs an in-depth analysis of Artificial Intelligence's transformation of manager roles (2024). The author differentiates between roles that can be automated, roles that need to be adapted, and roles that still remain unequivocally human. Notably, the research maps out managerial meta-roles: novel forms of leadership that emerge explicitly in AI-mediated environments. These comprise the Algorithmic Broker, who facilitates collaboration between human and machine contributions; the Algorithmic Articulator, who interprets and frames AI's logic and results to different stakeholders; the Trust Builder, charged to generate transparency and user trust, and the Ethical Ambassador, responsible for ensuring that AI is used in line with organisational norms. Such meta-roles illustrate an overarching shift whereby managers no longer simply respond to AI but instead become architects of socio-technical integration, finding equilibrium between efficiency and accountability. Lastly, transformative AI's influence on managers' work can never be appreciated separately from the enabling role of human capital. Empirical studies report that differences in pre-existing skills within the workforce strongly affect companies' abilities to implement AI technologies. For instance, as much as 50% of variance in AI adoption levels among European companies is accounted for by how highly educated workers within these businesses concentrate. Additionally, no noticeable dip in employment registers has been detected in these regions post-AI integration, which might indicate that skilled worker populations are less susceptible to substitution and more effective at influencing AI-driven change (Brey & van der Marel, 2024).

From these scholarly and non-scholarly contributions, it is apparent that, even though AI is increasingly being used in managerial life, the human element is still at center stage. In order to be effective in meeting these changes, managers shall be required to gain new competencies that merge technological consideration with emerging organisational and decision-making requirements.

2.5 Defining Competencies in the Managerial and Organizational Context

The above sections have established that Artificial Intelligence is transforming managers' work in fundamental ways, and that higher demands for new skills to interact effectively with intelligent systems, lead hybrid teams, and manage change in organizations exist. But before analyzing, in an effective and meaningful sense, which skills in AI contexts are needed, it is important to disambiguate words such as competence, skill, ability, and knowledge, which in academic and professional writing tend to be used loosely as synonyms of one another. The current section provides the theoretic foundation by dealing with the principal definitions, schemes, and conceptual differences underlying the study of skills of managers.

2.5.1 Definitions and Distinctions

In spite of its extensive application in academic and professional contexts, competency is still an unclear and in-consistently applied idea. A considerable source of confusion arises from the co-presence of two radically different approaches: input-based, where competencies are viewed as underlying individual characteristics like knowledge, skills, attitudes, and personality, and output-based, where competency is defined as demonstrated capability to enact specific activities to prescribed norms (Hoffmann, 1999). These viewpoints co-exist rather than being contradictory, as input-based schemes find regular application in training and development, while output-based schemes prevail in evaluating performances and certifying individuals. Additional complication arises from mixing and matching terms like competency, skill, ability, and knowledge regularly used with no real distinction among them (Wong, 2020). Knowledge generally points to theory or factually based learning, skills to learned capability to accomplish work accurately and efficaciously, abilities to more innate or established capability to accomplish work, mostly construed as more general and vague than skills. Competency, as an integrative idea, is defined as comprising knowledge, skills, and abilities, yet also attitudinal and behavioral factors that facilitate effective execution of work within one specific context or setting. Wong further points to context as well as to purpose affecting what competencies mean and serve (2020). For instance, an application of competency in recruitment might be geared to observable behaviors and quantifiable outcomes, while competency framed to support development of leaders might specify personality, orientation to learning, as well as adjustability. This functionality further complicates matching definition in academic, professional, as well as regulation contexts. Regulatory agencies, particularly in fields like health and training, lean toward output-defined competency which maps to issues of compliance, accountability, and risk avoidance (Moghabghab et al., 2018).

While skills tend to be broken down into “hard” and “soft” domains, more recent writings undermine such rigidity in this dichotomy. Lamri & Lubart suggest that both skill domains share underlying building blocks and that skills ought to be conceptualized as multidimensional constructs more than as discrete categories (2023). The authors suggest that any skill is supported by five core dimensions: knowledge (declarative information), active cognition (problem-solving and reasoning processes), conation (motivation, volition), affection (regulation of emotions), and sensory-motor skills (bodily or perceptual abilities). Such an analysis discloses that even paradigmatically hard skills necessitate motivation and emotion regulation, and that soft skills such as empathy or leadership also depend on cognitive and knowledge-based elements. Effective oral communication, for instance, draws upon verbal knowledge, emotion awareness, and cognitive flexibility. In this perspective, the old severing of what is generally understood as hard and as soft is less dichotomous than positioned among a context-dependent and aim-dependent continuum.

To enhance an even deeper understanding of the construct of knowledge, it is useful to look within to consider its internal taxonomy. Gorman suggests that it is possible to classify knowledge into a quadrupartite framework that replaces the declarative/procedural binary, dividing into information (what), skills (how), judgment (when) and wisdom (why) as basic knowledge types (2002). Each of these may occur in explicit or tacit form, that tacit knowledge is pivotal for advanced expertise, and for the transfer of technology. For example, while, in most instances, information can be documented and transferred in manuals, skills and judgment often depend on experience, intuition, and context-awareness, which defy formal codification.

Such conceptual imprecision is further compounded by the routine commingling of competence and capability, two terms that, despite sometimes being used as synonyms, refer to distinct meanings. Whereas competence is generally linked to an individual's current capacity to carry out specific tasks effectively, based on knowledge, abilities, and behavioral qualities, capability is indicative of an expanded, more fluid potential to adjust, to learn, and to perform in novel contexts (Nagarajan & Prabhu, 2015). From this perspective, competence is task-specific, observable, and measurable within bounded contexts and against standards of output. Capability, on the other hand, includes creativity, flexibility, and self-study, and is most applicable to multifaceted and unpredictable contexts. Additionally, while competence describes current application of known skills, capability is an indicator of preparedness for future demands and ongoing development. Such is particularly significant where context is marked by speedy technological change, where an emphasis on creating long-term agility may be as important as ensuring task execution in the near term.

Collectively, these conceptual differences illustrate the multidimensional character of managerial competence. They are not discrete, yet tightly interconnected, and their arrangement is subject to context, intent, and shifting workplace demands. In moving these theoretical underpinnings into practices, one needs to consider how competency approaches up to this point in time have operationalized this conception of managerial competence within various organisational and institutional contexts.

2.5.2 From Theory to Practice: Managerial Competency Frameworks

The insight into what constitutes an effective manager has resulted in various models of managerial competencies, presenting a structured picture of skills and behaviors essential to achieving managerial success. The literature varies from general, generic competency frameworks to context-specific frameworks, showing both theory development and applied usage within the discipline.

Several works suggest comprehensive models that embody the broad range of competencies that managers require. Khoshouei *et al.* illustrate one broad-coverage approach by developing an updated competency framework for 21st-century managers using extensive content analysis (2013). Eight broad competency areas were discovered in this study: value, analysis, decision-making, knowledge, adaptation, performance, leadership, and communication. This eight-factor model is particularly comprehensive; for instance, a "value" domain embraces ethical and cultural-based competencies, while distinct "leadership" and "communication" domains entail interpersonal competencies. The key to this study is an evidentially sound, cross-culturally inclusive competency framework that yields an extensive taxonomy of managerial abilities that is psychometrically sound and relevant to everyday application in current organizations.

A further wide-angle perspective is provided by Freitas & Odelius, who survey ten years of experimental research to establish what areas of competencies are most identified as typically classified in research studies (2018). The scholars discovered that the Quinn roles framework, an established framework of roles for managers, was most oft-cited as an underlying schema between 2005 and 2015 (used in 12 of 46 studies). In addition to the popularity of the Quinn model, what was also observed in recurring competency categories in most studies were: results orientation (orientation towards goals, clients, and outcomes), interpersonal skills and team working, leadership and motivation, flexibility to change (innovation and situational adaptability), communication, planning, knowledge, organization and control (effective allocation of resources and keeping track of them), attitudes and values (initiative, ethics, responsibility), and technical/domain skills. This review charts therefore a convergence of agreement about certain competency domains (leading people, communication, major objectives) and disagreement about others (this time, most notably, treatment of technical skills and of personal values). This analysis provides a meta-framework by demonstrating which groups of competencies have been taken up in research, and suggests that effort be directed to identifying a transversal set of core manager competencies that might be universally necessary.

Critically evaluating current generic competency models, Asumeng suggests an extended framework (2014). The author observed that major competency models in the literature (spanning behavioral, functional, job-based, holistic, multi-dimensional, and domain-specific approaches) tend to coalesce around a familiar set of skills: business skills, intra-personal skills, interpersonal skills, and leadership skills. These categories appear consistently as essential for effective managerial performance. However, Asumeng identified a notable gap: most models paid little attention to career development and mentoring competencies, despite theoretical and empirical evidence that such skills are important for managerial success. To fill this void, the paper proposes a "holistic domain" competency model that explicitly incorporates career management and mentoring skills alongside the traditional domains; the framework is presented in figure 2.3, from (Asumeng, 2014). In other words, the holistic domain model extends the competency framework into a longitudinal development realm, suggesting that effective managers not only need competencies for their immediate role (like strategic thinking or communication) but also the ability to mentor others and navigate their own career growth. This contribution is theoretical and integrative: Asumeng's model is presented as more comprehensive than earlier frameworks by unifying the usual skill domains with the often-overlooked mentoring/career domain, thereby advocating for a more expansive view of what managerial competence entails.

Figure 2.3: Holistic-Domain Model of Managerial Competencies, from (Asumeng, 2014)

While the above models propose high-level frameworks, other research targets competencies in specific organizational contexts or occupational roles. Hawi *et al.* pay attention to the relationship between managerial competencies and firm performance within a specific industry (2015). Examining four of Jordan's leading airline companies, they investigated to what degree a specific set of managerial competencies relate to measures of firm performance. Their framework revolved around four competencies of primary interest: team leadership, problem-solving and decision-making, strategic thinking and customer orientation, which were selected for apparent relevance in the airline industry. The results confirmed that all four competencies were associated with measures of organizational performance within this context. In more detail, analysis was revealed to be nuanced: for instance, a manager's strategic competency was strongly linked to firm innovativeness, and customer orientation to competitive advantage within the market. The value added of this study is twofold. On one hand, it provides an empirical confirmation that developing these competencies of management can lead to improved performance outcomes. On the other hand, it highlights that even within a generic competency framework, specific competencies (such as strategic orientation or customer orientation) might be responsible for specific dimensions of performance (innovation and competitive advantage, respectively).

Bolzan De Rezende & Blackwell created an integrated Project Management Competency Framework for project managers, based on role-specific needs (2019). By conducting a systematic review of the literature, synthesizing the dispersed project manager skill research, they create an integrated model for 81 specific competencies that pertain to project managers, organized into 11 thematic dimensions. These dimensions cover a broad range of managerial skill areas: for instance, influencing and communication correspond to interpersonal effectiveness; emotional (emotional intelligence) and contextual awareness address a manager's ability to navigate complexity and change; management and cognitive skills cover general management techniques and problem-solving ability; professionalism and personal attributes capture work ethic and traits like adaptability; and two knowledge-based dimensions distinguish between general knowledge and experience versus specific project management knowledge. In combining these domains, the authors not only detail the skill profile of effective project managers, but also create an accessible assessment instrument for measuring competencies within this profession. Their central contribution is a role-matched competency model that integrates general manager skills and specific project management know-how. This framework provides an indication of general competencies (e.g., communication, leadership influence) interfacing with domain-specific know-how in a project context, presenting a sophisticated model that organizations can utilize to measure and develop project management expertise.

Another context-driven study is provided by Konigova *et al.*, who examine managerial competencies in knowledge-based organizations (2012). In contrast to theory-led approaches, theirs is one that starts from observation: it sees what competencies organizations operating in knowledge-intensive industries actually require. The study's analysis of job adverts for managers in Czech knowledge-based businesses, and accompanying interviews, validated findings to assure confidence in them. A set of basic competencies that employers regularly require, an empirical survey uncovered, as follows: not unexpectedly, a few of these baseline qualifications were virtually universal: domain knowledge and experience, higher education (university degree), and working knowledge of at least one foreign language were basic requirements for managers in these companies. In addition to these fundamentals, most often requested competencies were experience in leadership (mentioned in 88% of sampled job adverts) and communication skills (59%), emphasizing just how crucial these were rated as being. Other of the high-scoring competencies were time flexibility, presentation and interpersonal skills, reliability and responsibility, organisational capability, independence and self-confidence, and proactive, dynamic attitude. In addition, a long tail of more specific skills (e.g. project management knowledge, creativity, analytical thinking, decision-making, willingness to learn, and strategic "systems thinking") appeared in smaller fractions of postings. The authors observed that while there is no complete consensus on all secondary competencies, many of these abilities can be clustered into broader categories; for instance, combining communication and negotiation into a single skill cluster, or viewing proactiveness, goal-orientation and "sense of purpose" together. The value of this study is in its applied, demand-led viewpoint: it maps competency frameworks into actual recruitment standards for knowledge-led businesses. The findings both confirm general themes of generic models (leadership, communication, strategic thinking surely appreciated in knowledge-based businesses) but also indicate that there is a requirement for flexible competency models that can bundle or rank skills in line with an organisation's specific requirements. In short, it fills in theory-led approaches with marketplace reality, showing which manager competencies actually set candidates apart in a knowledge-led economy.

These six sources collectively illustrate a rich stream of managerial competency frameworks, significant areas of convergence as well as clear divergences. One of the points of consensus throughout the studies is the centrality of specific competency domains: leadership and communication skills recur, time and time again, as critical dimensions of managers in nearly every model or context (Asumeng, 2014; Bolzan De Rezende & Blackwell, 2019; Freitas & Odelius, 2018; Hawi et al., 2015; Khoshouei et al., 2013; Konigova et al., 2012). Equally, strategic or analytical thinking skills (whether termed as problem-solving, planning, or result-driven mindset) recur as critical, echoing cognitive skills as an overriding requirement for managers(Asumeng, 2014; Bolzan De Rezende & Blackwell, 2019; Freitas & Odelius, 2018; Hawi et al., 2015; Khoshouei et al., 2013). This convergence is an indication that despite methodological differences or industries of study, there is an underlying set of managerial competencies that is generally acknowledged as fundamental.

On the other hand, each study brings an individualized slant or weight that brings nuance to what constitutes managerial competence. Some differences stem from context: industry-specific studies introduce industry-specific competencies or assign weight to various skills more substantially to adapt to their environment (Bolzan De Rezende & Blackwell, 2019; Hawi et al., 2015). The customer focus, for example, was a specific competency within the airline industry model as it is associated with competitive advantage, whereas it’s not as strongly separated in generic. Conversely, Bolzan De Rezende & Blackwell’s project management framework emphasizes such competencies as contextual intelligence and project knowledge, outlining that technical as well as situational awareness is fundamental to add to the framework of competencies for specific managerial roles (2019). Such domain-specific additions complement generic models by indicating that broad competency categories (such as "knowledge") can be broken down or taken further for specific fields. In conclusion, our synthesis of discussion of managerial competencies by definition oscillates between merging basic enabling skills and extending the horizon of competencies to add new or industry-specific properties. There is undoubtedly architectural uniformity in which underlying competencies, such as leading people, communicating, thinking strategically, and adapting, serve as the bulk of most frameworks.

2.6 Research Objectives and Questions

The sweeping transformation of organizations imbued by Artificial Intelligence has redefined managerial roles, competencies, and functions. As explained in previous sections, AI not only transforms the tools managers use, but also reconfigures decision-making dynamics, human-machine collaboration, and paradigms of leadership. In this new context, conventional competency frameworks increasingly get challenged, calling for an improved and updated understanding of what it means to be an effective manager in an AI context. Notwithstanding an expanding field of research in this domain, recent reviews identify significant gaps in the current literature. Aziz *et al.* refer to the lack of unified frameworks and categorizations of AI-relation managerial competencies, highlighting the heterogeneity and under-theorization of existing knowledge (2024). Likewise, Bevilacqua *et al.* highlight insufficient systematic studies on hybrid skillsets needed by top managers, stressing in particular the need to align technical and interpersonal competencies in strategic leadership roles (2025). In their perspective, there is insufficient research on how managers can best measure teams' current AI abilities, encourage ongoing learning, and develop upskilling or reskilling strategies that keep up with technological change. Such shortcomings further add to increasing obsolescence of solely technical skills and rising demands for transversal and adaptable competencies. Such heterogeneity has fueled what has been labeled the "AI leadership gap": an expanding contrast between the competencies conventionally linked to manager and executive roles and which in fact are needed to lead organizations in AI-driven transformation.

These results indicate that, although most studies consider the overall influence of AI on labor and leading, no reconciled perspective of the fundamental competencies needed for effective managers in AI contexts yet exists. Further, conceptual building blocks of competence, such as distinguishing between knowledge, skills, abilities, and more general behavioral capacities, tend to be applied unrealistically or not meaningfully contextualized within AI contexts. In answer to these shortcomings, this study intends to perform a Systematic Literature Review to identify, classify, and analyze how managerial competencies are conceptualized, categorized, and theorized within an AI context. This review enhances the theoretical building blocks laid down in chapter two and tries to supply an organized synthesis of scholarly work concerning this subject. Accordingly, the research is guided by the following questions:

- ***RQ1***: Which AI-related competencies are essential for board members and corporate executives in the current technological landscape?
- ***RQ2***: How are managerial roles evolving in response to the integration of AI into organizational processes?
- ***RQ3***: What ethical and regulatory considerations should be incorporated into the competency profile of corporate leadership roles?

These questions form the conceptual foundation of the study and guide the methodological design outlined in the following chapters.

3 Introduction to Methodology

To ensure compliance with methodological standards, the methodology of the present research followed a three-step process, as illustrated by figure 3.1:

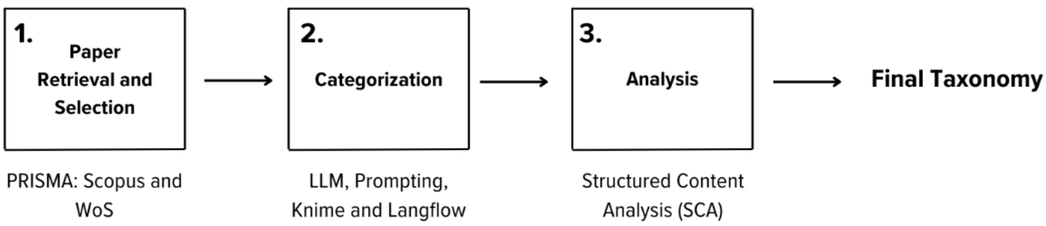

Figure 3.1: The three-stage process that led from the articles' retrieval to the taxonomy of managerial competencies.

The first phase is the starting point of every Systematic Literature Review, and consists of the identification of the articles database, which constitutes the body of the literature review; this phase was conducted according to PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol, using Scopus and Web of Science as bibliographic databases. Once the group of articles was selected, the second step aimed at extracting key information and summarizing key sections from the identified articles; this process was conducted by a Large Language Model, combined with human supervision for prompt engineering task, avoiding biases and errors in the LLM responses. From a technical perspective, the second phase of the research involved both Langflow v1.2.0[2] - an interactive tool that enables the visual design and execution of LLM workflows - and KNIME Analytics v5.4.0[3] - an open-source data analytics platform that facilitates workflow automation, data processing, and integration. Lastly, the output of the second stage was a dataset containing all the relevant data selected from the articles; starting with this information, a Structured Content Analysis (SCA) was applied to managerial competencies, to provide a clear and helpful taxonomy to segment the competencies that managers should require to reach success in the AI era. These methodologies will be deepened in the following sections, both from a theoretical point of view (sections 3.1, 3.2 and 3.3) and from their application in this research (sections 4.1, 4.2 and 4.3).

3.1 Systematic Literature Reviews and PRISMA Protocol

Systematic Literature Reviews represent an important methodological approach for the syntheses of knowledge from different disciplines, since the literature must build on works already produced in order to spot gaps and create new theoretical outputs. In contrast to narrative reviews, based often on the reviewer's subjective knowledge and whose selections can be influenced by selection bias and subjectivity, these reviews

[2] https://www.langflow.org/

[3] https://www.knime.com/knime-analytics-platform

follow a formal, transparent, and reproducible process (Lame, 2019; Nightingale, 2009; Okoli, 2015; Parums, 2021; Xiao & Watson, 2019). Methodological strictness guarantees the complete identification, assessment, and generalizability appraisal of the existing literature, making them an important tool for evidence-based reviews, especially in the fields of healthcare, the social sciences, and administration. Furthermore, among the principal guidelines, it is suggested that the reviews follow an homogeneous structure, following the style of empirical articles, with an Introduction, methodology, results and discussion/conclusions sections; in spite of the fact that the structure can be subject to variations, an argumentative flow is necessary in order for the reviews to be readable and academically solid (Fisch & Block, 2018). The origins of methodologies for the systematic review developed in association with the evidence-based medicine movement, in the second half of the 20th century. In the early stages, the need for formalized approaches to literature synthesis emerged after recalling concerns about variations in practising physicians and reliance on anecdotal guidelines, and the literature eventually drew on the methods for literature reviews being used in healthcare and other fields, including design research and engineering, though the same disciplines still experience difficulties in adapting methods with regard to standardization and taxonomy.

One major limitation is the absence of formal classification systems, hence the achievement of complete and reproducible literature search strategies (Lame, 2019). Another important characteristic of systematic reviews is the focus on the minimization of bias: in this regard, bias may manifest at several stages, including those related to the selection, publication, and data extraction phase. In the case of selection bias, it may occur if the selection and the exclusion criteria for the selection process in the literature analysis are not clearly stated from the very early stages, while the publication bias may occur if cases with the substantial result are in greater likelihood for publication, and hence may bias the result in the case of meta-analysis. In addition, data bias may occur if the process for extracting and synthesizing the data from articles included in the analysis is not performed in an independent, methodical manner (Nightingale, 2009). These risks can be addressed through the use of clear-cut inclusion and exclusion criteria, standardized quality measures, and two-stage independent screening (Xiao & Watson, 2019). In addition, meta-analysis is commonly suggested for use in the quantitative aggregation of the findings and the appraisal of statistical heterogeneity between the studies; analysis such as the Chi-square test, I^2 measurement, and forest plots assist in the detection of whether subgroup analyses should be performed (Nightingale, 2009).

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework was constituted as an accepted gold standard for facilitating transparency in systematic reviews. Developed from the QUOROM (Quality of Reporting of Meta-Analyses) Statement, PRISMA offers an organisational 27-item checklist for all methodological steps in the Systematic Literature Review, from defining the research question through data synthesis and assessment for bias (Moher et al., 2010; Vrabel, 2015). Conceptual and practical developments in the methodology for systematic reviews, specifically the need for broadening reporting beyond randomized trials to all types of systematic syntheses, pushed the movement from QUOROM towards PRISMA (Moher et al., 2009). One major advance in PRISMA is its flow diagram, which reports the screening, eligibility, and inclusion process for identified studies, providing visible documentation for the selection process in the included studies; the flow diagram offers an organisational method for reporting the number of studies screened, excluded, and included, providing clarity in the process of selection, and is regarded as best practice for displaying the review process and increasing replicability (Lame, 2019; Moher et al., 2009; Xiao & Watson, 2019). The PRISMA 2020 update furthered the standards for reporting, with the incorporation of requirements for revealing search strategies, pre-registration in the systematic reviews, and the inclusion of grey literature sources. One of the major developments included in PRISMA 2020 is the need for complete disclosure of the search strategies, including database search steps, registers, and other sources accessed. The need for disclosure guarantees reproducibility and verification for other researchers as a consequence. Although it has evolved, PRISMA is not a methodological manual for the conduct of systematic reviews, but rather for reporting them (Parums, 2021). One of the most important developments in PRISMA is the clear definition of systematic reviews and meta-analyses through its terminology. The framework undertakes the usage according to the definitions embraced in the Cochrane Collaboration, specifying the term for summarizing the result by studies in a Systematic Review as a 'synthesis' and applying the term 'meta-analysis' for using statistical methods for summating the estimate of the result from multiple studies. PRISMA guidelines stress the need for the methodological conduct in Systematic Reviews involving iteration, where inferences in the protocol may be allowed to be amended in case the need arises while following methodological transparency (Moher et al., 2010).

In business and management research, the use of systematic review methodologies increases, yet they still encounter distinctive disciplinary challenges. Fish & Block contend that literature reviews in the field of management remain misunderstood and used as annotated bibliographies, instead of being structured syntheses of knowledge (2018). To address this, six best practices are proposed, including clearly defining research questions, ensuring transparency in literature identification, balancing breadth and depth, organizing literature by conceptual themes, generating theoretical insights, and following a structured article format. In this sense, a critical challenge is balancing breadth and depth of the reviews, with a trade-off existing between covering a large number of studies (breadth) and providing detailed insights into key articles (depth); for this reason, researchers should avoid an exhaustive list of all studies and instead focus on the most relevant contributions. The application of PRISMA in the field of management has been studied by Mishra and Mishra, pointing out that, as in the case of healthcare, in which randomized controlled trials prevail, the field of management depends on diverse methodologies, such as qualitative research (2023). As a result, PRISMA requires adaptation to account for theoretical frameworks, qualitative syntheses, and mixed-methods approaches. Consequently, PRISMA must incorporate flexibility for treatment of the place of the theory, qualitative syntheses, and mixed-methodology approaches. PRISMA extensions, for example, PRISMA-S (searching), PRISMA-ScR (scoping reviews), and PRISMA-P (protocols), were created in order to adapt the reporting of the reviews in the different study settings (Moher et al., 2016). In addition to methodological issues, PRISMA played an important role in curbing the reproducibility crisis in research. According to many studies, it has emerged that systematic reviews prove difficult to replicate because reporting is poor (Vrabel, 2015). In enforcing rigorous reporting of the searching strategy, included criteria, and the methods used for syntheses, clear methodology such as PRISMA helps ensure the verifiability, and reproducibility of the systematic reviews. As the method changes with the development of systematic reviews, researchers are utilizing technological advances for efficiency purposes. Artificial intelligence-enhanced literature reviews, machine learning algorithms, and extracting data with the help of text-mining methods are being studied for boosting screening, classifying the studied articles, and data importing activities. Nevertheless, such innovations would still be subject to PRISMA's rigorous methodological standards in order not to sacrifice the guarantee for the method, transparence, and quality in research (Moher et al., 2010).

3.2 LLMs in Literature Reviews

The exponential increase in scientific literature poses enormous difficulties for researchers conducting literature reviews, necessitating novel strategies for maximizing efficiency and accuracy. LLMs prove to be revolutionary in such cases, allowing for the automating many steps in the review process, such as article retrieval, summarizing, classification, and synthesis (Hsu et al., 2024). In contrast to conventional methods, which necessitate massive manual effort in screening and extracting information, LLMs propose the scalable approach of automating the same and allowing the researcher to invest his effort in high-level analysis (Scherbakov et al., 2024). Hierarchical organization is among the core uses for LLMs in the literature review process. For instance, the CHIME framework utilizes LLMs for creating the hierarchical structures of science studies, efficiently classifying topics for research, and providing the researcher to work through large catalogs of literature with greater ease (Hsu et al., 2024). The process, however, is not completely automated and is refined through the actions of experts, marking the need for human intervention for ensuring the accuracy and consistency of the result.

Beyond classification, these models help immensely in the process of data extraction and the synthesizing process. Comparative analysis indicates that GPT-based models perform better in data extraction activities, with greater precision and recall rates, compared to BERT-based models (Scherbakov et al., 2024). Such an improvement finds particular significance in the case of systematic literature reviews, where it is imperative to find the right kind of research findings in order to build the wide-ranging knowledge base. Challenges still remain here, however, as the models remain prone to error and bias, and their outputs need thorough verification. One such problem area for LLM-based literature review is the hallucination phenomenon, where fabricated references and incorrect data are created in the model output. Such an occurrence necessitates human intervention in the process in order to maintain the validity of the research (Antu et al., 2023). Invariably, LLMs might be subjected to domain-specific complexity, necessitating the need for finetuning and the provision of supplementary training through special datasets in order for them to perform better. Such constraints affirm the point that the human-AI collaborative approach is still important in order to harness the complete power that LLMs may tap into while the academic literature still maintains its dependability.

The application of LLM in literature reviews comes with significant ethical considerations. Transparency is the core expectation in LLM-augmented research, ensuring the generated text is well-documented. Researchers must incorporate stringent verification methods in order to limit biases in the outputs from LLM and uphold academic integrity (Scherbakov et al., 2024). Growing dependence on AI-based insights calls for an organizational approach where AI-based findings are systematically cross-checked with hand-checked sources. One area that remains very viable for the application of LLM in SLRs is automated screening of articles. Recent studies illustrate how LLM can help with title and abstract screening, with an appreciable saving in the amount of time needed for the researcher to screen relevant publications for literature reviews (Dennstädt et al., 2024). Utilizing structured prompts, LLMs are able to screen the relevance of the studies in conformity with predetermined inclusion and exclusion criteria. In an empirical study, LLMs were tested across ten systematic review datasets in the biomedical domain, revealing high sensitivity in identifying relevant articles. Specificity, however, relied on the model employed and the structure of the prompt, pointing towards the fact that prompt engineering was pivotal in increasing accuracy.

In spite of these advances, some challenges need to be addressed in order for the potential of LLMs in literature reviews to be fully realized. One such major problem is the threat of information loss, with AI-summarized reports possibly leaving out significant details from the original sources. Researchers should also be extremely careful in identifying whether the work is produced through AI technology, such that AI works as an assistive tool for complementing conventional literature review practices instead of replacing them. In conclusion, the application of LLMs in systematic literature reviews represents a significant leap forward in automating research synthesis, screening, and categorization. Despite the enormous benefits LLMs afford in terms of efficiency and scalability, their incorporation into the workflow in academia should be done cautiously. Human oversight is still necessary, in authenticating insights provided through AI, as well as in the development of AI-based methodologies.

3.3 Structured Content Analysis (SCA)

Structured Content Analysis is an approach used in qualitative data analysis, with clearly replicable methods for extracting, categorizing, and synthesizing textual information. It is especially useful in systematic literature reviews and comparative analysis, as it offers rigor, consistency, and dependability in qualitative data treatment. In its many applications, the approach is distinguished through its systemized coding schemes, iterative process refinement, and data structure for extracting. It has been introduced by Jauch *et al.* as an approach for organizing case study analysis in a methodical and systemized manner, epecially in organizational analysis (1980). Their work criticizes the limitations in the usage of the questionnaires, and hence the lack of reliability in qualitative methodological approaches, such as response bias and time-specificity, that often limit qualitative analysis. As such, the application of the Structured Content Analysis has been suggested as a complementing method that provides explanatory power, longitudinal insights, and enhanced external validity. The essence of their method consists in the contents analysis schedule, an inbuilt framework for the extraction of preset details from case study reports. In differentiation from the conventional surveys that capture single-point perceptions, it allows the researcher the ability to monitor changes along prolonged intervals, in turn useful for organizational changes and strategy development. As described in figure 3.2., Kohlegger *et al.* further elaborate on the application of the approach as an analysis tool for the analysis of conceptual models, applying it in the area of maturity models, inspired from Mayring's 2008 method for qualitative content analysis (2009). The process employs an inductive process for categorizing, making it such that the result comes out in an authentic and organic manner from the data, and hence not limited by predetermined hypotheses. The methodical value in the work lies in its unpacking SCA as an efficient framework for the comparison of conceptual modes, in the reinforcement in its value for the application in the case of the development, and in the area of the theory and model classification. It further highlights the flexibility in its application in the usage for the area of an alternative method in other fields beyond that in textual analysis. Lastly, Vaz *et al.* applied this methodology in the context of systematic literature reviews, focusing on sustainability and innovation in the automotive sector (2017). In combination with bibliometric analysis and content analysis, the work showcases the application in the usage of the method for extracting data in synthezising the large corpus of the data. In contrast with conventional literature reviews, based on narrative descriptions and subjective interpretation, the above work employs the use of systematic coding for the classification of innovations related to sustainability. The method separates incremental from radical innovations; the work identifies the function of eco-innovation, revealing how SCA can formally organize knowledge in an area in the process of assuming an empirical dimension. The embedding of such methodology in the Systematic Literature Review ensures higher transparency and replicability, making it an indispensable mechanism for the formal review of large amounts of academic literature.

Together, these works exemplify the advantages of Structured Content Analysis in providing guarantees for transparency, reproducibility, and methodological soundness. Compared to qualitative methods, which could be very interpretative and resistant to replication, it yields a codified and planned method for data extraction, allowing for the comparison and aggregation of qualitative data in an efficient and sustained manner. Its implementation in multiple disciplines displays its flexibility as an instrument for synthesizing evidence. In the framework of systematic reviews, it mirrors best practices in planned data extraction and thematic classification, solidifying its place among qualitative research syntheses as an excellent methodology.

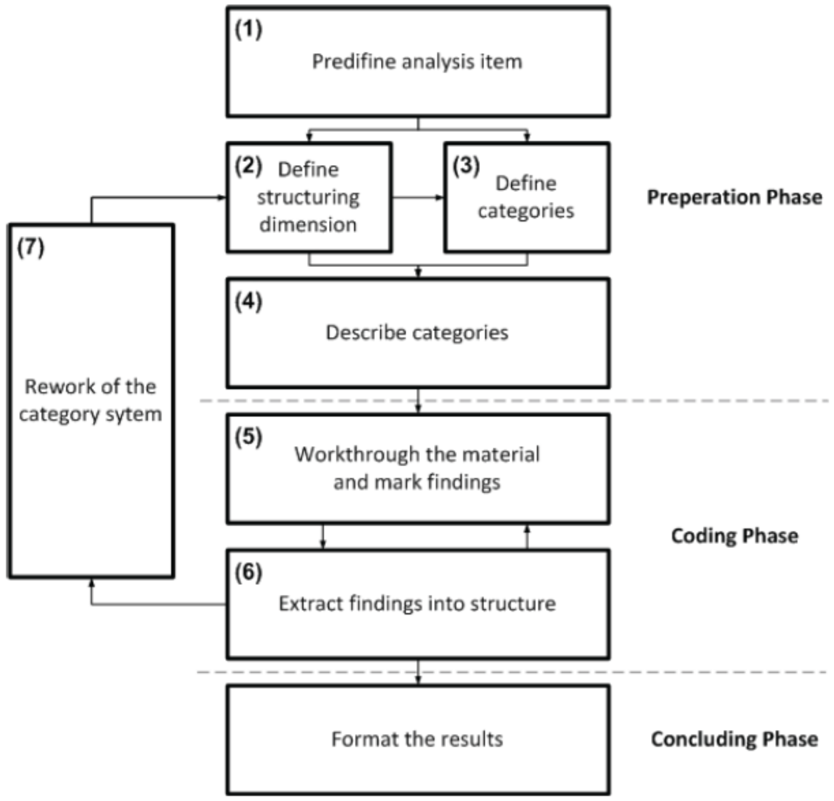

Figure 3.2: Process flow of a Structured Content Analysis, adapted from (Kohlegger et al., 2009)

4 Methodology

As anticipated in the introduction to Methodology, this section will further explore how the treated methodologies have been used in this study. Starting with the paper retrieval and selection, all the inclusion and exclusion criteria will be deepened, to ensure replicability of the research. Moving forward, the involvement of LLMs in this systematic review will be better explained, from the prompt engineering phase to the construction of a KNIME workflow to fully automate the LLM interaction process. Lastly, the application of Structured Content Analysis to the extract data will be examined, to understand how the final taxonomy was built from the managerial competencies contained in the generated dataset.

4.1 Paper Retrieval and Selection

The approach used in the following systematic review is informed by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol, the accepted gold standard for academic systematic reviews for its sound methodological design. This review focuses exclusively on academic literature to ensure methodological consistency and scientific reliability. This focus on academic sources ensures the inclusion of validated scientific knowledge produced by the research community, thereby offering a rigorous and methodologically sound perspective on the phenomenon under investigation.

Regarding scientific literature, the research was conducted using major bibliographic databases, specifically Scopus and Web of Science, with a structured and articulated search strategy. The primary query was constructed by combining terms related to three key dimensions:

(TITLE-ABS("artificial intelligence") OR TITLE-ABS(AI) OR TITLE-ABS("machine learning") OR TITLE-ABS("ML"))

AND

(TITLE-ABS("competenc") OR TITLE-ABS("skill"))

AND

(TITLE-ABS("board of director") OR TITLE-ABS("board member") OR TITLE-ABS(boardroom) OR TITLE-ABS("C-suite") OR TITLE-ABS("C-level") OR TITLE-ABS("chief executive") OR TITLE-ABS(CEO) OR TITLE-ABS(CFO) OR TITLE-ABS(CTO) OR TITLE-ABS("top manage") OR TITLE-ABS("senior manage **") OR TITLE-ABS("executive*") OR TITLE-ABS("corporate governance") OR TITLE-ABS("leaders*"))****

The search was further refined by applying filters related to document type (articles and review papers) and language (English), as well as by focusing on specific relevant disciplinary areas (Business, Management, Social Sciences).

To ensure the relevance and quality of the analyzed document corpus, the following inclusion criteria were applied:

- Peer-reviewed articles and review papers in English
- Focus on managerial skills in the AI era
- Implementation of AI in business contexts
- Ethical and regulatory implications of AI for business leaders
- Human-machine interaction in a managerial context

At the same time, the following exclusion criteria were defined:

- Purely technical AI studies with no managerial focus
- Single case studies that are not generalizable
- Studies focused solely on technological aspects without managerial implications
- Documents not accessible in full-text

In the first phase, we conducted a preliminary screening based solely on the titles and abstracts of the identified documents. This step enabled an initial selection of relevant documents while excluding those that were clearly unrelated to our research objectives. During this phase, each document was assessed based on its apparent relevance to the core research questions guiding our investigation. As a result, 110 documents were identified as relevant from an initial corpus of 189 contributions. From the 110 documents, some of them were not considered due to the impossibility to access them; thus, 95 articles were effectively analized in this systematic literature review.

4.2 Articles Categorization

In order to overtake the limitations related to the application of LLMs in literature reviews, the present study offers a mixed approach, in which the database of articles has been identified through human judgment, and LLMs have been only used to summarize and extract relevant information, with the aim of creating a "human-in-the-loop" process, leaving the LLM the task of summarizing and identifying key points of the articles, in which his ability has already been demonstrated (Antu et al., 2023). In particular, we asked the LLM to generate an output for each of the following requests:

- Managerial competencies: which refers to the managerial competencies, skills or knowledge explicitly or implicitly identified in the analyzed articles. This dimension represents the core of the review, as it directly informs the construction of the taxonomy of executive competencies in AI-driven contexts.
- Application area: in order to contextualize the findings and perform sectoral and industrial meta-analysis, we requested the model to identify the sector, industry or field where the study has been performed. Where possible, this was mapped to the International Standard Industrial Classification of All Economic Activities (ISIC) taxonomy corresponding to the research, to compare studies across domains.
- Empiric results: for each article, the LLM was asked to summarize the main findings derived from empirical analysis. It involved major outcomes or insights presented in the reports from the authors, with the objective of capturing the evidence base informing the identified competencies.
- Managerial implications: this output focused on the practical takeaways suggested by each article. The model pulled out information about how the findings from the study might affect, inform, or direct managerial action, decisions, or tactics.
- Best practices: the LLM was requested to identify any tangible examples of best practices cited or suggested in the studies. They may be case implementations, leadership styles, or AI implementation strategies presented as successful or replicable.
- Ethics considerations: in light of the increasing prominence played by ethical considerations in the incorporation of AI, this prompt aimed at any commentary regarding fairness, accountability, transparency, data privacy, or other normative elements specifically covered in the articles.
- Methodology (description): in this section, the LLM provided a wide description of the methodological approach adopted in each study. The output included the type of research design, as well as the data collection methods, analytical techniques, and any relevant procedural details.
- Methodology (keyword): in parallel with the description, the LLM was requested to classify the article into a predetermined taxonomy of methodological types (e.g., qualitative, quantitative, mixed methods). This provided consistency in methodologies categorization throughout the dataset.
- Theoretical Implications: this output emphasized the ways in which every article contributed to the academic discussion as a whole. The LLM was prompted to find new theory propositions, expansions on existing models, or new interpretations of established concepts in the area of AI and management.
- Limitations: the LLM identified the limitations recognized in the literature, e.g., restrictions in the samples, methodological bias, or the confines in the scope. It helped us determine the quality and limits of the body of existing knowledge.
- Future research: the model encapsulated the future directions for research suggested by the authors. It was generally in the final parts of each paper and comprised directions for theoretical elaboration, methodological advancement, or empirical validation.

- Theoretical framework: in this case, the LLM was requested to rebuild the underlying conceptual model employed in the study, defining the included variables, the relationships among them, the framework logic, and, if any, the hypotheses or propositions that were being tested.
- Fit Score: finally, the model was said to assign a synthetic score from 1 to 5, reflecting the degree to which the article aligned with the objectives of the present systematic literature review. The score was not based on clear criteria, instead being left up to the semantic interpretation of the model for relevance, contextual compatibility, and thematic cohesion among all the contributions.

4.2.1 Designing Effective Prompts for the Systematic Review

In order to obtain relevant and coherent information from the LLM, a specific prompt was utilized for each of the presented requests. The effectiveness of LLMs in generating accurate outputs is highly dependent on the design and refinement of the prompts used to guide their responses (Lin, 2024). Prompt engineering was important in order to assure the outputs derived from LLM were accurate, meaningful and consistent with the particular needs of the systematic review. A point in essence in the process is the setting of the temperature parameter – between 0 and 1- that greatly affects the variability and coherence of model responses. Lower temperature values tend to produce more deterministic and rational outputs, making them suited for academic research where consistency and factual replicability are paramount; conversely, higher temperature settings introduce greater variability and creativity, which can sometimes result in hallucinations and less precise responses (Ekin, 2023). Consistent with the guidelines, the setting of the temperature consisted in the value 0, in order to prevent hallucinations in the summarizing of the articles' contents, taking into account the high number of tokens stemming from the text of each article.

Moreover, an additional essential component of prompt engineering is iterative refinement, which, even in non conversational contexts, remains fundamental for optimizing the effectiveness of the single prompts. Even if each query in this study was designed to be processed independently, the prompts were systematically improved over multiple iterations to enhance clarity, specificity, and output alignment with the objectives of the research. Established best practices in the field of prompt engineering state that changes in wording, setting, and specificity can profoundly affect the quality of responses, and hence iteration forms an unavoidable part of the optimization process (Ekin, 2023; White et al., 2023). This coincides with formal methodologies such as the REFINE approach, which promotes ongoing refinement of the prompts through systematic rephrasing, contextual tests, loops of back-end quality control, iterative adjustments, and through review of outputs (J. Park & Choo, 2024).

The framework for the prompts in the present work conformed to the Role-Task-Expected Features-Example model, aimed at having the LLM consistently interpret and perform tasks in an exact, reproducible manner. The clear definition of the LLM function, along with the clear definition of the goals for the task, resulted in a methodical approach towards directing the model response behavior. While the Role-Task-Expected

Features-Example framework might not be universally standardized, its design parameters closely relate to established methods for prompting, such as Few-Shot Prompting, where the provision of contextual examples is necessary in order to lead the model in its comprehension and the formation of responses (Sahoo et al., 2024). By incorporating examples derived from a manually reviewed subset of articles, the prompts allowed the LLM to learn patterns of responses, ensuring enhanced coherence, consistency, fit with the criterion for the research and an improved stylistic response. More precisely, a single example was only provided for managerial competencies, due to the excessive length of the prompt; for all the remaining requests two examples were provided, excluding Fit Score, in which no example was provided to the LLM, owing to the nature of the request. The rationale for giving the LLM the benefit only of one or two examples was the belief that in tasks where the model has been trained on large, high-quality dataset, zero-shot prompting, for example, where singular instruction is provided in the absence of clear examples, works best. In tasks such as those in the academic field, however, zero-shot prompts might result in fuzzy, underdeveloped responses, for the model needs extra contextual information in order to gain deeper comprehension. In contrast, few-shot prompting uses selected examples as part of the prompt, enabling the model better to conform to anticipated response structure and content (B. Chen et al., 2023; Lin, 2024). This method is consistent with the PARTS model, in providing the definition for basic elements in constructing the prompt, such as Persona (the role assigned to the LLM), Aim (the goal of the response), Recipients (the target audience), Theme (tone and restrictions), and Structure (desired response format) (J. Park & Choo, 2024). The application of the assignment of roles in prompts has been recognized as being an important determinant in the accuracy of LLM responses, as it defines the boundaries in the context and guarantees the generation of domain-specific and accurate responses.

One other important consideration in prompt engineering is the application of reusable templates, which normalize the format of prompts in order to increase scalability and reproducibility. Research indicates that template-based prompting is most successful in ensuring that LLMs output well-structured and predictable responses, eliminating inconsistencies in multiple queries (White et al., 2023). By keeping the format uniform, researchers can normalize the process of deriving major insights, including theoretical implications, managerial competencies, and methodological steps, enabling better efficiency and organization in analysis of academic sources. Use of templates also lowers the cognitive burden on researchers, in that, an optimized structure of prompts, once identified, can be applied in an efficient manner to multiple queries without the need for significant alterations. Effectiveness in prompt engineering is strongly connected with AI literacy, an area that affects a researcher in designing, optimizing, and interpreting LLM outputs. AI literacy literature indicates that an appreciation for the mechanics of LLMs, including their bias, contextual constraints, and response variability, is imperative for the optimization of the design for prompts (Knoth et al., 2024). AI literacy helps the researcher in being prepared for probable model mistakes, in optimizing prompt structures and, accordingly, in critically evaluating the validity and reliability of AI outputs. This study leveraged an iterative learning process: through an in-depth analysis of AI outputs, the prompts were optimized, thereby ensuring that the requirements for academic rigor and specificity in systematic literature reviews were upheld. Domain knowledge also features in the process, as LLMs depend on expertized contextual framing in order to correctly interpret speciality and nuanced content. Without clear design for prompts, LLMs might incorrectly interpret complicated domain-specific questions, generating in complete or incorrect responses, thereby in need for qualifying through human verification.

To illustrate the practical application of these methodological principles, the following is an example of a prompt used to extract managerial competencies from the designed articles:

"*Act as an experienced academic researcher of Business Management who focuses on systematic literature reviews on AI and management. You are assisting in classifying an academic paper related to managerial competencies in the AI era as part of a systematic literature review. Your task is to analyze the following academic paper and generate a description of the identified managerial competencies and skills. Managerial competencies refer specifically to the knowledge, skills, and abilities that managers should develop to effectively lead, make decisions, and manage teams in the AI era. If the paper discusses managerial or business-related competencies or skills that should be developed or created by managers in order to achieve success in the AI era, describe them by reporting the most important findings in a way that is as close as possible to the original text. Otherwise, if the identified competencies are not related to managers or to a business context, respond with: NOT-DEFINED. Use the following example for structuring your output. Example:*

##

Knowledge and understanding of AI technology; AI mindset, which means to be flexible and with a high degree of curiosity about AI related topic. Then, we have AI leadership capabilities, that refer to the ability to convince important stakeholders within the firm; ability to navigate AI abstraction (Navigability), related to the ability to focus on the future, understanding the potential of AI in its initial stages, without any concrete expectation concerning financial returns in the near future. Lastly, the Ability to make AI-based decisions, perceived as faster and more reliable than intuitive decisions.

##

Ensure the generated output matches the writing style, detail level and format in the provided example".

As shown in the example, the role indicated that the LLM was said to act as an academic researcher of Business Management who focuses on systematic literature reviews on AI and management. Thist first part of the prompt was common to all the requests. Moving forward, the specific task was explained to the LLM, depending on the information it had to extract from the articles, that in the example corresponds to managerial competencies. Specifying the managerial competencies needed to be reported in a way that is as close as possible to the original text refers to the expected features section of the prompt. Lastly, a single example was provided in order to avoid an excessive length of the prompt, with the example deriving from a manual summary of a small subset of 5 articles, made to offer examples to the LLM for all the requests. As visible in the example prompt, the LLM was allowed to answer "NOT-DEFINED" when the information found in the article were out of our research scope; this prompting technique, known as Negative Prompting, was used with the aim to reduce LLM's hallucinations and provide only responses when the articles were about our main research topic. As a whole, employing negative prompts helps guide the model to produce content that adheres to specific constraints, making the output more useful and appropriate for the given context (Lin, 2024). In this context, this prompting technique was adopted to avoid the LLM generated responses not inherent with our objectives; doing so, we only obtained managerial competencies, empiric results and managerial implications related to an AI context, which is the objective of the present systematic literature review. This technique was applied to several prompts, excluding the ones related to information always present in academic studies, such as methodology (description), limitations, theoretical implications and future research.

4.2.2 Technical Background: Workflow Automation and AI Integration

Moving to the technical background of the systematic literature review, this section explores the methodology from a more technical perspective, in a way that allows a better understanding of the integration of the LLM in the present study. More specifically, Langflow v1.2.0 - an interactive tool that enables the visual design and execution of LLM workflows – and KNIME Analytics v5.4.0 - an open-source data analytics platform that facilitates workflow automation, data processing, and integration – have been utilized for the research development. A simple workflow was built on Langflow, involving only three components: chat input, referring to the prompt that serves as the input for the LLM's response, Google Generative AI, in particular Gemini 2.0 Flash model – the core LLM processing unit, with its temperature set to 0, as discussed in Section 4.2.1– and the chat output component, which corresponds to the final output from the LLM. Clearly, the Google Generative AI component allowed us to connect to the Gemini Flash 2.0 model with an appropriate API key. Having built such simple workflow, the interaction with the LLM could have happened only utilizing the Langflow tool but, with the aim of creating a systematic way to summarize different sections of the articles, the second step involved KNIME Analytics Platform.

In fact, in parallel to Langflow, a more complex workflow was developed on KNIME Analytics platform to build an automatized workflow designed to extract and summarize specific sections of the articles. Starting with 'PDF parser' and 'document and data extractor' nodes, the articles' PDFs were uploaded, and their text was extracted; at this stage of the process, the output was a table with only two columns, corresponding to the title and the text extracted from the articles. Then, a 'string manipulation' node allowed us to concatenate such extracted text with the predefined prompts, preparing it for LLM processing, to be sent to the Gemini Flash 2.0 model. Given the impossibility to connect to Google Generative AI models directly from KNIME Analytics platform, the following node was a component that, by indicating the Server URL, the Flow ID and the Langflow API key, permitted us to connect to the designed Langflow workflow, that, in turn, was connected to Gemini Flash 2.0 model. After this component, the following nodes were utilized to rename and reorder the obtained output.

More precisely, to prevent a parallel execution of multiple requests to the LLM, the workflow was replicated for each query, ensuring that only the PDF parsing and document extraction steps were shared among all instances. Moreover, a 'Group Loop Start' node was placed between the document extraction and string manipulation stages, allowing each article to be submitted to the LLM individually; after the output formatting stage, a 'Group Loop End' node was applied, preventing excessive computational overload from Langflow processing multiple simultaneous requests. Doing so, we were able to reduce the computational overload derived from Langflow, with too many requests processed at the same time. The generated workflow allowed us to process the requests one at a time and, thanks to the designed loops, the articles one at a time. Upon completion of all requests for each article, 'Joiner' nodes were finally employed to aggregate the final results; the articles titles served as the primary key for an inner join operation, ensuring that all processed outputs were systematically merged into a single dataset. At the end of this stage, 3 out of 95 articles in the corpus were not processed because their text could not be extracted from the source file. For this reason, the number of articles effectively analyzed corresponds to 92, as illustrated by figure 4.1.

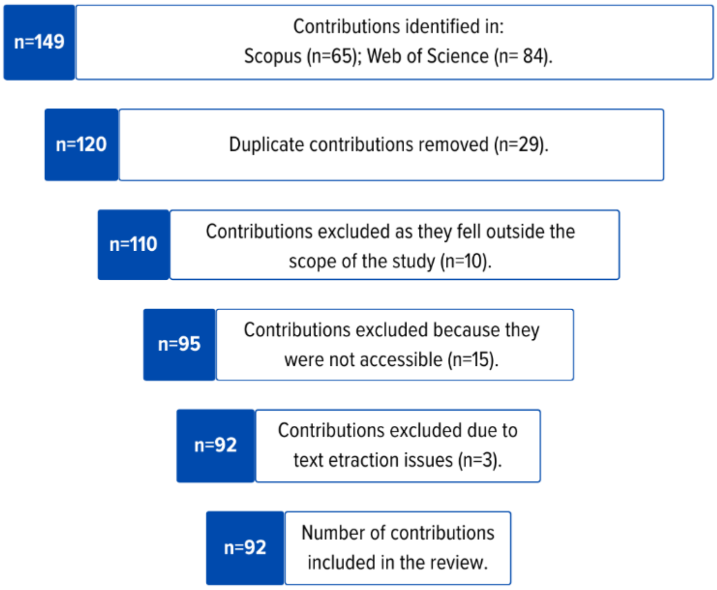

Figure 4.1: Funnel diagram of the article selection process for the systematic literature review.

4.3 Applying SCA to Categorize Managerial Competencies

Once the second phase was ended, the result was a single dataset containing the requested information for all 92 analyzed articles (i.e., managerial competencies, area of application, methodology, fit score, etc.). Focusing only on the managerial competencies' column of the dataset, a Structured Content Analysis through human judgment was applied to classify all the skills and competencies. The analysis aimed at detecting explicit mentions of managerial competencies, leadership traits, and organizational competencies needed in AI-based settings. We analyzed each article for the text portions referring specifically to managerial skills or abilities in the implementation of Artificial Intelligence. From these portions, grouped together in recurring thematic patterns, we derived the foundation for a structured classification. For ensuring consistency in the categorization, we iteratively checked and tuned the competency groups, merging overlapping themes and ensuring consistency among the sources. The final taxonomy provides for the structured synopsis of managerial competencies and knowledge domains, grouped according to their function in facilitating AI-based decision-making, human-machine collaboration, and organizational leadership in an AI-augmented setting. Using this approach, we achieved methodical yet adaptable synthesis of the competencies, leading toward an exact replicability and transparent approach for the comprehension of how such technology transforms managerial roles and competencies.

5 Results and Discussion

The following sections present the results of the present Systematic Literature Review, organized into three main areas: (i) managerial competencies, (ii) numerical meta-analysis, and (iii) thematic synthesis of non-aggregated qualitative insights. To provide a more comprehensive overview of the reviewed literature, Appendix A offers a detailed classification of all contributions whose fit score is greater than 3, including managerial competencies' description, managerial implications, application areas and methodologies.

5.1 Results of Managerial Competencies

Given the prompt utilized for the managerial competencies section, a list of managerial skills, competencies and knowledge included in the analyzed papers was compiled. Through Structured Content Analysis and human judgment, four families of competencies were identified, providing insightful information for managers to successfully exploit Artificial Intelligence. These families were named as follows: "Strategic and Decision-Making Competencies", "Technical and Analytical Skills", "Ethical and Legal Regulatory Knowledge" and "Leadership and Change Management".

Clearly, the present names were assigned depending on the source and type of the competencies and skills contained in each of the classified families. Both "Strategic and Decision-Making competencies" and "Leadership and Change Management" families primarily emphasize the human dimension of AI adoption, encompassing the ability to evaluate, make informed decisions, and lead organizational change in an increasingly automated environment. The "Technical and Analytical skills" family deals with technical skills, imparting the required expertise to operate and engage in interaction with AI systems. Lastly, the "Ethical and Legal Regulatory knowledge" family addresses the ethical and legal issues, making AI implementation accountable, compliant, and in line with regulatory and societal requirements. The four above-mentioned categories of competencies together give a full set of the skills required in order for managers to be able not only to properly implement Artificial Intelligence in their companies, but also to promote technological development and sustainable business expansion. More specifically, each of them includes between two and six groups of skills. The analysis has driven a two-level hierarchy diagram, having a total of 4 categories and 16 key areas of skills: the resulting final taxonomy is presented in figure 5.1.

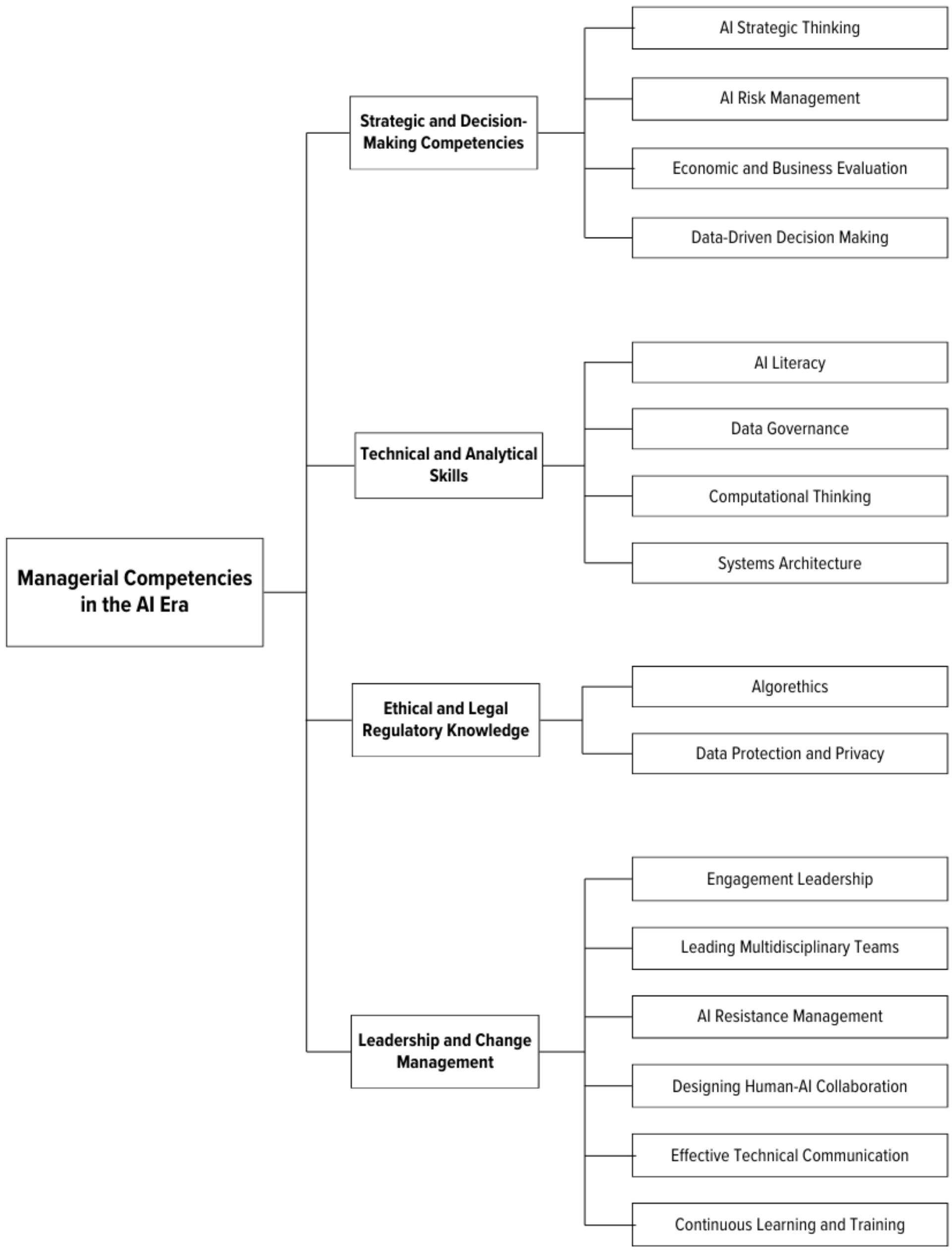

Figure 5.1: Two-level hierarchy diagram of managerial competencies

5.1.1 Strategic and Decision-Making Competencies

The first family of competencies is related to strategic and decision-making skills that, according to the analyzed articles, emerge as fundamental for managers in the AI era. Caro outlines strategic leadership capabilities and long-term vision, and points out the necessity for developing shared visions and overcoming perceptual differences in e-health projects (2008). The economic and business evaluation of AI has been trated by Baumgartner *et al.*, where a deep concern for the necessity of developing skills enabling managers to properly assess the economic impact and profitability of investments in Artificial Intelligence has been underlined (2024). Managerial critical judgment and decision-making skills in complex contexts emerge from the study of Jorzik *et al.*, where the necessity of a data-driven and experimentation mindset has been highly recommended for managers (2024). Lastly, Surbakti *et al.* focus on data understanding and knowledge of AI-supported decision-making processes (2024). From those researches, four competency areas emerged as part of the strategic and decision-making family of competencies. “AI Strategic thinking” concerns the awareness of emerging trends in the technological area and the capacity to foresee their impact on the organization and design future scenarios as well as skilfully integrate data and AI into business strategy; “AI Risk Management” concerns the awareness of risks and specific issues related to the application of AI solutions as well as of AI-related legislation and the capacity to identify as well as assess and handle those risks effectively. “Economic and Business evaluation” goes deep on the capacity to assess the economic and financial cost and benefits of AI application in the organization and the awareness of how and what to measure and quantify the economic value of corporate data and identify opportunities for monetization. Finally, “Data-driven decision making” goes deeper in understanding algorithms and their workings as well as in the capacity to interpret results achieved from advanced models and translate them in skilled decision-making processes in the business context.

5.1.1.1 AI Strategic Thinking

In the literature, strategic thinking has emerged as an essential competency for organizational leaders, which allows leaders to cope with uncertainty, complexity, and competition in dynamic environments. It's a two-way process of analytical planning and creative synthesis so that the leader can formulate and evolve strategies over time. From a managerial view, strategic thinking is not an exclusively rational and systematic approach but also encompasses elements of intuition, flexibility, and divergent thinking. A central construct in strategic thinking is systems thinking, which calls upon the leader to perceive the organization as a holistic and interconnected system. Doing so, decision-makers can analyze internal and external environmental variables and determine their effects on strategic decisions (Steptoe-Warren et al., 2011). In addition, strategic thinking and planning are also understood as two modes of reasoning by Heracleous, wherein strategic thinking consists of a creative, intuitive, and divergent approach, and strategic planning consists of a structured, analytical, and convergent approach (1998). From this school of thought, planning cannot create strategies but rather remains an operative tool employed in their implementation as a result of higher-level strategic thinking. It's on account of this view that the author dismisses strategic thinking as a purely creative and intuitive phenomenon and argues that strategic thinking has to be analytical and make use of structured methodologies such as industry analysis, value chain analysis, and scenario planning.

The quick integration of Artificial Intelligence in organisational processes calls for a strategic and visionary approach on the part of top managers. AI Strategic Thinking has also become an important competency increasingly seen as imperative, which allows managers to foresee advancements in Artificial Intelligence, analyse their effects and calibrate the use of AI according to business goals. Accordingly, critical thinking here becomes a core managerial competency in contemporary competitive markets. Being able to critically assess AI generated insights and judge the risks as well as the complex decision-making involved in AI deployment is essential (Richthofen et al., 2022). In addition to this, organisations need a strategic and visionary mindset in order to be able to reap the transformational effects of AI properly (Baumgartner et al., 2024): it's not just an automation tool but an engine of innovation and success in implementation depends on managerial foresight and flexibility. Part of AI Strategic Thinking includes the capacity of dealing with levels of abstraction in AI and thus 'Navigability': according to this definition, managers should create a conceptual sense of such technologies and their uses in Business Model Innovation and think according to long-run opportunities rather than incumbent short-run profits. The capacity of pre-empting AI evolution at the nascent stages and not having a strict anticipation of returns in the short-run from an economic sense becomes of relevance in defining an organisation's strategic direction. This mindset enables leaders to prioritize nonfinancial outcomes, before considering direct profitability (Jorzik et al., 2024). When implementing AI in organisations, having a strategic mindset on resources deployment and planning on AI adoption goals is necessary (S. Chowdhury et al., 2023). On this line of action, managers must learn and deploy digital transformation approaches embracing AI deployment and this includes the amplification of programme and portfolio concepts on governing a programme as well as employing AI tools on the work design and analytics levels (Tominc et al., 2023). Moving forward, Walkowiak identifies different thinking and cognition as crucial, which means having the capacity of thinking and solving differently and thus prioritising the development of innovation in the workplace (2021). AI itself sometimes works as a facilitator of cognitive capacities on this line where it helps managers improve their problem-solving and decision-making abilities (Abbasi et al., 2025). Additionally, staying informed about emerging technological trends is vital. Managers will develop the capacity for absorbing and understanding information on AI advancements and their wider applications at the business and societal levels (Hearn et al., 2023). Such knowledge not only pertains to Artificial Intelligence and its advancement but rather includes a sensitivity to related technologies like cloud computing, data analytics, blockchain, 5G, and robotics that cumulatively define the developing digitized environment (Watson et al., 2021). In conclusion, AI Strategic Thinking isn't solely a matter of knowing about such technology but about aligning it to a wider strategic blueprint; it demands critical thinking coupled with strategic foresight. Managers who obtain these abilities will be able to cope better with the complexities of adopting Artificial Intelligence and foster sustainable innovation in their organizations.

5.1.1.2 AI Risk Management

According to Dionne, risk management strategies became more sophisticated with the emergence of derivatives in the 1970s and 1980s (2013). Corporate risk management aims to establish a solid and structured framework that enables companies to navigate risk and uncertainty effectively. As risks exist almost everywhere in financial and economic operations, their recognition, evaluation, and management must become part of a corporation's strategic planning and be monitored at the top level, the board of directors. A holistic approach to risk management must undergo continuous assessment, monitoring, and control of all the risks and their interconnectedness. The author's formulation of risk management can be employed not just in financial and economic operations but also in the take-up and deployment of Artificial Intelligence since a changing competitive landscape exists and AI Risk Management must become another key competency and be part of the management awareness (Almeida, 2025). Successful risk management approaches assist organizations in predicting and mitigating security attacks so AI deployment will not impair data reliability or business continuity (Hearn et al., 2023; Shahzad, 2024a). The power to see both the benefits and risks of AI take-up must also be another critical competency so organizations will develop both strategic and adaptive responses (Peifer & Terstegen, 2024). Evidently, successful risk management approaches must be provided with adequate knowledge of AI-related directives such as the European Union's Artificial Intelligence Act as this directive has a decisive function in prescribing the acceptable boundaries of legitimate AI deployment (Petcu et al., 2024). Deepening this crucial topic, this Act passed by the Europen Union in 2024 has written into law the world's first extensive and binding horizontal regulation of Artificial Intelligence. The act creates a single common legal framework for developing, deploying, and utilizing AI systems in the EU based on a risk approach categorizing AI applications in four types: unacceptable, high-risk, limited-risk, and minimal-risk. Unacceptable risk applications are forbidden and high-risk systems (e.g., those affecting fundamental rights, or affecting or impacting on the area of health or safety) have strict requirements on transparency, data governance, human oversight and auditability as well as on cybersecurity requirements. The limited-risk systems must meet the requirements for transparency obligations and minimal-risk systems are exempted mostly from enhanced regulations (| European Parliamentary Research Service, 2024). On the whole, these regulations put in place precise guidelines for the deployment of AI technologies responsibly and safely so that AI systems are aligned and harmonized with societal values and core rights. Strong internal policies must be developed by organizations so they can follow these regulatory requirements and prevent risks of misuse of data, discrimination through algorithms, and non-transparency (Kulkarni et al., 2024; Lichtenthaler, 2022).

5.1.1.3 Economic and Business Evaluation

The competency of being able to ascertain the economic impact of AI deployment is a core competency of managers in the AI era. This demands strong business acumen (Anomah et al., 2024) and the capacity for assessing AI introduction from an economic sense so as to ensure investments create organizational value and returns (Baumgartner et al., 2024). A critical part of economic assessment includes having the capacity to harmonize optimization and developing new business models through adopting a portfolio approach on multiple initiatives so as to allocate resources judiciously and create maximum impact (Lichtenthaler, 2022). At this juncture, cost-benefit analysis comes in handy since it helps managers make decisions by comparing the financial and operation costs and benefits of AI deployment (Surbakti et al., 2024). Additionally, cost management will be critical so as not to make innovations from AI unsustainable and lose efficiency and scalability (Karki & Hadikusumo, 2023). Economic evaluation of AI deployment calls for extensive awareness of the firm's end-to-end activity system and the ecosystem surrounding the firm. Understanding drivers of capturing and creating value will be key in deciding whether and how such innovations will create competitive advantage and long-term financial viability (Y. Chen et al., 2024). An additional challenge in business and economic evaluation is finding ways to integrate AI into operations in a manner that is both human-centric and economically sustainable (Peifer & Terstegen, 2024). It will be a matter of finding a balance between technical efficiency and ethical and labor considerations such as not disrupting organizational dynamics but rather improving it. As a final key component of AI-related economic evaluation will be the criticality of determining success thresholds for scaling up technology in a project-based scenario (Levitt et al., 2024).

For a better understanding of the scalability concept, according to Uchenna Joseph Umoga *et al.*, scalability has emerged as a critical challenge in the development and deployment of AI systems, particularly in complex environments (2024). As networks and operational contexts expand, the capacity for processing large scale data efficiently becomes a necessary trivial task whose processing may be limited by processing capacity limits, memory capacity limits, and energy consumption limits. As a solution for the aforementioned issues, distributed computing, parallel processing, and superior optimization algorithms should be utilized in order to improve performance and overcome scalability challenges. Likewise, Chowdhury *et al.* define scalability as the ability of an AI system to scale up its capabilities when workloads become higher without sacrifice of efficiency or performance (2024). This view highlights the fact that scalability goes beyond the hardware and encompasses AI models, algorithms, infrastructure as well as cloud services. Although it is predominantly a technical term, scalability affects companies' revenues and costs since it may not be feasible at all times to scale AI models and algorithms for other areas of the business based on their scalability. In general, having well-defined benchmarks and key performance indicators (KPIs) permits managers to systematically determine the feasibility and impact of AI efforts as well as assist decision making on their expansion and long-term viability.

5.1.1.4 Data-driven Decision Making

The growth in the application of Artificial Intelligence in decision-making makes it essential for managers to enhance advanced problem-solving skills and a keen sense of AI capacity and boundaries. A critical competency in this regard would be the capacity for problem recognition and problem-solving and the capacity for the assessment of the AI competency of external partners in making knowledgeable decisions. Moreover, executives must also have a realistic sense of AI capacity and limits when applied in business operations (Baumgartner et al., 2024). The most important skill in this area would be decision-making based on AI: this essential competency highly relies on the level at which managers are able to explain AI outputs and monitor AI-powered decision-making processes (S. Chowdhury et al., 2023). Generally, data-driven decision-making would be seen as quicker, quantitative, and better compared to human judgment based on intuition. Advanced algorithms can decipher good information from large datasets and identify patterns not observable through traditional means. This brings an edge to organizations when they can incorporate data-driven information in strategic planning effectively. Effective AI-driven decision-making also depends on the preparedness of Top Management in trusting and interpreting generated information in a logical manner (Jorzik et al., 2024). Managers should be sensitive in the interpretation of AI-generated information in making decisions and overseeing scheduling of projects, predictive analytics and digital helpers like chatbots (Tominc et al., 2023). AI facilitates processes simplification, automation improvement, and predictive modeling and decision-making based on facts. Finding opportunities for AI-driven automation and strategic oversight also calls for optimizing workflows (Sposato, 2024). This also requires strong analytical skills to forecast trends and guide business strategy (Nurshazana Zainuddin et al., 2023; Pantea et al., 2024). Data science skills through the ability to handle both structured and unstructured data make organizations able to extract relevant insights and optimize decision-making processes (Baumgartner et al., 2024). Integrating AI-enabled ecosystems into business operations calls for HR managers and executives having digital and data science skills so as to make human resources management and strategic planning of workforces aligned with AI-initiated changes (J. Lee & Song, 2024).

The integrated intelligence concept describing the complementarity of data analytics and AI with human expertise emphasizes the managerial imperative of filling the gap between human decision-making and developing technology (Lichtenthaler, 2022). Data competency in data understanding goes beyond technical competency and includes an understanding of interpreting data for strategic and sustainability decision-making purposes. Managers must be able to analyze data related to environmental performance and supply chain optimization, identifying opportunities for improvement to meet sustainability goals (Bag & Rahman, 2024). Furthermore, professionals in accounting and finance are required to adapt their skill sets to the disruptive influence of Big Data, as data analytics increasingly shapes their roles. Data interpretation and strategic analysis competency will be necessary in order to remain competitive in a changing digital economy (Pantea et al., 2024). Similarly, senior leaders must develop data-driven strategic thinking in order to make decisions primarily based on the huge amount of real-time data collected and processed via AI systems. In the changing era, leveraging AI for insight production and performance optimization will be a key determinant of organization success (Watson et al., 2021). Managers must acquire a set of analytical competency so as to categorize and prioritize issues related to AI accordingly. Although AI will enhance decision-making capacity, final decisions must remain under human jurisdiction so as not to create recommendations at variance with ethical and organizational imperatives (Jorzik et al., 2024). Managers must acquire a problem-solving orientation whereby they solve AI-associated challenges effectively (Hearn et al., 2023; Karki & Hadikusumo, 2023). This involves acquiring a problem-centric approach wherein AI serves as a means of decision-making facilitation and not as a substitute for human reasoning (Surbakti et al., 2024). The capacity for solving critical issues will become even more important as AI increases in magnitude and extent of application in areas such as organization change and operation efficiency improvement (Korepin et al., 2020).

Beyond traditional decision-making skills, newer skills like green creative skills, which correspond to intellectual skills for developing innovative responses to sustainability challenges, gain prominence in decision environments driven by AI (Ogbeibu et al., 2021). Likewise, financial acumen continues to be important since AI can be used to analyze financial information, predict trends, and assist decision-making at strategic levels (Pantea et al., 2024), especially for Business Analyst roles (De Mauro et al., 2018). The other managerial imperative concerns balancing human judgment and machine recommendations (Kolbjørnsrud et al., 2017); although AI can enhance decision-making on complex decisions, simpler administrative decisions tend to be automated and taken away from humans and replaced by AI systems (Giraud et al., 2023). As a result, developing an understanding of the role of AI in supporting human capacity remains essential and calls on leaders to create a corporate culture sensitive to the symbiotic fit between human skill and AI-enabled insight (Sposato, 2024). Last but not least, actualization of AI-enabled decision-making hangs on the deployment of AI tools both in form of software and hardware used by business organizations to maximize AI's capacity for decisional efficiency (Fenwick et al., 2024).

5.1.2 Technical and Analytical Skills

The second family of managerial competencies focuses on technical and analytical AI-related skills, widely discussed in the existing literature. In the research conducted by Baumgartner *et al.* reference is made to the knowledge of AI applications, the available company data, and system interfaces (2024). The requirement for a profound understanding of AI technologies and their possibilities as well as for a flexible mindset geared toward continuous learning has also been indicated by Jorzik *et al.* (2024). Pinski *et al.* delves into the importance of AI literacy for top managers and how this competency plays a key role in business orientation and implementation (2024). Data analysis-related competencies are central and emerge primarily in the research conducted by Richtofen *et al.*, who underscores the necessity of managing both structured and unstructured data (2022). Finally, the study conducted by Karki & Hadikusumo outlines technical competencies related to security and the use of machine learning techniques (2023). According to these findings, four areas of competencies were defined under the family of Technical and Analytical skills: the first group, named "AI Literacy", mainly refers to the knowledge and understanding of AI basic terminologies, concepts and functions, how AI applications work and act and the ability to evaluate performance, reliability, and generalization metrics of AI models in order to comprehend the reasons behind the choices made by AI tools; the second group, named "Data Governance", is primarily related to familiarity with processes, methodologies, and techniques for managing structured and unstructured data at the corporate level, including processes for data quality management and metadata documentation. Finally, the third named "Computational thinking" explores experience in the fundamentals of computational thinking and the capacity of applying the approach in developing and solving complex problems in a systematic and algorithmic way and grasping the logic and methods behind AI solutions, while "Systems Architecture" defines the awareness of enterprise systems as well as their integration in an efficient manner with AI tools and solutions.

5.1.2.1 AI Literacy

In the existing literature on this topic, AI Literacy has been referred to as a body of abilities which allows individuals to critically analyze, communicate and cooperate with AI and effectively apply it in multiple areas.

Long & Magerko conceptualized a framework that categorizes AI literacy in five thematic areas of understanding what AI consists of, knowing what it can perform, understanding the way it operates, assessing ethical implications, and examining its societal perceptions (2020). Similarly, through an exploratory literature review, Ng *et al.* have established four key aspects of AI literacy as knowing and understanding about AI, applying AI, assessing and developing AI, and resolving ethical concerns (2021). The first focuses on individuals knowing and understanding at a basic level of functioning and knowing what it can do in daily applications. The second involves acquiring useful AI-related skills so individuals may apply AI in numerous contexts. The third deals with higher-order thinking abilities like critical assessment of such technologies and designing innovative applications. The fourth focuses on the ethical aspects of AI and emphasizes fairness, responsibility, and transparency.

Successful deployment of AI demands managers fill the gap between technical skills and business planning and acquire a better understanding of AI functions and functionalities. These embrace awareness in Deep Learning, Machine Learning and Neural Networks and also the capacity to measure AI performance and functionalities (Baumgartner et al., 2024). Evaluation of the performances of such tools and innovations forms a core competency through which managers can interpret better the reasoning behind decisions and predictions generated by Artificial Intelligence; drawing from the existing literature, as highlighted by Naser & Alavi, performance evaluation of AI encompasses a variety of measures through which different features of a predictive accuracy and strength of a model are evaluated (2023). Traditional metrics like Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and correlation coefficients (r, R^2) remain popular as means through which the difference between predicted and true values in regression predictions can be accessed. Though these metrics provide a helpful measure of the accuracy of a model, they may not fully capture the complexity of real-world settings since they may be sensitive to outliers or may not test the extent of a generalization of the model from the train set of data. In classification models, precision, recall and F1-score remain popular metrics through which such models can be evaluated. These metrics of a performance of a model in those applications in which class imbalances or misclassification penalties may be critical considerations. The research also highlights the fact that a single measure may not be enough for a complete evaluation of AI models. Instead, multiple-metric evaluation is proposed through the application of multiple evaluation criteria if a better understanding of the strength and weakness of a model should be obtained. And finally, above and beyond specific measures themselves, the necessity of strong validation procedures as critical, such as cross-validation procedures and sensitivity analyses, so as not to simply optimize a model for a given set of data but achieve generalization effectively on novel data as well. Without this sort of a test, the danger of overfitting looms whereby a performance of a model seems good when a model is trained but fails when adopted in novel instances. Specifically, overfitting happens when a model gets excessively specific to the training data and therefore excels on known data but has poor generalization on new observations not seen before. Such a model would be very accurate when working on the training set but would not be able to provide reliable responses on testing or out-of-sample data, and this represents a challenge that poses a serious problem in machine learning. The disparity between training and test performance indicates the model has learned the data by heart and not the underlying patterns. Despite overfitting initially showing impressive results, it turns out differently when used on actual data, and performance plummets (Julius M. Kernbach & Victor E. Staartjes, 2021). This calls for a good choice of metrics under the intended application and decision-making situation so as not just to be accurate but also reliable and interpretable when applying AI solutions.

AI literacy, also understood as the critical ability to engage with AI, is necessary for making informed decisions and ensuring AI implementation in a responsible manner (Pinski et al., 2024). Executives do not necessarily need to be AI specialists but must acquire a strong conceptual understanding of AI technologies and their existing and future possibilities and limitations (Baumgartner et al., 2024; Jorzik et al., 2024), so they can realign it according to business objectives and redesign HR processes accordingly (S. Chowdhury et al., 2023). The conceptual understanding is not only a pre-requisite for decision-making on a sound footing but also increases managerial efficiency in utilizing AI-driven opportunities (Giraud et al., 2023). In addition to this conceptual understanding, technical proficiency and analytical skills as well as technical acumen in a technologically driven environment (Karki & Hadikusumo, 2023; Shahzad, 2024a). These competencies also apply to educational applications where AI aids in curriculum development and differentiated learning approaches (Abbasi et al., 2025). Business executives must also enhance digital abilities in cloud computing as a pre-requisite for overseeing digital transformation initiatives (Gaffley & Pelser, 2021). The repercussions of digitization and automation can be seen clearly in sectors like real estate and construction where gaps between technologically advanced abilities at the graduate level and implementation at the ground level emerged as a priority (C. L. Lee et al., 2024). Likewise, AI-supported solutions in the construction industry reengineer the dynamics of industries and therefore call for a profound sense of understanding how digital solutions make things more efficient (Alnaser et al., 2024). The application of AI at the operative level in various sectors validates the requirement for both technical and operative AI skills in managers. In library and information management, robotic, chatbots and voice assistants assist in self-service, stock holding and reference service; in contrast, Natural Language Processing improves text translation, information retrieval and automated recognition of text. Text Data Mining is utilized for monitoring for academic impact and searching scholarly networks and recognition and image processing for security purposes, digital preservation and accessibility in archival material (Ali et al., 2024). With AI transforming industries from education and business management through real estate and construction, organizations will need to invest in technical and AI literacy development for their leaders. The capacity to comprehend the workings of these applications as well as the vocabulary and key concepts behind them will be a deciding factor in making sustainable and ethical AI integration a reality.

5.1.2.2 Data Governance

The concept of data governance has raised its importance recently, as it is now essential for companies to deal with. From a theoretical perspective, Janssen *et al.* emphasize that AI-based Big Data Algorithmic Systems rely on enormous datasets which tend to be from various sources and thus data quality, security, and governance become critical challenges (2020). Without good governance structures in place, the systems risk generating unreliable or biased or non-compliance outputs. The work also presents a data governance framework for AI systems and defines 13 design principles for accountability, regulatory compliance, and ethical data use. The framework encompasses data stewardship and reiterates that organizations not only must responsibly accumulate and maintain data but also must set clear ownership and accountability procedures in place. The most significant contribution of this work lies in its multi-level approach toward AI data governance where governance takes place at multiple levels ranging from single organizations through organizations' networks and regulatory agencies and calls for interoperability and self-sovereign identities so that individuals and organizations can take control of data access and use. The authors contend that data governance goes beyond AI models and must encompass the total life cycle of data and algorithms as well. The most significant finding from the research is that AI cannot be possible without good data governance.

In this regard, the capacity for managing data effectively is critical in the era of AI so must be achieved by managers through a profound insight and understanding of available data in their companies. At the executive level, data governance and data management (Bag & Rahman, 2024) are identified as two of the most important resources in the digital period. CEOs should be aware of strategic roles of data collection, storage, analysis, report, and utilization so that they take precedence in digital transformation efforts. This highlights the importances of assigning Chief Information Officers to be charged with data governance through the assistance of data scientists and analysts who specialize in machine algorithms and predictive modeling for making decision through AI (Gaffley & Pelser, 2021). Overall, managing data in the right manner and having specific data governance tenets will be crucial for managers and organizations so they can be understood as a true intangible asset and not merely their economical value.

5.1.2.3 Computational Thinking

Beyond general literacy concerning Artificial Intelligence, the ability of connecting business needs to AI-powered applications through computational thinking is a key competency for the execution of AI as effectively as possible. Computational thinking has been referred to as a core cognitive capacity in existing literature extending computational science and affecting problem-solving, system design, as well as analytical thinking in subject areas other than computer science. Wing believes computational thinking isn't programming but a method of problem-solving utilizing computer science-derived concepts and principles about abstraction, decomposition, and the kind of reasoning involved in algorithms (2006). From a conceptual level, computational thinking means knowing what kinds of things can be solved from a computational viewpoint and the ways in which computational models of things can be developed in ways so they become tractable and also efficient and scalable solutions. Similarly, Selby & Woollard define computational thinking as "*a focused approach to problem solving, incorporating thought processes that utilize abstraction, decomposition, algorithmic design, evaluation, and generalizations"* (2010).

For the organizations, proficiency in Python, R, Java, or Scala is important for developing and customizing AI-driven solutions, enabling businesses to optimize processes and automate decision-making (Baumgartner et al., 2024). More specifically, the coding skills and the ability to write scripts for querying databases are mostly related to Big Data Developers and Data Scientists roles (De Mauro et al., 2018).

5.1.2.4 Systems Architecture

Understanding the application area where AI is brought in enables managers to map AI applications onto industry-specific challenges and organizational requirements. Understanding available systems and interfaces in the organization is also crucial since AI solutions must be seamless integration-friendly with existing technologic bases. Conceptually, organization of elements and their interconnectivity in every system forms the system's architecture, be it a computer system or software or even a social system. For instance, in a computer system, CPU, memory and I/O devices form part of the architecture as well as buses and ports connecting them together. Likewise, in a university as a social system, students, professors, and courses interact through specialized relations and patterns of work. Any architecture has a function and the components interact to produce explicit or implicit functions. The function in the case of informatic systems relates strongly to application areas the software aims at serving. A good software architecture must harmonize with the goal of the consumers of the software so as to assist them in conducting their jobs and facilitating efficient interaction within the system as a whole (Chung & Subramanian, 2005).

Under this application area, specific skills in systems architecture involve data architecture design, design of databases and corporate data ecosystems and cloud computer and distributed processing: these skills form part of Big Data Engineer and Big Data Developer jobs in organizations (De Mauro et al., 2018). An important example is the implementation of AI in HR areas, where companies must be able to implement AI-aided IT systems into talent management, staff recruitment and workforce analytics so as to achieve both operation effectiveness and conformity to ethical as well as regulatory requirements (Pinski et al., 2024). As AI deployment continues to spread, technical programming skills, the integration of systems and strategic business skills will be at the core of realizing AI’s full breadth of contributions in organizational functions.

5.1.3 Ethical and Legal Regulatory Knowledge

The ethical, regulatory, and governance aspects of AI are key topics of research in many studies. As ever-evolving innovative technologies become increasingly part of organizational operations, responsible and sustainable utilization demands a systematic approach to regulatory compliance and ethical decision-making. As noted by Fenwick *et al.*, organizational values directing AI deployment are key drivers of accountability and trust (2024). Ethical savvy continues to be seen as a critical competency for governance of AI; Shahzad underscores the necessity of ethical perception and the capacity for foresighting and mitigating risks from AI deployment (2024a). Likewise, Baumgartner *et al.* examine issues of data protection and privacy and highlight the importance of data sensitivity as a key managerial competency in AI ecosystems (2024). Beyond the concern of privacy, AI governance also has to contend with vulnerabilities and new threat risks, a theme noted by Almeida as requiring stronger governance constructs so as not to be remiss in managing risks from AI (2025). Two areas of competency were established as reported by this key information: “Algorethics” involves knowing the ethical side of AI and the capacity for inflicting remedial steps where possible, in order to identify and neutralize possible biases in algorithms and making requirements in designing and sticking to ethical standards, converting moral values into computational formats for AI algorithms; “Legal and Regulatory Knowledge” deals with legal constructs, policy and regulatory compliance and data protection and privacy concepts that are essential in the modern AI era.

5.1.3.1 Algorethics

The concept of “Algorethics”, a combination of algorithms and ehics, has been introduced in the literature by Benanti, who provides a a detailed framework to the integration of ethics in AI development and governance (2020). The author examines the philosophical and computer science foundations of the ehics applicable to Artificial Intelligence and claims that this field pushes classical ethical models aside because of its independent decision-making process and its dependence upon biased datasets. In this sense, four core principles have been introduced to guarantee that AI systems align with human values: anticipation, transparency, personalization and adequacy. Similarly, Benanti highlights the socio-political dimensions of algorethics, with a focus on the global implications of AI governance and the risk of power concentration in the hands of a few technology corporations (2023). The author warns against a data oligarchy where the feedback over such technological systems could result in ethical disparities and social injustices and require regulation and multidisciplinary intervention. This work also discusses the Rome Call for AI Ethics, a project demanding the construction of AI systems that maintain human dignity, inclusivity and transparency. Drawing on such articles and definitions, Mantini stresses the bidirectional interaction between anthropology and technology and admits that ethics should be incorporated in technological development (2022). To frame this ethical aspect, the author outlines a horizontal axis (i.e., the Social Ethics of Technology incorporating responsibility, fairness and power) and a vertical axis (i.e., the Transcendental Motives of Technology involving anthropology, freedom-creativity and eschatology). This framework provides both ethical coherence and motivation behind technological progress. The center point of this perspective is the Dynamical Techno-Algor-Ethical Composition: a framework coupling the integrity of technology with ethical and dynamic principles to guide the design of the so-called “Good Algorithms”, which refers to AI systems respecting human dignity and societal values

Based on the theory of Algorethics, ethical awareness is a key competency in enabling wise AI-based decision-making so that leaders serve as a moral compass to their organization and maintain important ethical norms in AI-powered business model innovation (Baumgartner et al., 2024; Jorzik et al., 2024). Ethical acumen demands leaders to be aware of inherent biases and assist in responsible and ethical decision-making while also protecting against improper use of Artificial Intelligence tools (Giraud et al., 2023; Shahzad, 2024). This role is extended beyond leadership and impacts organizational culture through increased diversity and ethical awareness in the use of AI (J. Lee & Song, 2024). The concern over the risk of discrimination through biased algorithms and accountability issues related to fairness and trust in AI-based decisions have attracted great attention in research and policy circles and highlight the strong importance of governance principles and rules (Fetais et al., 2022; Murire, 2024; Watson et al., 2021). Ethical governance also needs to take care of socio-political dynamics and their effects upon AI development and utilization to ensure the usage of AI solutions aligning with the greater needs and values of the people (Caro, 2008). Organizational policies must also be implemented to ensure ethical transparency and fairness and responsible utilization of AI to avoid biases and promote accountability while countering the potential misinterpretations about privacy and management of the data (Kulkarni et al., 2024; Lichtenthaler, 2022; Sobhanmanesh et al., 2023). Entrepreneurs and decision-makers will also need to ensure the goals and targets related to the use of AI are defined in ethics-based consideration and are aware of the limitations and potential threats connected to the use of AI-generated data (Shepherd & Majchrzak, 2022).

The disruptive technologies also require consideration of the workplace transformation they bring about. While digitalization will lead to job creation and elimination, feeding the fears of skill devaluation and the displacement of workers is also the concern to address first. Worker involvement in creating and implementing AI is thus imperative to ensure a mitigation of negative impacts and the development of a more people-centric AI transformation (Peifer & Terstegen, 2024; Qvist-Sørensen, 2020). The same concerns arise for human-focused applications of AI too, where ethical, sociological, and legal concerns need to direct the way forward in the development process, especially in sectors such as agriculture and conventional labor industry sectors (Petcu et al., 2024). Where the requirement primarily applies in industries such as agriculture is especially significant since responsible leadership is imperative to incorporate AI and IoT technologies in a sustainable and ethical way (Petcu et al., 2024). Another emerging concern is the effect of AI on intellectual property and content management. Generative models such as ChatGPT can generate biased content, plagiarized content, or copyright infringement since they are incapable of detecting the biases in the training dataset or internet sources they consider (Karakose et al., 2023). Such threats bring to the fore the need for safeguards in the content generated through AI and the establishment of more stringent policies to avert potential abuse and intellectual property violations (Shepherd & Majchrzak, 2022). In the end, AI needs to complement and honor human values and reinforce transparency, fairness as well as sustainability over the long-term focus (Ken et al., 2016). Formulation of ethics that directs the capabilities and potential of the same towards organizational and societal needs is imperative to promote responsible integration of the same.

5.1.3.2 Data Protection and Privacy

The integration of Artificial Intelligence in business and industrial environments necessitates strong legal framework awareness, regulatory adherence and cybersecurity practices. Organisations utilizing AI need to navigate the complex landscape of regulations and ethics standards to make sure the use of AI contributes to principles of transparency, fairness and accountability. One important part of legal and regulatory awareness is adherence to existing policy and governance standards, such as the Protection of Personal Information (POPI) Act and the use of ISO standards (Petcu et al., 2024).

Further specifically on this point, the POPI Act, operative since 2019, was implemented to direct protection and privacy in data. This Act lies on eight principles, including accountability, which requires that the responsible party ensures compliance with all conditions for lawful processing, and processing limitation, which mandates that personal data be handled lawfully and in a way that respects the privacy of the data subject. The purpose specification principle obligates the disclosure to the data subjects of the particular purposes behind the collection of the data, while the further processing limitation provides for the extension to subsequent uses in the same way the initial purposes are compatible. Information quality commits the controllers to maintaining the personal data current, accurate, and complete. Openness obligates transparency in the collection process, where data subjects need to be disclosed the use their information will serve, while security safeguards entice the installation and use of proper technical and organization measures to secure the integrity and confidentiality of the data. Finally, the principle of data subject participation grants individuals the right to access their personal information and to request corrections or deletions where applicable (Mbonye et al., 2024). At the same time, Adebola Folorunso *et al.* highlighted the importance of the ISO/IEC 27000 family of standards within the ISO Standards, to guarantee structured and effective information security practices (2024). Inside this family, ISO/IEC 27005 is discussed as a key component in managing information security risk, offering a methodology for identifying and evaluating threats in alignment with business goals. In parallel, ISO/IEC 27701 extends its scope to include privacy management capabilities, allowing organizations to implement a Privacy Information Management System (PIMS) that aligns with global data protection regulations like the GDPR. Additionally, ISO/IEC 27017 and 27018 address cloud-specific concerns, focusing on best practices for secure cloud service usage and the protection of personally identifiable information in cloud environments.

Closely linked to regulatory compliance is the domain of data protection, which is an essential pillar in the responsible management of AI-driven processes. As organizations accumulate vast amounts of data from digital transformation initiatives, it is crucial to establish mechanisms that guarantee data sovereignty, transparency, and user consent in data processing activities (Peifer & Terstegen, 2024). Employees and stakeholders should know their data is being handled, and business organizations should comply with privacy legislation to foster trust and steer clear of regulatory punishment (Baumgartner et al., 2024). In this regard, the role of Human Resource Management departments is important in safeguarding employee data, especially in the case of automation and workforce management through the use of AI, where concerns over job security and fair labor practices may occur (Fenwick et al., 2024). Beyond privacy legislation and compliance, cybersecurity is also a key factor to consider. Systems powered by AI need protection from cybersecurity attacks as improper design leaves them open to malicious use, including spyware, risky software, worms, and viruses (Nene, 2024). Businesses should use strong network and infrastructure protection measures through secure system design, threat and risk management, and risk mitigation measures (Almeida, 2025). At a broader level, governance mechanisms through AI should also address issues with ethical risk and organizational responsibility. Leaders are tasked with monitoring sensitive information being processed through the use of AI to ensure the flow of data is in line with the law, ethics, and trust-based concerns (Kolbjørnsrud et al., 2017). By creating well-defined legal and regulatory rules in terms of protecting and preserving data and privacy, business organizations can comply with the law, manage risks to their business, and gain trust in innovations created through the use of AI. The use of open and secure policies is key to the sustenance of business integrity and trust in the use of AI in applications.

5.1.4 Leadership and Change Management

Successful AI adoption depends on the ability to lead and manage change through strong leaders who can guide teams through transformation processes. Key to this competency is the ability to train and manage multidisciplinary teams and involve end users actively in the transitions related to AI to bring about easy integration and acceptance (Baumgartner et al., 2024). Good AI leadership is commonly defined as being that of an "AI evangelist", a role able to energize employees and establish a comprehensive perspective of AI implementation within the organization (Jorzik et al., 2024). Strong communication and management of the stakeholders are the key elements in this context wherein leaders need to foster the ability to handle varying environments with flexibility, resilience, and agility (Rehan et al., 2024). In addition, sustainable management and diversity management are emerging as top priorities. Employing a style of leadership centered upon empathy, open communication, and adaptive communication can profoundly enhance the adoption of AI and organizational alignment (Aldighrir, 2024). Closing the gap between technological innovation and practical usage is also a key challenge and emphasizes the need for universities and the business world to work hand in hand to equip future leaders with the skills to manage the transformations induced by AI (C. L. Lee et al., 2024). According to these findings, six groups of competencies were identified under the Leadership and Change Management family: "Engagement Leadership" refers to an innovative mindset and openness to technology that today's leaders require to engage and motivate employess in AI adoption; "Leading Multidisciplinary teams" mainly discusses the ability to assemble, coordinate, and lead multidisciplinary teams in AI projects, managing interactions between people and algorithms while fostering collaboration, emotional intelligence, and the effective integration of diverse skills. Moreover, "AI Resistance Management" focuses on managers' ability to defeat the cultural obstacles that prevent the adoption and integration of AI within companies and to provide emotional and operational support to individuals in managing concerns and resistance during the digital transition; "Designing Human-AI Collaboration" is about the ability to define roles and responsibilities, design effective workflows, and develop AI solutions that prioritize human-centric approaches, fostering seamless collaboration between people and algorithms. Lastly, "Effective technical Communication" delves into the capacity of managers to explain and spread AI concepts to non-technical staff, while "Continuous learning and training" refers to the continuous learning mindest that managers should require to stay up to date with the evolving scenarios, and their ability to upskill those who are not familiar with AI tools and processes.

5.1.4.1 Engagement Leadership

From a theoretical standpoint, engaging leadership is defined as a leadership style that facilitates, strengthens, connects, and inspires employees to enhance their engagement at work. According to Schaufeli, engaging leadership satisfies employees' basic psychological needs for autonomy, competence, relatedness, and meaning, thereby fostering intrinsic motivation (2021). The research presents empirical evidence supportive of the fact that need satisfaction mediates the link between engaging leadership and work engagement via other routes through job characteristics and personal resources as well. Engaging leadership is underscored as requiring leaders to empower employees, offer chances for development, foster teamwork and promote purpose as key to enhanced engagement and reduced rates of burnout and better job performance.

A core aspect of engagement leadership is the disposition towards and appreciation of technology, as leaders are able to keep pace with innovation and actively seek out new opportunities (Baumgartner et al., 2024). This Artificial Intelligence Mindset demands curiosity and willingness to experiment and learn through experience, since leaders are constantly seeking evidence-based insights and shifting their strategic intervention accordingly based on advances in AI (Jorzik et al., 2024). Being flexible and open-minded can facilitate acceptance of AI, and this is the reason why open-mindedness is considered as a non-technical managerial skill that optimize the use of AI (Giraud et al., 2023). The organizational strategy towards the use of AI, termed as AI orientation, once again necessitates leaders to map corporate objective with the capabilities of AI so that the combination of technology is technically and strategically feasible and advantageous (Pinski et al., 2024). Collaborative ability and flexibility are just as essential since transformations through AI require interfunction collaboration and necessitate leaders to work across different functions, fill across-function gaps in understanding and promote collective intelligence (Shahzad, 2024a).

Beyond adaptability, leaders need to foster innovation and creativity to push forward with AI-driven solutions to drive business performance. Green creativity and green task motivation, for instance, are examples of ways leaders can make sustainability-focused innovation part of the mix when adopting AI, creating a culture of green-conscious thinking when making business decisions (Ogbeibu et al., 2021). More broadly, soft skills such as empathy, honesty, and flexibility are important to ensure the implementation of AI is done in a way that is ethical and inclusive and enhances trust between employees and stakeholders to boost engagement and productivity (S. Chowdhury et al., 2023; Nurshazana Zainuddin et al., 2023). Cognitive abilities are also essential in this context: recognizing patterns, attention to detail, and resilience enable the ability to interpret insights produced by AI, finish complex tasks and maintain focus on long-term innovation strategy (Walkowiak, 2021). The ability to make fact-driven decisions, "manage by fact" in other words, is also increasingly important since AI supplies leaders with an unprecedented amount of data to analyze (Kolbjørnsrud et al., 2017). Organizational culture is important when it comes to developing attitudinal competencies since it acts as the driving force behind innovation and creativity (Alnaser et al., 2024), adaptability and strategic agility (Fenwick et al., 2024). Leaders need to be in the position to respond rapidly to unexpected events, competitive threats and emerging AI-driven business opportunities and use agility and fast decision-making to maintain a competitive edge (Watson et al., 2021). By creating an orientation towards being adaptable and being able to innovate, leaders can effectively manage the complexities of transforming through AI and position their organizations to thrive in the long term.

5.1.4.2 Leading Multidisciplinary Teams

Effective organization-wide integration of Artificial Intelligence necessitates new styles of project management since the adoption of AI creates special challenges in team coordination, resource management, and strategic fit. AI project leaders need to have a combination of technical skill, leadership skill, and emotional intelligence in order to effectively manage cross-functional teams and ensure the efficient and goal-congruent delivery of AI projects (Baumgartner et al., 2024). Hence, emotional intelligence is conceptually defined as the ability to recognize, apply, understand, and manage emotions in the self and other people. Specifically, the first branch, perception of emotions, means being able to accurately recognize emotions in facial expressions, voices, and other behaviors. This is the most elementary ability, the scaffolding upon which more complex emotional processing rests. The second branch, using emotions, means using emotions to assist cognitive activities such as problem-solving and creativity. Specifically, a slightly sad mood can increase analytical thinking while a good mood promotes creativity. The third branch, understanding emotions, includes the ability to translate emotional language, to recognize subtle differences in emotions and to forecast emotional changes over time. The fourth branch, managing emotions, means regulating the emotional response in the self and other people and is a key skill to exercise when being a good leader, resolving conflict and when communicating effectively (Salovey & Grewal, 2005).

In this way, a key responsibility for AI project leaders is the capability to manage and lead AI project teams and ensure that the projects are on course and aligned with organizational goals. This entails being responsible for the entire cycle of the project from conceptualization to implementation while maintaining a methodological approach to the management of the project (Baumgartner et al., 2024; Peifer & Terstegen, 2024). Such projects also need leaders to manage interdisciplinarity through facilitating the exchange and interaction between technical and business teams to promote creative resolutions involving AI-driven solutions (Richthofen et al., 2022; Surbakti et al., 2024). AI project managers also need to respond to drastic changes in cost, schedule, and risk management since the integration of AI typically triggers unforeseeable complexities necessitating adaptive styles of management. Leaders should emphasize upskilling in areas where they cannot excel using AI, such as team development and management, stakeholders' management, and strategic decision-making to enable the use of tools while human skills are still the key to resolving complex issues; this emphasizes the need to invest in training in AI programs based on areas such as bridging the gaps in the management of AI projects and gender-based disparities in AI skills between project managers (Fridgeirsson et al., 2021). Balanced-styled management with a combination of technical ability and emotional intelligence is important to manage teams and retain the workforce in the context of AI projects (Sposato, 2024). The ability to form and manage diverse and cross-functional teams and ensure they foster the workplace and work environment is important and requires the capability possessed by AI leaders to do so (Aldighrir, 2024; Bag & Rahman, 2024). Sustaining leadership behaviors based on long-term thinking, employee appreciation, and empowering people are important in the management of AI transitions; further, diversity management skills are key to developing the AI-friendly work atmosphere where open communication and diverse views are encouraged and contribute to enriching the management and development of AI projects (Aldighrir, 2024).

The agility of AI project leadership is another success-defining factor and entails responding to changing demands and utilizing authentic styles of leadership that suit complex AI environments (Levitt et al., 2024). They need to be able to work in VUCA (Volatility, Uncertainty, Complexity, Ambiguity) and BANI (Brittle, Anxious, Nonlinear, Incomprehensible) environments and to navigate through resilience and flexibility while directing the AI-driven changes (Rehan et al., 2024). While common values such as communication, teamwork, and transparency can be located in both paradigms, their connotations are far different. In VUCA, communication is about clarity, while in BANI it is about emotional intelligence; in VUCA, teamwork is structured, in BANI, it must be flexible and resilient. This comparison emphasizes the need to adopt a new way of thinking for project leaders through emotional literacy, ethical reflexivity, and system-wide resilience moving beyond the structured thinking in VUCA to the deeply human-centered flexibility in BANI environments (Bushuyev et al., 2023). Effective communication and relation-building are core elements of AI project leadership since the adoption of AI necessitates extremely collaborative styles of leadership. Effective means should be implemented to share the knowledge and build the diverse skills and competencies as well as the expertise related to AI through the projects teams (S. Chowdhury et al., 2023). Project managers also need to actively manage the expectations of the stakeholders and manage the resistance to the change driven by AI and make the goals of the project suitable and matching to the capability of the workforce available (Rehan et al., 2024).

Finally, the style of leadership used in AI projects largely influences team performance and dynamics. Avoiding laissez-faire management is very important since it causes role confusion and workload disparities and can later restrict workers' ability to exercise empathetic creativity and problem-solving (Luo et al., 2025). Instead, leaders in AI projects should adopt a structured yet adaptive style of leadership where they ensure transparent decision-making processes, prioritize the well-being of employees, and use AI to boost, not topple, organizational processes (Nurshazana Zainuddin et al., 2023). To this end, the styles of leadership need to change towards such a direction where they promote agile thinking within the organization. This entails being able to effectively communicate the aims and desires of the company, internal training and facilitation, and furthering continuous learning and sharing of knowledge with employees, the working teams, and leaders alike. Such leaders value collaboration over hierarchy, promote a common vision, and empower and coach their working teams (Tominc et al., 2023). Generally, through a balancing act in leadership, the manager of AI projects can coordinate technological change while maintaining team integration and flexibility and use the AI-driven change as a strategic edge.

5.1.4.3 AI Resistance Management

Effective adoption of Artificial Intelligence in the organization needs more than the technical deployment alone: it demands a deeper change in the way leaders lead, organizational behavior, and the adaptation of the workforce. Adoption of AI is not about incorporating new technologies alone but also about reframing the corporate mind-set, working patterns, and the essence of work itself. To make this shift work, the manager needs to show willingness to alter and a proactive stance towards the transformation through AI and ensure both the workforce and organizational processes are synchronied with the pace of technological changes (Jorzik et al., 2024). Effective AI leadership incorporates the skill to serve as an "AI evangelist", espousing the comprehensive agenda towards the integration of AI and creating organizational coherence and concurrence while engaging stakeholders and inspiring the workforce. The leaders need to convey the strategic positioning of the role of the firm through AI and also foster enthusiasm and trust so the employees equate the AI as a facilitator and not a disruptor (Jorzik et al., 2024). This calls for a blend of skillful communication, emotional quotient, and the capacity to adopt new ways since the transformations through AI are bound to evoke resistance and demotivation from the staff. The business leaders should recognize the same and offer emotional and professional support to the team, reward participation, and actively recognize the contributions to reassure the morale through the times of transition period (Lichtenthaler, 2022).

5.1.4.4 Designing Human-AI Collaboration

Change management in AI adoption transcends the philosophy of leadership to encompass strategic redesigning of work processes, job functions, and models of human and machine collaboration. Bureaucratic hierarchies and workflows need to be rethought, and leaders need to rethink organizational architectures proactively to merge human and AI capabilities seamlessly (Peifer & Terstegen, 2024). Hence, the mandate to manage change at the strategic and operational levels alike is critical and necessitates the acquisition of competencies in organizational design, digital transformation, and business model innovation powered by AI (Hearn et al., 2023). Managers need to ensure successful and sustainable adoption of AI through cultural transformation and bridging the skill divide through upskilling and reskilling processes. Fostering digital fluency and training employees in using AI-powered tools and adjusting to dynamic business processes is critical to reduce disruption and accelerate eventual adoption of AI over the long term (Broo & Schooling, 2023). Further empowering employees through delegation and mechanisms of passing the baton also enhances internal capability and enables firms to extract value out of AI more effectively (Shahzad, 2024). In this direction, the potential to use AI to manage routine work can free up workers to focus on high-value interpersonal interactions and activities (Luo et al., 2025). A transparent and well-defined change management strategy is also essential in order to align the workforce with the envisioned AI initiatives. Senior leaders need to define structured communication matrices and outline carefully the AI adoption roadmap, the changes the job will witness, and the impact the job will experience as a result. Defining responsibilities and clarity when working in tandem with AI are critical to minimize confusion and boost performance levels (Luo et al., 2025). Without this clarity, it will lead to the risk of resistance and demotivation further increasing the organization's resistance to adoption and lowering the usage rates achieved through AI; further, HR managers have a critical responsibility to gauge digital preparedness through readiness assessment and ensure technological infrastructures and employee competencies align with digital integration goals (S. Chowdhury et al., 2023). AI-driven change management is also a continuous process and necessitates agility and responsiveness. Senior leaders need to operate as change agents and foster forward-looking cultures great enough to enable employees to continuously upskill, accommodate new technologies emerging and adopt AI as a change agent and enable innovation through it (Watson et al., 2021).

Beyond internal transformation, leaders also need to be sensitive to the wider socio-political and business contexts shaping the adoption of AI. Having the capability to drive large-scale process changes, re-engineer business processes, and harmonize AI strategy with market developments is essential when digitalization is transforming entire industries (Caro, 2008). Work in agile environments requires skills in designing and maintaining flexible organization forms accommodating hybrid working, fast adaptation, and strong employee engagement. Managers need to have the capability to foster a work culture able to embrace the spirit of experimentation, iterative learning, and responsiveness to outward changes (Tominc et al., 2023). Moreover, as more and more business processes rely increasingly upon AI, corporate culture needs to change to accommodate data-driven and model-based strategy and reinforce the use of AI as a strategic business facilitator (Gaffley & Pelser, 2021). In the end, successful management of change through AI is more than technological preparedness: it is creating a culture of innovation and employee empowerment and is supportive of AI being used to enrich business processes rather than disrupt them.

5.1.4.5 Effective Technical Communication

With AI transforming business processes and workplace dynamics, leaders need to ensure employees comprehend, accept, and are willing to collaborate with AI technologies. This calls for open, honest, and inclusive communication, complemented with targeted training programs empowering employees with the skills to excel in an AI-driven work ecosystem. Communication is a key facilitator of the adoption of AI, making workers fully aware and engaged and capable of operating tools powered by AI. According to Mauro *et al.*, communication emerged as one of the key skills demanded of workers employed as Business Analyst, owing to their position between the technological and business sides where they are expected to translate complex technological abstractions to actionable insights to the nontechnical stakeholders and vice versa

(2018). Along this line, the ability in the executives needs to come forward to explicate AI applications in straightforward terms to the staff and alleviate workers' concerns and engage in honest and structured comments towards the adoption of AI (Baumgartner et al., 2024). Within organizational communication discipline, Chowdhury *et al.* envision the role of knowledge management in developing and sharing and using AI-associated knowledge to build collective wisdom and facilitating innovation (2023). Open and honest communication builds trust in AI-driven transformation, particularly in environments where the workers can envision job losses or workflow disturbances (Richthofen et al., 2022). An adequate communication strategy in using AI necessitates departmental networks and collaborations to ensure AI initiatives are aligned with broader business goals in the organization (Shahzad, 2024). Besides this, leaders need to effectively communicate confidently AI-driven facts and consequences so that their value can get perceived while the limitations are acknowledged too (Baumgartner et al., 2024). Communicating the elaborate vision of Industry 4.0 where workers are at the center and continuing to drive technological advances is the key to discouraging resistance and enabling seamless adoption of AI (Hearn et al., 2023). Beyond internal communication, AI leadership also requires strategic networking and stakeholder engagement. Leaders must cultivate strong relationships with influential figures within the organization, using effective communication techniques to influence decision-making and drive AI initiatives forward (Bag & Rahman, 2024). Meanwhile, cross-disciplinary cooperation is also important since adept integration of AI requires smooth coordination across technical departments, business departments, and external partners (Watson et al., 2021). Nevertheless, the discussion of eroded communication skills in graduates necessitates enhanced cooperation between universities and industries to reinforce such skills in future professionals (C. L. Lee et al., 2024).

5.1.4.6 Continuous Learning and Training

Both training and ongoing learning are equally important in the adoption of AI and mean that workers are not just aware of the use of AI but also possess the practical acumen to work alongside it effectively. Ongoing upskill and reskill are key to staying effective in the role while working in environments driven by AI. Working professionals need to consciously shed outdated methods, relearn new strategies, and learn new skills to remain current in the fast-changing digital world (Anomah et al., 2024; Nene, 2024).

This ongoing method of learning is advocated in the existing body of work in the field where it has been shown through evidence that the growth mindset, which refers to the thinking that intelligence and talents are not fixed but are capable of being developed through work and advice, significantly influences motivation and performance. Praising work is not enough; rather, workers need to be given the right tools, strategy to learn, and feedback to make significant gains happen. Companies successfully practicing the growth mindset build where the workers are empowered, encouraged, and driven to take challenges, cooperate, and innovate. This is contrary to where companies practicing the fixed mindset, where intelligence and ability are viewed as innate and static, witness increased levels of competition and fear of failure and unethical behavior since the workers are more keen on acquiring status rather than developing (Dweck, 2015, 2016). The more recent work of the author also warns against false growth mindsets, where people or organizations proclaim the use of growth but do not successfully apply it in ways meaningful to achieve ends. This entails the idea that a pure growth mindset is available when in fact everyone possesses a combination of both fixed and growth-type mindsets and these change over experience and growth. The other fallacy is the idea that the teaching and encouragement of the growth mindset will achieve success when in fact it takes intentional practice, organized feedback, and continuous reflection to maintain it.

Following the growth mindset definition, organizations should prioritize training in AI skills to promote human-AI coaption and enable employees to use AI to maximize productivity instead of seeing it as a disruptive force (Aulia & Lin, 2024). Training in AI should extend beyond skill-building in technics to promote digital fluency and flexibility to cope with new technologies (Broo & Schooling, 2023). Structured training should include the processes of equipping employees to proactively work with AI technologies in their work processes and routines. Employees should get a perception of the impact of AI applications on their work processes and boost their self-efficacy and self-confidence in using AI tools as well as comprehend their general implications on the work processess (Peifer & Terstegen, 2024). This should include hands-on training in using AI in making business and organizational decisions and in data analysis and automating workflow processes to make workers feel empowered and capable in working environments enhanced through AI (Y. Chen et al., 2024). Managers should also invest in the development of leaders through programs where team leaders are empowered with the ability to guide and manage human-AI teams (Luo et al., 2025). This should involve establishing well-articulated AI-driven goals and goals-framing intended to promote equitable delegation and allocation of tasks between and across human and AI systems and employees should be provided with consistent support. Additional consideration in training should focus on the sector or industry-specific applications and their corresponding AI training instances (e.g., training in the use of AI in agriculture will promote high efficiency and value production) (Petcu et al., 2024). An emerging theme in training in AI is cognitive skill-building related to AI use, such as interlingual respeaking (IRSP), improving working memory and ability to switch tasks, core skills needed to streamline human-AI interaction in real-time applications (Wallinheimo et al., 2023). Beyond technology skills training, creating a continuous training and development work climate builds and sustains employees' agility and responsiveness and facilitates the employee capability to cope and work with new and emerging technologies (Sposato, 2024). Due to the reasons mentioned above, training is key to complementing the seamless integration of AI working methodologies and processes and enhancing its efficacy and value within the organization.

5.1.5 Comparative Overview

Prior to the numerical meta-analysis, the comparative analysis between the recommended taxonomy and the considered pre-AI competency models is shown in Table 5.1, in order to comprehend the evolution of managerial needs to respond to the new issues presented by the extensive use of AI.

Model	Key competencies identified
(Hawi et al., 2015)	Leadership, problem solving, decision making, customer focus, strategic planning.
(Asumeng, 2014)	• Intrapersonal skills (i.e., self control, self-awareness, creativity, emotional stability, willingness to take a stand, career ambition, hardworking, achievement–orientation, perseverance) • Interpersonal skills (i.e., team building, networking, sensitivity to employees'concerns, understanding other ideas and interests) • Leadership (i.e., providing direction, support, motivating others, inspiring, resolving conflicts, managing diversity) • Technical/business skills (i.e., business acumen, analytic thinking, decision-making, managing human resources) • Creer skills (i.e., work commitment, work efficacy, perseverance) • Mentoring skills (i.e., coaching, empathy, desire to help others).
(Khoshouei et al., 2013)	Value, analysis, decision-making, knowledge, adaptation, performance, leadership, communication.
(Freitas & Odelius, 2018)	• Results orientation (clients, processes, costs, market, products, projects, etc.) • People and team skills (interpersonal relationship, cooperation, etc.) • Leadership, coordination and motivation • Ability with change (innovation and situational adaptability skills) • Communication • Planning • Attitudes and values (ethics, initiative, commitment, etc.) • Knowledge management • Knowledge and technical skills • Organisation and control (resource allocation, mobilisation, and monitoring).
(Bolzan De Rezende & Blackwell, 2019)	• Influencing skills (leadership, conflict management, influence/persuasion, motivating others, negotiation and charisma) • Communication skills (verbal, written and listening communication; open, clear, direct and concise communication) • Team working skills (collaboration, support, developing others, team building, delegation, escalation and trustworthiness)

	• Emotional skills (stress management, interpersonal skills, interpersonal sensitivity, self-awareness, self-motivation and empathy) • Contextual skills (adaptability, contextual awareness, strategic alignement, politic awareness and networking • Management skills (monitor and control, planning, directiveness, organization and coordination, prioritization) • Cognitive skills (problem solving, creativity and innovativeness, decision-making, critical analysis, strategic perspective and system thinking, vision and imagination, intuitiveness and learning) • Professionalism (ethics and accountability) • Knowledge and experience (technical expertise, experience, business expertise and administrative expertise) • Project management knowledge (manage human resources, time, stakeholders, risk, quality, costs, procurement, scope, resource, requirements and integration. Methods, customer management, healthy and safety management, knowledge management, change management and supply chain management) • Personal skills and attributes (achievement orientation, commitment, initiative, confidence, openness, detailist, courage, sense of humor, multi task and discipline).
(Konigova et al., 2012)	Experience in leadership, Communication skills, Time flexibility, Presentable behaviour and presentation skills, Reliability and responsibility, Organizational skills, Independence, Self-confidence, Dynamic person with a proactive approach, Negotiation skills, Analytical skills, Hardworking, Goal-oriented, Stress resistance, Project management skills, Loyalty, Creativity, Accuracy, Systems thinking, Decision-making skills, Willingness to learn, Sense of purpose, Process-oriented.
Proposed taxonomy	• Strategic and Decision-Making competencies: AI strategic thinking, AI risk management, economic and business evaluation, data-driven decision making • Technical and Analytical skills: AI literacy, data governance, computational thinking, systems architecture • Ethical and Legal regulatory knwoledge: algorethics, data protection and privacy • Leadership and Change management: engagement leadership, leading multidisciplinary teams, AI resistance management, designing human-AI collaboration, effective technical communication, continuous learning and training.

Table 5.1: Overview of competency areas in existing frameworks and in the present AI-focused taxonomy

5.2 Numerical Meta-Analysis

In parallel to the structured content analysis, a numerical meta-analysis was performed to quantitatively determine the attributes of the considered articles. This method allowed the detection of repeating patterns across the studies, e.g., methodological choices, areas of application, and general concordance with the research goals. This numeric evaluation complements the qualitative taxonomy in providing wider insights into the concordance, frequency, and pertinence of the considered contributions. The combination of this technique provides descriptive and inferential insights and facilitates the more solid interpretation of the research domain.

5.2.1 Application Areas and Sectors

As mentioned in Section 4.2, the output of the application area request reflects, where applicable, the International Standard Industrial Classification of All Economic Activities (ISIC) code of each research, so that it has been possible to aggregate the output to realize this numerical analysis. Before presenting the application areas meta-analysis results, it is important to clarify the meaning of the label "NOT - DEFINED", which appears in some records. This label does not indicate a failure of the LLM to process or classify the content; as explained in Section 4.2.1, it is instead a deliberate prompting mechanism designed to help the LLM avoid forcing a classification when the content does not provide sufficient or appropriate information to do so. Because of this fact, it reflects the character of a number of academic papers, e.g., qualitative research work, theoretical discussion, or conceptual papers, where the work does not mention directly a particular sector of economic activity. Therefore, the lack of sectoral classification in those cases does not represent a flaw in the method but rather a true rendering of the initial content in the articles. For the purposes of improving readability and visual clarity in the aggregated results, these records were subsequently relabeled as "GENERAL" in the graphical representations.

The relative distribution of application areas is illustrated by figure 5.2, which shows a significant concentration in the education sector (23.7%) and in studies with general application (24.7%). Both areas alone account collectively for almost half of the papers reviewed and can reflect either a high emphasis upon educational environments or incomplete sectoral classification in many papers. The professional, scientific and technical activities sector follows at 13.4%, while other sectors such as manufacturing (8.2%), construction, finance, and ICT are less represented (each at or below 4.1%). Sectors such as transportation, healthcare, real estate, and arts are marginally represented, each accounting for only about 1% of the total studies.

More specifically, the ranking of contributions by application area is presented in figure 5.3, with the category “GENERAL” including the highest number of studies (n = 24), followed by “P - Education” (n = 23) and “M - Professional, scientific and technical activities” (n = 13). However, when observing relative frequencies, these three domains alone account for over 60% of the total sample, so that the other sectors or application areas are mostly marginal within the analyzed database. Lastly, the total number of observations (n = 97) exceeds the number of unique studies analyzed (n = 92) because some articles were associated with multiple application areas and thus counted more than once. This approach reflects the interdisciplinary nature of certain studies and provides a more accurate representation of the distribution across sectors.

Application Area	Relative Frequencies
GENERAL	24.7%
P - Education	23.7%
M - Professional, scientific and technical activities	13.4%
C - Manufacturing	8.2%
F - Construction	4.1%
J - Information and communication	4.1%
K - Financial and insurance activities	4.1%
N - Administrative and support service activities	4.1%
O - Public administration and defence; compulsory social security	4.1%
A - Agriculture, forestry and fishing	2.1%
Q - Human health and social work activities	2.1%
H - Transportation and storage	1.0%
G - Wholesale and retail trade; repair and selling of motor vehicles and motorcycles	1.0%
I - Accommodation and food service activities	1.0%
L - Real estate activities	1.0%
R - Arts, entertainment and recreation	1.0%
Total	**100.0%**

Figure 5.2: Table showing relative frequencies of the application areas of the contributions analyzed.

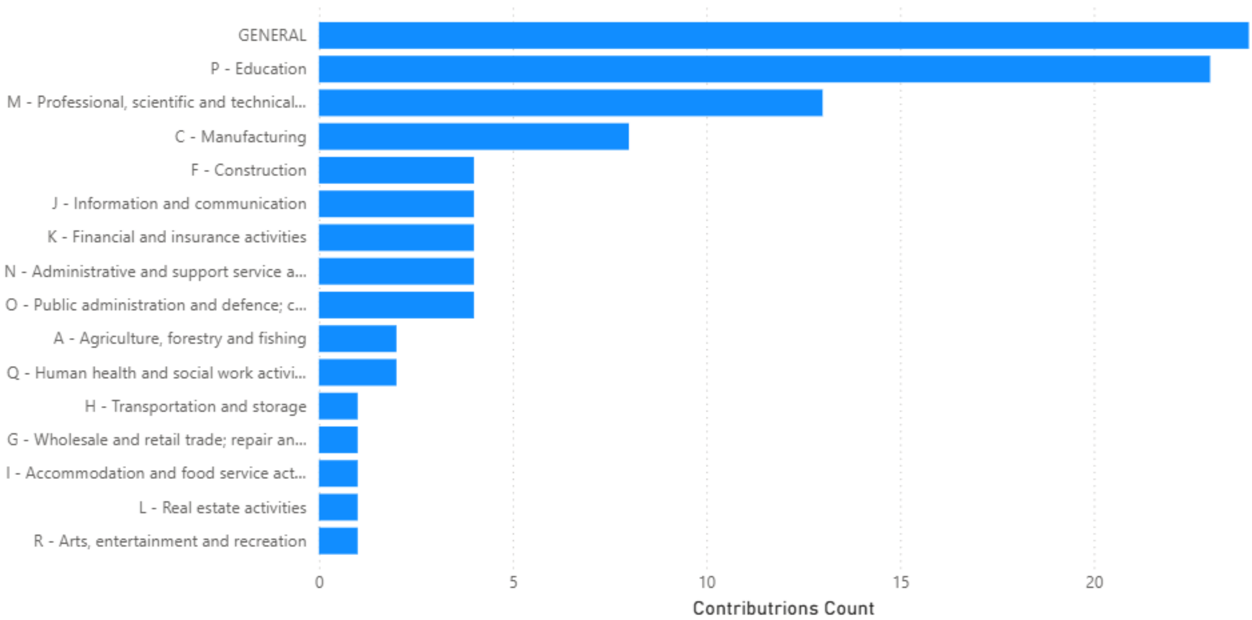

Figure 5.3: Horizontal bar chart showing the ranking of contributions by application area.

To refine the methodological framework of the quantitative meta-analysis, a classification of economic activities into three broad sectors was introduced: primary, secondary, and tertiary. This sectoral distinction facilitates a more structured interpretation of the empirical findings by enabling comparisons across different economic domains. The categorization follows the International Standard Industrial Classification of All Economic Activities (ISIC), Revision 4, established by the United Nations. The allocation of ISIC sections to the three sectors is illustrated by table 5.2.

Sector	**ISIC Rev.4 Sections**	**Description**
Primary	A, B	Agriculture, forestry and fishing (A); Mining and quarrying (B).
Secondary	C	Manufacturing (C).
Tertiary	From D to U	Electricity, gas, steam and air conditioning supply (D); Water supply; sewerage, waste management and remediation activities (E); Construction (F); Wholesale and retail trade; repair of motor vehicles and motorcycles (G); Transportation and storage (H); Accommodation and food service activities (I); Information and communication (J); Financial and insurance activities (K); Real estate activities (L); Professional, scientific and technical activities (M); Administrative and support service activities (N); Public administration and defence; compulsory social security (O); Education (P); Human health and social work activities (Q); Arts, entertainment and recreation (R); Other service activities (S); Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use (T); Activities of extraterritorial organizations and bodies (U).

Table 5.2: Sectoral classification of economic activities according to ISIC Rev.4.

Based on this classification, the records were manually aggregated into three macro-categories: Primary, Secondary and Tertiary sectors. In line with the methodological approach described above, records classified as "GENERAL" were excluded from the following aggregation. This choice was made to ensure that the comparison among the Primary, Secondary, and Tertiary sectors reflects only those studies that explicitly refer to a defined economic activity. As a result, the following analysis is based on the remaining 73 records, which could be reliably assigned to one of the three macro-sectors.

The results are presented in figures 5.4 and 5.5 and are distributed as follows: Tertiary sector (n= 63, 86.3%), Secondary sector (n= 8, 11.0%), and Primary sector (n= 2, 2.7%). These figures clearly indicate that the majority of contributions are situated within the service domain, while studies related to manufacturing and extractive industries are significantly underrepresented. This corroborates with Kataria & Devershi Mehta, who found that AI adoption is notably higher in tertiary sectors such as finance, healthcare, e-commerce, telecommunications and IT & Software Services, where AI is used to boost effectiveness, productivity, and customer experience; in contrast, industries like manufacturing have a lower AI adoption rate (2025).

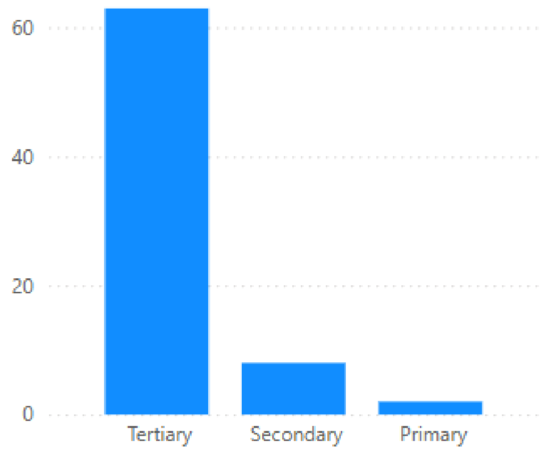

Figure 5.4: Vertical bar chart showing the ranking of contributions by sector.

Sector	Relative Frequencies	Count
Tertiary	86.3%	63
Secondary	11.0%	8
Primary	2.7%	2
Total	**100.0%**	**73**

Figure 5.5: Table showing absolute and relative frequencies of sectors of the analyzed articles.

5.2.2 Methodologies

As mentioned in section 4.2, the request for "Methodology (keyword)" was based on a taxonomy that has been provided to the LLM, which is comprehensive of different types of research, including qualitative, quantitative, mixed and experimental.

As shown in figure 5.6, the analyzed database shows a prevalence of qualitative approaches, which are used in 46 out of 92 articles representing exactly 50% of the total sample. Most common methods within this macro-category are content analysis (n=26), case study (n=11), and interviews (n=9), validating the exploratory character of much such research in the field. Quantitative methodologies are utilized in 33 articles equaling 35.9% of the sample. Among them are such types as survey-based research (n=14) and statistical analysis (n=11), then further ways include cross-sectional design (n=6), and much less frequently experiments and longitudinal designs (both with n=1). These results illustrate the high incidence of organized and evidence-based methodologies aimed at quantitatively measuring and testing relations.

Mixed methods approaches appear in 5 studies (5.5%), and both sequential explanatory (n=3) and concurrent triangulation (n=2) designs are represented. This reflects a minimal but existing attempt to integrate quantitative rigor and qualitative depth. Moreover, experimental designs, including field experiments (n=2) and quasi-experimental research (n=1), were used in 3 studies (3.3%), and reflect a borderline concern with causality and controlled interventions. Lastly, only 5 studies (5.4%) could not be classified within the proposed methodological taxonomy.

Methodology (Keyword)	Relative Frequencies	Count
QUALITATIVE - CONTENT ANALYSIS	28.3%	26
QUANTITATIVE - SURVEYS	15.2%	14
QUALITATIVE - CASE STUDIES	12.0%	11
QUANTITATIVE - STATISTICAL ANALYSIS	12.0%	11
QUALITATIVE - INTERVIEWS	9.8%	9
QUANTITATIVE - CROSS-SECTIONAL STUDIES	6.5%	6
NOT - DEFINED	5.4%	5
MIXED - SEQUENTIAL EXPLANATORY DESIGN	3.3%	3
EXPERIMENTAL - FIELD EXPERIMENT	2.2%	2
MIXED - CONCURRENT TRIANGULATION DESIGN	2.2%	2
EXPERIMENTAL - QUASI-EXPERIMENTAL RESEARCH	1.1%	1
QUANTITATIVE - EXPERIMENTS	1.1%	1
QUANTITATIVE - LONGITUDINAL STUDIES	1.1%	1
Total	**100.0%**	**92**

Figure 5.6: Table showing absolute and relative frequencies of methodologies of the contributions

The initial five studies labeled as "NOT – DEFINED" underwent the second round of human evaluation, whereby their lack of empirical research design appeared to stem from their being conceptual or theoretical in nature. There was no data collection, sampling strategy, or analytical protocol representative of the typical qualitative, quantitative, mixed, or experimental case in those studies. To rectify this matter and achieve methodological completeness, the initial taxonomy was adjusted to incorporate the two new categories labeled as "CONCEPTUAL" and "THEORETICAL", intended to accommodate non-empirical work that nevertheless provides insights via model development, critical debate, or theoretical integration. Upon this adjustment, the formerfive article instances labeled as "NOT – DEFINED" underwent the process for the second time using the LLM and KNIME Analytics and Langflow according to the process outlined in Section 4.2.2. As illustrated by figure 5.7, at this time the LLM was able to classify them under one of the two newly introduced categories, resulting in a complete categorization of the methodologies, without any unclassified study. All other results remained unchanged, with the exception of the "NOT – DEFINED" (n=5) category, which was split into "THEORETICAL" (n = 3; 3.3%) and "CONCEPTUAL" (n = 2; 2.2%).

Methodology (Keyword)	Relative Frequencies	Count
QUALITATIVE - CONTENT ANALYSIS	28.3%	26
QUANTITATIVE - SURVEYS	15.2%	14
QUALITATIVE - CASE STUDIES	12.0%	11
QUANTITATIVE - STATISTICAL ANALYSIS	12.0%	11
QUALITATIVE - INTERVIEWS	9.8%	9
QUANTITATIVE - CROSS-SECTIONAL STUDIES	6.5%	6
MIXED - SEQUENTIAL EXPLANATORY DESIGN	3.3%	3
THEORETICAL	3.3%	3
CONCEPTUAL	2.2%	2
EXPERIMENTAL - FIELD EXPERIMENT	2.2%	2
MIXED - CONCURRENT TRIANGULATION DESIGN	2.2%	2
EXPERIMENTAL - QUASI-EXPERIMENTAL RESEARCH	1.1%	1
QUANTITATIVE - EXPERIMENTS	1.1%	1
QUANTITATIVE - LONGITUDINAL STUDIES	1.1%	1
Total	**100.0%**	**92**

Figure 5.7: Table showing absolute and relative frequencies of methodologies of the contributions after the prompted taxonomy was updated to include "CONCEPTUAL" and "THEORETICAL".

5.2.3 Fit Scores

The fit score, as mentioned in section 4.2, is a syntetic score between 1 and 5 assigned to each article that reflects the extent to which it fits with the objective of our systematic review.

As shown in figures 5.8 and 5.9, its distribution across the 92 studies shows that the majority of contributions demonstrate a moderate to strong alignment with the thematic focus of the systematic review. In particular, 42.4% of the studies achieved a score of 4 reflecting a high level of thematic relevance while 17.4% scored the highest available score of 5 and thereby suggesting a perfect fit. In contrast, 30.4% of the studies scored 3 reflecting the degree of a moderate fit and just 9.8% scored 2 reflecting the weak degree of focus related to the central research theme. Notably, no study received the lowest score of 1, confirming that all selected contributions had at least a minimal degree of relevance. This distribution supports the overall consistency and coherence of the selected literature, with over 59% of the studies (scores 4 and 5) demonstrating a clear and strong fit.

Fit Score	Relative Frequencies	Count
2	9.8%	9
3	30.4%	28
4	42.4%	39
5	17.4%	16
Total	**100.0%**	**92**

Figure 5.8: Table showing absolute and relative frequencies of fit scores of the contributions.

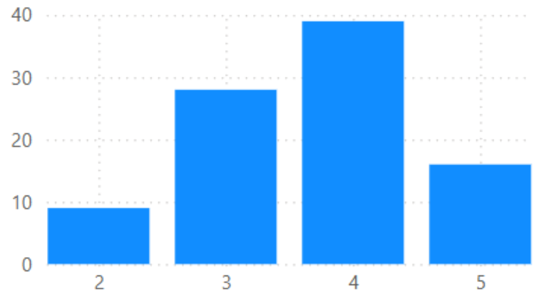

Figure 5.9: Histogram showing the distribution of fit scores among contributions.

To provide a synthetic indicator of overall alignment, the average Fit Score across the 92 studies was calculated as follows:

$$Average\ Fit\ Score = \frac{(2*9)+(3*28)+(4*39)+(5*16)}{92} = 3.7$$

The resulting score of 3.7 out of 5 confirms a generally strong coherence between the selected literature and the objectives of the research.

5.3 Thematic Synthesis

The content of this section consists of a qualitative analysis of the most recurrent topics identified across the remaining outputs of the systematic review, which include empirical results, managerial implications, ethical considerations, best practices, theoretical implications, limitations, and future research directions.

5.3.1 Empiric Results

First, foundational AI competencies for effective organizational adoption and innovation are highly underscored in importance. Baumgartner *et al.* offer evidence from quantitative survey responses from 215 companies, which identifies five Artificial Intelligence-related competency clusters: AI decision-making, AI use, AI foundational, AI development, and leadership & moderation (2024). The results clearly indicate that AI foundational competencies, which correspond to those related to understanding such technologies and their potential, are both the most critical and the least available across organizations. These competences enhance firms' abilities to identify AI use cases, integrate it into processes, and effectively utilize it within internal systems. Moreover, organizations with higher foundational and development-related AI competencies possess higher innovation abilities, hence validating such knowledge bases' centrality in AI-driven competitiveness. Second, empirical evidence highlights top management's strategic and cognitive involvement in AI-led transformations as highly important. In this sense, Jorzik *et al.* propose a framework that identifies five competencies and eight essential roles for executives leading AI-based innovation processes (2024). Such findings from predominantly upper-management interviews highlight that not just AI project sponsorship, but even new business model creation facilitated by AI, depends critically upon leadership. Supportively, Pinski *et al.* confirm this assertion empirically, as higher AI literacy among top management teams relates to higher AI orientation and increases companies' AI implementation skills related to human resources (2024). Crucially, the research illustrates that such a relation is moderated by firm type, with higher impacts in startups compared to incumbents, indicating that organizational context may moderate the strategic effect of managerially demanded AI literacy. Finally, what enables organizations' adaptation to AI disruptions is inextricably tied with their internal preparedness, leadership traits, and change approach. Contextual forces such as change resistance and leadership style condition AI receptibility in professional fields such as accounting (Anomah et al., 2024). Leadership traits, particularly adaptability and vision, along with an organization's preparatory position toward AI dictate its potential in traversing change and retaining professionalism.

5.3.2 Managerial and Practical Implications

The review analysis of managerial implications from the considered literature identifies three essential themes underpinning how organizations should react to increasing Artificial Intelligence integration into management. The first theme relates to the need for systemically building AI-related capability across organizational levels. Organizations should proactively identify which competencies are both critical for AI adoption and scarce in their current workforce. On this basis, firms are advised to implement targeted training and upskilling programs that anticipate future AI demands. Training should not only address technical skills but also promote interdisciplinary understanding, enabling employees to communicate across functional and hierarchical boundaries (Baumgartner et al., 2024). The use of "boundary spanners" has been proposed in order to bridge collaboration between IT experts, subject matter experts, and business strategists. In addition, higher education and vocational training centers are exhorted to streamline curricula along emerging workplace requirements. Executives need to specifically cultivate a general socio-technical understanding of AI even if they are not directly involved in implementation to embed AI meaningfully and well into business processes. The second theme is built around the symbolic and strategic role played by top management in shaping AI-driven innovation. This has been extensively discussed by Jorzik *et al.*, who underscore the need for a leadership style marked by curiosity, flexibility, and experimental spirit (2024). The research posits that top managers need not necessarily turn themselves into AI experts but need an understanding of AI potential and limitations in order to lead its implementation fruitfully. Top managers are encouraged to lead AI initiatives organization-wide, driving an "AI mission" and fueling a learning and empowerment sensibility. Managers are called upon not just to facilitate distributed decision-making but delegate responsibility for AI activities into the hands of teams and individuals. Self-assessment is further prescribed as a practice for managers periodically spotting talent gaps in AI literacy and building plans for addressing them. On the basis of such observations, AI literacy enhances both AI orientation and implementation capability (Pinski et al., 2024). Lastly, the third theme relates to using AI-based predictive models for augmenting strategic foresight. Sobhanmanesh *et al.* offer a machine learning-based pipeline that enables business leaders and policymakers to simulate rates of technology adoption across regions and industries (2023). Such models facilitate decision making for resource allocation, investment, and planning for workforce requirements. This is an example of how AI goes beyond automation and can be a strategic instrument for coping with uncertainty and foretelling opposition to technological change. Predictive analytics can help organizations simulate probable scenarios, evaluate their consequences, and make educated decisions about their path for digital transformation.

Briefly, the literature reviewed here converges in the view that AI success in organizations is the result of something beyond investment in technology. Rather, there needs to be a re-shaping of managers' competencies, leadership behavior, and decision-making processes. Not just filling skills gaps through formal learning but creating a leadership climate such that uncertainty is accepted, delegation is fostered, and decision-making is based on evidence rather than intuition. These results imply a shift in how managers actually work today in an age of AI, from hierarchical control and intuitive judgment toward adaptive coordination and analytics-driven action.

5.3.3 Ethical Considerations

The ethical implications of Artificial Intelligence in managerial contexts are increasingly recognized as essential to both organizational responsibility and strategic foresight. The reviewed academic contributions collectively underscore three main themes: (i) the integration of ethical reasoning into AI-related competencies, (ii) the organizational and societal governance frameworks required to mitigate risk, and (iii) the critical interrogation of AI's effects on transparency, human agency, and bias.

The first thematic thread relates to embedding ethical competence within overall organizational and managerial AI competencies. Ethical awareness, particularly toward protecting personal data and the well-being of staff and workers, is posited as a central competence in AI decision-making and leadership frameworks (Baumgartner et al., 2024). Likewise, Kulkarni *et al.* investigate ethical preparedness as highly correlated with enterprises' social sustainability orientation, needing integrated strategies that harmonize technological uptake and local values and stakeholders' expectations (2024). Moreover, executive education should explicitly focus on moral decision making and value alignment when working with intelligent machines (Peifer & Terstegen, 2024). The second thread tackles structural and institutional arrangements for enabling ethical AI deployment. Challenges related to ethics like privacy, job substitution, and disinformation are treated as issues to be managed through firm policy, predictive analytics, and national workforce initiatives (Sobhanmanesh et al., 2023). Likewise, regulatory frameworks that lead toward transparency, responsibility, and government-led AI project acceptance are required (Fetais et al., 2022). Meanwhile, Human Resource Management has to envision and manage ethical implications of algorithmic platforms for workers, specifically about fairness in assessment and hiring processes (Fenwick et al., 2024). The third thread discloses apprehensions about bias, intellectual property, and human accountability dissolution in AI-facilitated decision making. Karakose *et al.* critically reflect upon generative AI use in knowledge creation, pointing out plagiarism threats, partisan outputs, and lack of clarity (2023). Similarly, another crucial matter is ethical justification for subdelegating high-stakes decision making (e.g., like that made in combat) outside human agency, as human virtues and responsibility cannot be reproduced or substituted by machines (Hasselberger, 2024). Finally, it is important to keep in mind that algorithmic leadership could lessen transparency and undermine participative ethical foundations for democratic workplace cultures (Ken et al., 2016).

Summing up, all these contributions put together insist that ethics cannot be an afterthought when deploying AI. Instead, ethical thinking should shape organizational design, leadership building, and corporate governance right from the beginning. This involves not just reducing harm and addressing bias but nurturing a reflection and accountability culture as well. As these innovative systems are embedded in strategic and operational spaces, ethical considerations therefore need to develop along with them, not as hindrances to innovation, but as crucial aspects of sustainable and socially accountable development.

5.3.4 Best Practices

A careful review of the literature identifies a subset of contributions that offer actionable and empirically validated best practices for AI adoptions and management. These are based upon empirical evidence, case analysis, or theoretically derived managerial frameworks and are applied meaningfully across organizations seeking to scale their capabilities.

One excellent definition for best practice comes from Richthofen *et al.*, who highlight participative change management and realistic expectation-setting as essential (2022). Support from top leadership is considered paramount but ineffective if supplemented by inclusive communication strategies and open governance procedures. Orchestrating AI change through a sociotechnical methodology is considered as a best practice, balancing human issues and technological deployment within change management processes. Another high standard example is high-performance cultures, which thrive when combining structured analytics and intuitive, experience-based decision-making. This hybrid-intelligence methodology is defined as a decision-maker's strategic best practice when making uncertain choices (Lichtenthaler, 2022). The practice is about creating human judgment feedback loops for machine learning outputs, allowing for a dynamic, adaptive decision framework. In executive education and strategic alignment, a well-established model for upskilling upper leadership is needed (Peifer & Terstegen, 2024). The best practices are incorporating AI-related training into overall leadership development programs, focusing on strategic foresight, ethical sensitivity, and cross-functional working. This is underpinned by an awareness that, in order for leadership to successfully lead AI change, leadership itself has to change not just technologically but culturally as well. Last, inter-organizational cooperation is under emphasis. Here, best practice identified is setting up learning ecosystems between industry stakeholders and educations institutions for collaborative talent-pipeline development for nascent AI processes. This aligns skillsets but, through knowledge sharing, spurs innovation as well (Hearn et al., 2023).

5.3.5 Theoretical Implications

Contemporary literature on managerial competencies in an age of AI converges on a few recurring theoretical themes. A leading concern is the reconceptualization of frameworks for management and leadership competency based upon an understanding of the requirements for AI environments. Extended traditional competency theory is found in numerous studies that describe new skill sets marrying AI literacy and data-driven decision making with human-related skills such as creativity, ethical judgment, and flexibility. For instance, scholars have empirically cataloged scores of AI-related skills into integrated competence themes related to organizational innovation capacity (Baumgartner et al., 2024). Equally, top executives' expertise in AI has been proposed as an essential upper echelon theory extension, elaborating further upon how a leadership group's "digital know-how" and familiarity with AI technology generate value for firms (Pinski et al., 2024). Throughout the discipline, there is a focus upon being agile and having a growth mindset for learning as leadership characteristics in an age of AI (Watson et al., 2021). These contributions together indicate that leadership theories and manager competencies need to be revised to incorporate a portfolio blend of traditional and digital skills, a blend between technological competence and enduring human skills.

A second core implication is a revamp of leadership theory in light of AI's impact. Scholars contend that good leadership in digitally transforming organizations increasingly includes directing human–AI partnership and augmented decision-making processes. For instance, research on "digital leadership" offers new frameworks for leaders to manage contradictory requirements (e.g., creating innovation while preserving stability) when implementing AI and connected technology (Shahzad, 2024a). Concurrently, scholars are exploring the ethical and strategic dilemmas of partial automation within leadership positions. Ken *et al.* caution about new moral complexity when AI systems perform decision making and incorporates mechanisms to keep human accountability at center (2016). These findings enhance leadership theory in ways that consider AI as both actor and instrument in organizational decision processes, while continuing to highlight human judgment, ethical frameworks, and flexibility at organizational top levels.

The literature also continuously associates AI-era competencies with organizational innovation and dynamic capability theories. Top management competencies are regarded as drivers for using AI for business model innovation and strategic renewal. By stipulating how managers practice sensing, seizing, and transforming capabilities through skills related to AI, researchers apply the dynamic capabilities framework in an AI-enabled innovation setting (Jorzik et al., 2024). Similarly, research into digital transformation emphasizes that an organization's capacity for AI-enabled innovation depends upon manager skills for continuously sensing technology trends and seizing emerging digital opportunities while rearranging resources and processes. Empirical observations from SMEs confirm that higher digital maturity, induced by strategic management and an adaptive organizational culture, increases the firm's ability to adapt in turbulent, technology-led markets, thereby validating dynamic capabilities theory in a digital setting (Touijer & Elabjani, 2025). Well beyond firm-based innovation, even wider innovation ecosystem theories are being reinterpreted to support AI: for instance, mapping government–industry–academia interplay in national AI ecosystems has sharpened our theoretical knowledge about how networks of innovation actors operate in an age of Artificial Intelligence.

Altogether, these studies reset innovation management theory to consider explanations for AI not as new technology, but as an integral part of organizational capability and competitiveness. Empirical research into AI deployment in knowledge work shows that AI instruments typically augment human workers, defining new roles and skills requirements rather than substituting for them: a conclusion consonant with organizational learning theory through underlining opportunities for growth and upskilling (Richthofen et al., 2022). To this effect, researchers urge education and hiring programs that cultivate higher-order cognitive and social skills such as creativity, critical thinking, and collaboration as well as AI-related technical skills (Kolbjørnsrud et al., 2017). Not even in management education does one hear calls for integrating AI-focused content into curricula in order to foster future leaders capable of addressing digital transformation challenges (Dworaczek et al., 2024). Overall, theoretical agreement holds that sustained organizational flexibility in the age of AI depends upon an environment of ongoing learning and human–technology collaboration whereby advancements in AI keep pace with advances in managerial knowledge, ethical principles, and innovative methods for learning.

5.3.6 Limitations

The growing literature around managerial competencies in an age of AI always cites constraints that moderate the strength and applicability of its results. A leading problem is relying upon small or non-representative samples. Numerous studies were based upon small numbers of interview respondents or survey respondents, discounting statistical power and representativeness. For instance, qualitative interviews with fewer participants-based research accepts that its sample size inherently restricts generalizability (Broo & Schooling, 2023; C. L. Lee et al., 2024; Watson et al., 2021). Similarly, those relying upon just a restricted number of experts from a single country admit that their sample may not reflect all diversity of views in that environment or in others (Arenal et al., 2020). Such sample-size and composition concerns raise questions about validity for wide-ranging results in an inherently heterogeneous field such as AI-related management.

Another recurring limitation is the narrow sectoral or geographic focus in many investigations. Numerous studies are within one country or industry, which the authors acknowledge as a limitation for broader applicability. Single-country or single-sector investigations warn that findings from their research may not generalize across cultures or regulatory settings (Alenezi et al., 2024; Anomah et al., 2024; Aulia & Lin, 2024; Barodi & Lalaoui, 2025; Baumgartner et al., 2024; Donoso & Gallardo, 2024; Jorzik et al., 2024; R. Kumar & Gupta, 2024; C. L. Lee et al., 2024; Ofstad & Bartel-Radic, 2024; Tominc et al., 2023). In general, when research is within one geographic, cultural, or industrial context, its external validity is constrained from the beginning. Research design and collecting restrictions in methodology also loom large throughout these limitation sections. Many investigations have exploratory, cross-sectional designs, which present difficulties for establishing causality and objectivity. Interview-based and qualitative case study investigations deliver meaningful insights but are inherently constrained in their generality and are vulnerable to respondent or researcher bias (Arenal et al., 2020; Broo & Schooling, 2023; Dworaczek et al., 2024; Kolbjørnsrud et al., 2017; C. L. Lee et al., 2024; Nurshazana Zainuddin et al., 2023). Survey investigations too recognize that cross-section designs offer merely a snapshot and that using self-reported data has the potential for bias (Aldighrir, 2024; Aulia & Lin, 2024; Chatterjee et al., 2022). Some too bring forward measurement problems or unbalanced sampling (e.g., overrepresentation of certain groups), which further challenge their results' robustness. These methodology constraints mean that relationships and competency frameworks found should be viewed cautiously.

Lastly, several publications mention conceptual and scope-related shortcomings. A few are entirely conceptual, which authors state as an inadequacy because such proposed frameworks have no empirical underpinning (Fenwick et al., 2024; Satesh et al., 2023; Shahzad, 2024a; Shepherd & Majchrzak, 2022). Lacking evidence-based underpinning, such competency models are provisional. Others consider just a part of competencies or environments, excluding crucial dimensions. Writers concede that narrowing down attention to just technical skills at the cost of soft skills, or just studying a narrow time span, provides an incomplete view. Literature reviews are equally bounded by scope or time and may exclude pertinent research (S. Chowdhury et al., 2023; Dieterle et al., 2024; Dworaczek et al., 2024; Karakose & Tülübaş, 2023; Murire, 2024; Rehan et al., 2024).

Overall, the existing body of work that examines managerial skills in the age of AI shares certain recurring limitations in terms of restricted sample sizes, analyses tied specifically to context, and methodological shortcomings, all of which cumulatively invite caution when applying the results at a more comprehensive level. These shortcomings highlight the necessity for further work to use enhanced, comparative, and longitudinal designs, which would increase both empirical depth and theoretical scope in this fast-changing topic area.

5.3.7 Future Research Directions

One significant gap is a need for studying managerial AI competence across various contexts and organizational qualities together. Numerous investigations call for longitudinal research outside single environments, comparing various industries, cultures, organizations, firm sizes and nations (Baumgartner et al., 2024; Nurshazana Zainuddin et al., 2023; Richthofen et al., 2022; Rismani & Moon, 2023). Equally significant is studying how internal factors like organizational culture, structure, and resources mediate the effectiveness of such competence. These include investigating how human competence and organizational resources cooperatively impact AI implementation success and innovation performance (S. Chowdhury et al., 2023). Filling in both external context and internal dynamics would provide more generalizable and integrated insights into AI competency requirements. Having moved toward evolution and longitudinal views, AI-related competency for managers is dynamic and continuously evolves along with changing technology and work practices.

Longitudinal and process-based designs should be adopted in future research to capture how requirements for manager skills vary across various stages of AI adoption since AI projects have that long a span, and due to changing work practices, longitudinal research is essential for understanding further knowledge work evolution (Richthofen et al., 2022). Such methods can capture how competencies arise and others disappear as AI system maturity increases and workflow incorporates them. For instance, accounting investigations highlight how crucial it is for scholars to monitor how human expertise shifts along the evolution of AI aids in order to assist managers (Anomah et al., 2024). Taking researchers beyond cross-sectional observations in this manner would light up competency progression along AI-enabled environments. A host of questions arise concerning leadership and ethics for AI-enabled organizations. Conventional theories about leadership are likely to need revisiting when AI systems play a significant contribution toward or automate decision-making processes. Research would need to investigate new forms of leadership competencies and structures (e.g., shared or distributed leadership with AI) and how leaders work together with AI while continuing human oversight; along such lines, further research is required for studying ethical consequences involved in leaving major decisional choices for AI system delegation when there is no human veto involved (Ken et al., 2016).

Lastly, future research should examine how workforce sustainability in increasingly automated working environments can be ensured through optimized training and career development strategies, specifically addressing psychological and social issues faced by workers (Gómez Gandía et al., 2025). Another direction includes exploring the contribution that higher education establishments, including library schools, can make in preparing professionals through new curricula and AI-related training programs (Ali et al., 2024). Recruitment and training strategies for maximizing intelligent system value and selecting soft skills for productive human–AI collaboration should be explored by scholars (Kolbjørnsrud et al., 2017). These questions would provide evidence for informing theoretical explanations for workforce change while delivering actionable recommendations for training program development tailored for 21st-century workplace requirements (Bedoya-Guerrero et al., 2024).

In summary, further research across contextual, temporal, ethical, and educational dimensions is needed for building a solid and flexible understanding of managerial competencies in an era of AI.

6 Conclusions

In this research, we explored how Artificial Intelligence is affecting the development of managerial competencies in today's organizations. Instead of reaffirming known frameworks, the focus was on revealing how novel technologies reshape the duties and talent requirements for managers. Using a standardized and technology-enabled review process, the work identified and categorized the central AI-linked competencies into a structured taxonomy. This taxonomy provides a high-level categorization of the knowledge, talents, and skills that become increasingly pertinent for managers working in the existing changing landscape, where the place of AI is now central. Notably, the newly identified competencies that emerge from the review are not limited to the areas of technology; instead, the emphasis lies in the capacity for handling complexity, the development of trust in AI systems, and the ability to steer socio-technical changes in an inclusive and ethical manner (Abbondante et al., 2025).

As mentioned in section 2.6, this study was guided by three research questions. ***RQ1*** inquired into the AI competencies necessary for board members and senior corporate executives in today's high-tech world. The analysis uncovered that the executives need to acquire an optimal combination of visionary strategy, data-driven decision-making capacity, and an elementary grasp of AI systems and their business implications. Technical literacy is supplemented with cognitive flexibility and uncertainty management, revealing those as necessary qualities for leading organizations through multifaceted technological changes.

RQ2 inquired into changes in managerial roles in light of AI adoption. The findings chart an unmistakable shift in the executive leadership function: from commanding, operational control toward enabling, cross-functional coordination. Executives increasingly need to interpret algorithmic outputs, mediate between human and machine players, and cultivate an organizational culture for continuous adaptation. Their work shifts less toward issuing instructions and correspondingly more toward orchestrating multiple stakeholders' interactions, both humans and digital.

Lastly, ***RQ3*** emphasized the ethical and regulatory aspects of executive leadership in AI environments. The findings reveal that contemporary executives need to integrate algorithmic fairness, algorithmic transparency, data privacy, and legal and regulatory compliance into everyday decision-making. Ethical stewardship is not peripheral; it is an integral competency affecting organizational legitimacy, stakeholder trust, and risk management. In that sense, the capacity for anticipating regulatory changes and for tracking AI projects against ethical standards is an integral characteristic of effective leadership.

From a theoretical standpoint, this work contributes toward the ongoing process of revising managerial competency models, advancing beyond conventional models inadequate for capturing the disruptive impact of AI. The work provides an empirically rich, multidimensional taxonomy that can be used in informing subsequent academic work in organizational behavior, digital business transformation, and leadership research. The taxonomy developed here provides the foundation for subsequent conceptual work and perhaps an anchor for scholars operating along the interface between management, technology, and organizational behavior. In the second place, the methodological incorporation of Large Language Models in the Systematic Literature Review process is in itself an innovative approach toward synthesizing information in management research. While LLMs have been widely criticized in literature in regard to their uses in business and in management, given the risk for hallucinations, their incorporation into academic workflows is relatively much less extensively covered. In fact, this work demonstrates that, if prompted through the process of engineeering and situated in human-in-the-loop, such tools can be used toward the efficient detection, categorization, and synthesizing of complicated qualitative information. For the literature, the methodological leap, in incorporating the Large Language Models in the process, contributes toward the increasingly large topic in AI-enabled methodologies, providing an emulable method for the undertaking large-scale reviews in other fields. From a theoretical standpoint, it shakes traditional divisions between the contribution of the human versus the machine in the generation of knowledge, suggesting the proposal of a hybrid model in which the Large Language Models serve as cognitive extenders for the researcher, whose contribution is that, through such extenders, it intensifies the researcher's capacity for handling and systemizing piecemeal information. This hybridization may facilitate new frontiers in the field in those interdisciplined topics in which the quantity, diversity, and heterogeneity of published work make hand synthesizing success increasingly untenable.

Beyond its theoretical contributions, this research has significant practical value for digitalizing organizations. The implication is that successful AI incorporation is not only about technological preparedness, but it is equally about deep reconsideration of managerial tasks and organizational dynamics. Training and development programs, for instance, would need to change. Firms would need to create learning tracks that integrate AI literacy, for instance, learning about the algorithmic logic, quality of the data, and model constraints, along with the development of non-technical skills, such as communicating with the data teams, ethical decision-making, and handling resistances. Such two-track training would equip managers with the ability to act as bridges between the technical and business sides, rendering AI outputs actionable.

Second, the taxonomy built in this work can help guide the design of new managerial competency models. HR departments may adopt it as a reference point for updating recruitment standards, performance assessments, and leadership model descriptions. Doing that, organizations can advance beyond broad, generic soft skills and towards domain-specific competencies aligned with the impact of AI technologies on strategy.

Third, the research underscores the imperative for adaptive leadership. Managers need to lead teams in the midst of high uncertainty, where insights based on data may clash with intuition or entrenched norms. They need an organizational culture that encourages experimentation, learning from failure, and honest discussion between human and machine agents. Leaders should then build trust in algorithmic systems, not through blind reliance, but through informed supervision and transparent governance. Furthermore, the research identifies the need for organizational design and culture shift. As routine tasks are automated and decision-making is rebalanced, hierarchies flatten, workflows become cross-functional, and the source of knowledge shifts toward data-heavy positions. Managers will need to manage across silos, synthesize multidisciplinary insights, and foster inclusive collaboration among historically segregated departments, such as IT, HR, marketing, legal, and operations.

Finally, there are strategic considerations. Companies that map and build such competencies ahead of schedule may capture competitive advantage in technology adaptation, talent attraction, capacity for innovation, and ability to sustain resilience. Those who overlook the human aspects of AI may fail in implementation, even with the most advanced tools at hand.

Although its relevance and innovativeness, the work has its limitations. It is important to acknowledge these in order not only to frame the findings, but to indicate potential avenues for further refinement and empirical testing.

First, the literature analyzed was bounded in its scope by temporal, linguistic, and methodological parameters. Searching and analysis were processed early in 2025, so the latest advances, especially those released in the past few months, might not be included in the final taxonomy. In such an active field as AI and managerial research, such temporal restriction might lead to the omission of rapidly rising views, new models, or new definitions for managerial positions. Second, the review relied exclusively on peer-reviewed English-language academic literature, omitting grey literature, practitioners' reports, and sources other than English language and other cultures. As such, the findings might not represent views from non-Western environments, as well as from fields in which publication is less recurrent but organizational innovation is still significant.

Second, the work drew on an innovative methodological strategy that combined conventional Systematic Review protocols with LLM-powered content synthesis. Although the hybrid method augmented scalability and facilitated large-scale text corpus analysis, it created new methodological issues. The prompts provided for guiding the LLMs were intentionally crafted and iteratively optimized. Nonetheless, the interpretative process necessarily entailed some subjectivist intervention. While such instruments were not applied in screening articles in the first instance, since that was done manually through abstract close reading, they were enlisted for pulling out and summarizing pertinent information in already included full texts. This distinction is important, as it preserved the conceptual integrity of the initial inclusion phase. Nevertheless, there remain potential disadvantages stemming from the LLMs: the models may disregard contextual subtlety, translate concepts into too generic language, or refine abstract theoretical constructs inaccurately.

A third constraint is that, while the study was specifically tailored to concentrate on executive leaders and senior managerial positions, the identified and grouped competencies in the taxonomy were drawn from an eclectic body of literature, some being relatively practical in orientation, while others were less practical. While the taxonomy presents an organized amalgam of existing academic thought, it may not capture the detailed nuances of how such competencies are construed, implemented, and prioritized in particular sectors or organizational settings. Specifically, executive competencies being influenced by sectoral, firm size, or national regulatory contexts was an area beyond the scope of the study.

Lastly, this work is still conceptual in nature. Although it is based on an organized and rigorous literature review process, the suggested taxonomy of competencies has yet to be validated in empirical work. Interviews with working managers, focus groups, or survey-based research might experiment with the application of the framework in actual organizational settings. Such empirical verification would not only affirm the applicability of the competency identified, but would reveal potential gaps, inconsistencies, or emergent characteristics not represented in the literature. In its absence, the suggested framework should be regarded as the starting point for further analysis, rather than a definitive model.

Based on the insights and limitations presented, the following directions for further research can be seen. As the interface between Artificial Intelligence and executive leadership develops, greater empirical analysis and contextual differentiation will be necessary in order to develop theory and advance practice. One of the most pressing tasks is empirical verification of the taxonomy of the identified competencies in this work. Although the framework is based on systematic literature synthesis, it has not been verified against real-world data. Future work might use qualitative methods or quantitative methods in order to determine whether and how the listed competencies are identified, grown, and used by executive leaders in varying organizational forms. Another fruitful direction lies in the analysis of differences in such managerial skills in different sectors and cultures. For instance, the requirements for healthcare or finance managers may be vastly different from those in manufacturing or education. Likewise, the adoption of AI technologies and the perception of managerial skills should be influenced by national culture, regulatory environments, and institutional maturity. Comparative analyses in industries or nations may further refine the taxonomy and increase its external validity.

Furthermore, future research should explore how executive skills change in response to the increasing incorporation of AI tools, autonomous agents, and other new technologies in the field. Longitudinal design is best suited to monitor dynamic patterns of change, as the pace of technological advancement can rapidly redraw the lines of responsibility in managerial roles. Skills that emerge as currently necessary in this project may become the norm in a few years, and others may fall from favor as systems become increasingly autonomous or decision-making forms shift. Both monitoring the changes along the passage of time would yield insight into how executives learn to manage technological disruption: through formal learning, informal learning, organizational support, or personal experimentation. It would also enable observers to map stages of resistance, plateau, or acceleration in the development of competency, providing richer insight into the learning curve for AI-driven leadership.

Finally, another necessary area for future work is exploring the relationship between executive competencies and organizational outcomes. Although this study concentrated on determining the competencies that should be developed in order for the executive to cope with the large-scale implementation of AI, follow-up work would involve determining if and how these competencies translate into organizational-level impacts. For instance, scholars could study if executives possessing high AI-related competencies perform better in leading successful digital transformations, drive innovation, or enhance the quality decision-making. Knowledge about the relationship would further illuminate the interplay between an individual-level competency and organizational-level capacities, such as knowledge management, flexibility, or innovation preparedness. Such an approach would help in the development of holistic models linking leadership, AI maturity, and strategic performance.

These future directions offer valuable avenues for further scholarly investigation, and they give rise to a fundamental question: what forms of leadership will be required in increasingly AI-driven contexts? The integration of Artificial Intelligence into executive leadership is not a transient phenomenon; it is a profound and structural redefinition of what it means to lead. This study has shown that the competencies required by corporate leaders are not simply changing: they are being reimagined from the ground up and reconstructured at a foundational level, under the pressure of technologies that do not sleep and do not hesitate. Leadership in the AI era is no longer about control, or visionary rethoric alone. It is about translation: between human values and algorithmic logic; between long-term strategy and real-time data; between ethical imperatives and operational efficiency. Today's leaders must be able to act as interpreters between worlds that were once separate but now coexist within the same decision-making space.

Perhaps the most radical transformation lies not in the tools themselves, but in the expectations: we expect leaders not only to understand AI, but to absorb its logic without losing their humanity. To act quickly, but also responsibly. To delegate to algorithms, but to remain accountable. To innovate, while still protecting the fragile ecosystem of trust upon which every organization is built. There is no predefined script for leadership in this era. The competencies identified in this study are not static prescriptions, they are dynamic indicators, coordinates on a moving map. In the presence of ongoing disruption, leadership is an exercise in ongoing adaptation. In an always-changing technological world, the most valuable ability may not be knowing all the answers, but being able to chart through uncertainty with strategic vision, ethical acumen, and adaptive intelligence.

APPENDIX A

Title and Reference	**Managerial Competencies**	**Main Findings**	**Application Area**	**Methodology**
Key competences for the adoption of AI-based innovations in organisations (Baumgartner et al., 2024)	Strategic thinking; AI-related legal, ethical, and economic awareness; Problem-solving and change management skills. Basic and advanced AI knowledge (terminology, tools, trends, data, ML/DL/NN); Data analysis and programming skills. Leadership and communication capabilities for cross-functional AI projects; User involvement and sensitivity to employees' concerns.	AI adoption requires strategic workforce alignment, competence gap management, and tailored training. Socio-technical understanding and boundary-spanning roles are key for cross-functional collaboration.	GENERAL	QUANTITATIVE – SURVEYS
Artificial Intelligence-Enabled Business Model Innovation: Competencies and Roles of Top Management (Jorzik et al., 2024)	Basic understanding of AI technologies and their limits; curiosity, flexibility, and willingness to learn about AI; ability to promote a holistic AI vision and engage stakeholders (AI evangelist attitude); empathy and communication skills to guide organizational change; capacity to navigate AI abstraction and anticipate structural impacts; ethical awareness in AI adoption; ability to lead human–AI collaboration; analytical mindset and trust in data-driven insights; capacity to balance AI-based decisions with human judgment.	Top Management should foster a learning mindset, promote AI awareness, and empower teams. A basic understanding of AI, openness to experimentation, and critical evaluation of AI outcomes are key to guiding transformation.	GENERAL	QUALITATIVE – INTERVIEWS
A Conversation with ChatGPT about Digital Leadership and Technology	n.a.	School leaders can use AI tools to support strategic vision, professional development, and data-driven decisions, but must critically assess content	P - Education	QUALITATIVE – CONTENT

Integration: Comparative Analysis Based on Human–AI Collaboration (Karakose et al., 2023)		relevance. AI should also be leveraged to enhance collaboration and technology adoption within schools.		ANALYSIS
AI Literacy for the top management: An upper echelons perspective on corporate AI orientation and implementation ability (Pinski et al., 2024)	AI literacy, intended as the ability to critically use, evaluate, and interact with AI systems; AI orientation, reflecting the strategic alignment of organizational goals with AI adoption; HR-related AI implementation ability, referring to the capacity to integrate AI into human resources systems and processes.	AI literacy is a key skill for executive roles, especially in high-AI-potential sectors. Shareholders should promote its development among leaders, while executives must foster adaptability, enable data-centric cultures, and tailor AI strategies based on firm characteristics.	GENERAL	QUANTITATIVE – STATISTICAL ANALYSIS
Adapting to AI: exploring the implications of AI integration in shaping the accounting and auditing profession for developing economies (Anomah et al., 2024)	Continuous upskilling and reskilling; Strong business acumen; Interpersonal skills; Critical thinking; Communication abilities.	Accounting professionals in developing economies should enhance adaptability through continuous upskilling, soft skills development, and business acumen. Institutions and professional bodies must align strategies and training to support resilience and competitiveness in the AI era.	K - Financial and insurance activities	QUANTITATIVE – CROSS - SECTIONAL STUDIES
Adopting AI in the Context of Knowledge Work:	Ability to perform tasks requiring reasoning and empathy; adaptability to new roles and emerging skill requirements; technical skills in using	Managers should support AI initiatives through leadership, resources, and a culture of experimentation.	GENERAL	QUALITATIVE – CASE

Empirical Insights from German Organizations (Richthofen et al., 2022)	open-source tools; teamwork in interdisciplinary and agile settings; strong digital affinity.	Involving employees via communication and training helps manage resistance. Integrating expert knowledge and monitoring evolving roles are key to adapting structures and tailoring skill development.		STUDIES
An authoritative study on the near future effect of artificial intelligence on project management knowledge areas (Fridgeirsson et al., 2021)	n.a.	AI integration reshapes project cost, schedule, and risk management. Project managers should upskill in human-centric areas like team and stakeholder management. Targeted training is needed to bridge AI knowledge gaps, with attention to gender-specific needs.	GENERAL	QUANTITATIVE – CROSS-SECTIONAL STUDIES
Applying IIoT and AI - Opportunities, requirements and challenges for industrial machine and equipment manufacturers to expand their services (Qvist-Sørensen, 2020)	n.a.	Industrial firms must rethink their USP and service logic, shifting from product-centered to customer-centered models. Senior management should adopt agile structures and digital mindsets, define service goals, and develop pricing aligned with value. Engaging in strategic dialogue with key clients is essential to support digital transformation.	C – Manufacturing	QUALITATIVE – CASE STUDIES

Artificial Intelligence and Agility-Based Model for Successful Project Implementation and Company Competitiveness (Tominc et al., 2023)	Agile leadership involves transforming leadership styles to promote agile thinking, communicate goals, support learning, and empower teams. Agile team competencies include adaptability, continuous learning, self-organization, and collective decision-making. Managing agile environments means creating flexible structures, supporting hybrid work, and fostering rapid adaptation. Managers must adopt AI through digital strategies, delegate routine tasks to AI systems, interpret AI insights, and use AI to improve innovation, decision quality, and competitiveness.	Companies should foster a culture of adaptability, collaboration, and continuous learning to lead agile teams effectively. Managers must invest in skill development, empower teams, and explore AI tools to automate tasks and enhance decision making, integrating technologies like predictive analytics and NLP into project workflows.	GENERAL	QUANTITATIVE – CROSS-SECTIONAL STUDIES
Artificial Intelligence and Its Role in Shaping Organizational Work Practices and Culture (Murire, 2024)	n.a.	Organisations should invest in training, partnerships, and talent strategies to support AI integration. Leadership must align AI with company culture through clear vision and governance. Regular assessment of AI's impact on people and cross-functional collaboration are key to successful adoption.	GENERAL	QUALITATIVE – CONTENT ANALYSIS
Artificial Intelligence and the Transformation of Higher Education Institutions: A Systems Approach	n.a.	Higher education institutions leaders must adopt systems thinking to navigate AI transformation and guide adaptive strategies. They should anticipate future skill needs, integrate AI tools like personalized assistants with caution, and promote small-scale experimentation to	P – Education	QUALITATIVE – CONTENT ANALYSIS

(Katsamakas et al., 2024)		inform broader policies and ensure balanced, sustainable implementation.		
Artificial intelligence technology readiness for social sustainability and business ethics: Evidence from MSMEs in developing nations (Kulkarni et al., 2024)	n.a.	Small and medium-sized enterprises should adopt AI with a focus on ethical and social sustainability, evaluating their organizational, technological, and environmental readiness. Managers must ensure transparency, accountability, and fairness, recognizing AI's broader societal impact. Long-term vision, leadership commitment, and support from public institutions are essential to promote responsible and culturally relevant adoption.	C – Manufacturing	QUANTITATIVE – SURVEYS
Artificial Intelligence - Qualification and Competence Development Requirements for Executives (Peifer & Terstegen, 2024)	Ability to shape the framework for AI implementation; facilitate employee engagement and knowledge sharing; take full project responsibility; apply work design and change management skills; communicate AI concepts in socio-technical contexts; identify AI-related trends and risks; use AI in a humane and efficient way; explain processes clearly to align stakeholders; support the organizational purpose of AI adoption; act confidently and help shape working conditions influenced by AI.	Executives should guide AI implementation by balancing technology, efficiency, and human needs. Training programs must include technical and data literacy, while employee participation and transparency are key to fostering acceptance. Human-oriented AI design helps reduce job insecurity, and cross-functional project groups can support inclusive and responsible integration.	M - Professional, scientific and technical activities	QUANTITATIVE – SURVEYS

Comparative analysis of EU-based cybersecurity skills frameworks (Almeida, 2025)	Network and infrastructure security; risk management and governance; secure systems design and development; incident response and threat management.	The study supports the development of adaptive and standardized cybersecurity training aligned with industry needs, including AI security. It encourages collaboration among institutions and policymakers to build cohesive frameworks, integrate human factors, and address the evolving threat landscape.	J - Information and communication	QUALITATIVE – CONTENT ANALYSIS
Cooperative learning through boundary spanning: how a corporate learning department ensures that trainers and content stay current (Ofstad & Bartel-Radic, 2024)	n.a.	Corporate learning should support boundary spanning to foster collaboration in digital transformation. Managers must promote a learning culture, offer virtual learning, manage trainer capacity, and use people-centered strategies like job rotation and cross-regional meetings. Addressing cultural barriers and encouraging networking are key to developing inclusive learning environments.	N - Administrative and support service activities	QUALITATIVE – CASE STUDIES
Impact of AI ethics on school administrators' decision-making: the role of sustainable leadership	Sustainable leadership behaviors, including long-term thinking, valuing employees, and team empowerment; diversity management skills that foster inclusive environments where diverse perspectives are acknowledged and challenges are openly addressed.	School administrators should enhance decision-making by strengthening their ethical approach to AI, sustainable leadership, and diversity management. Training should support fair and effective educational outcomes, while institutional	P – Education	QUANTITATIVE – CROSS-SECTIONAL STUDIES

behaviors and diversity management skills (Aldighrir, 2024)		efforts must integrate these skills into school leadership development.		
Decision Support Concept for Improvement of Sustainability-Related Competencies (Abina et al., 2022)	n.a.	HR departments can enhance employee training by using assessment tools to support sustainability-related skills. A systematic, personalized approach fosters lifelong learning and supports the transition to a circular and socially responsible economy.	C – Manufacturing	QUALITATIVE – CONTENT ANALYSIS
Master in administration and its connection with artificial intelligence for leaders of the future (Dworaczek et al., 2024)	n.a.	MBA programs should include AI topics to prepare graduates for technological integration. Managers must strengthen human skills, lead ethically, and manage change while promoting innovation. Organisations should address the emotional and social implications of AI to ensure inclusive, responsible, and human-centered adoption.	P – Education	QUALITATIVE – CONTENT ANALYSIS
Digital transformation of organization using AI-CRM: From microfoundational perspective	Change management abilities to drive digital transformation; individual-level capabilities that support and influence the successful adoption of AI and other emerging technologies.	The adoption of AI-CRM systems requires developing individual capabilities at the micro level and addressing employees' resistance through targeted training. Leadership support is	M - Profesional, scientific and techni	QUANTITATIVE – SURVEYS

with leadership support (Chatterjee et al., 2022)		essential to foster a digital culture and emotionally motivate staff, enabling competitive advantage through AI-driven customer relationship management.	cal activit ies	
Digital twins in infrastructure: definitions, current practices, challenges and strategies (Broo & Schooling, 2023)	n.a.	To enable digital twin adoption, managers should drive digital and cultural transformation, close skill gaps, and enhance workforce digital fluency. Clear goals, transparency, and cultural communication are essential, along with improving industry appeal through favorable work conditions and employee well-being initiatives.	GEN ERAL	QUALI TATIV E – INTER VIEWS
Core competencies for digital leadership development: a perspective from the lens of paradox theory (Shahzad, 2024a)	Technological and strategic acumen; adaptability; effective communication; collaborative and ethical aptitude; ability to empower and delegate for knowledge transfer; risk management; networking and collaboration; leadership beliefs supporting digital leadership adoption.	Digital leaders should enhance data literacy and tech proficiency, foster a culture of innovation, and promote ethical, user-centered use of VR/AR. Training, collaboration, and experiential learning are key to improving communication, adaptability, and leadership in remote and dynamic work environments.	GEN ERAL	QUALI TATIV E – CONT ENT ANAL YSIS
Machine learning for the identification of competent project	Leadership and communication skills; personal and technical competencies; problem-solving and coping abilities; stakeholder and relationship management; organizational and	The proposed model supports HR in construction by assessing project manager performance and aiding recruitment decisions. It	F – Const ructio n	MIXE D – SEQUE NTIAL EXPLA

managers for construction projects in Nepal (Karki & Hadikusumo, 2023)	planning skills; team development and delegation; analytical thinking; time and cost management; decision-making skills; health and safety knowledge.	enables self-evaluation, facilitates performance monitoring, and can be developed into a user-friendly tool for widespread use across various project types.		NATORY DESIGN
Leadership training and development in the age of artificial intelligence (Sposato, 2024)	Ability to oversee AI-driven decision-making with human oversight; understanding AI's role in augmenting human capabilities; combining technical and emotional intelligence for team management; workforce planning and AI-based reskilling; knowledge to improve efficiency through AI tools; ability to identify areas for automation; foresight on tech advancements; talent management in AI contexts; promotion of continuous learning; managing diverse, cross-functional teams.	Corporate leaders should design AI-focused training that blends theory and practice, adapts leadership styles, and fosters strategic collaboration. Ethical considerations, organizational readiness, and cross-functional team building are essential, supported by e-learning, mentorship, and a strong culture of lifelong learning.	GENERAL	QUALITATIVE – CONTENT ANALYSIS
Mixing data analytics with intuition: Liverpool Football Club scores with integrated intelligence (Lichtenthaler, 2022)	Strategic understanding of AI and analytics; ability to integrate technological and human intelligence; competence in balancing optimization with innovative business models; openness to experimental transformation and failure; readiness to evolve leadership behaviors by emphasizing empathy, emotional intelligence, and people skills to complement AI use.	Executives should integrate AI with human expertise, balancing process optimization with innovation. Leadership must evolve to embrace experimentation and emphasize empathy and people skills. HR departments may need to adapt to manage the human–AI interface effectively.	R - Arts, entertainment and recreation	QUALITATIVE – CASE STUDIES
A Delphi study on digital maturity and digital competitivenes	n.a.	Small businesses should adopt cloud services and AI to streamline processes and enhance customer value. With support from	GENERAL	QUALITATIVE – CONTENT

s in the context of digital transformation (Touijer & Elabjani, 2025)		policymakers through funding, skill-building, and digital infrastructure, they can improve adaptability, efficiency, and competitiveness in the digital era.		ANALYSIS
Service employees' STARA awareness and proactive service performance (Hur & Shin, 2024)	n.a.	Service firms should train employees to develop skills for working with advanced technologies, reduce fear of automation, and promote proactive behavior. Empowering leadership and involvement in decision-making help reframe technological change as an opportunity, not a threat.	G - Wholesale and retail trade; repair and selling of motor vehicles and motor cycles	QUANTITATIVE – CROSS - SECTIONAL STUDIES
An egalitarian talent selection model to support learning organizations (Leao & Fontana, 2024)	n.a.	The model helps companies refine recruitment by improving their understanding of job requirements and ideal candidate profiles. It emphasizes soft skills, values like stability and egalitarianism, and highlights the need for distinct employer profiles to sustain organizational culture.	M - Professional, scientific and technical activities	QUANTITATIVE – STATISTICAL ANALYSIS

Education and training for industry 4.0: a case study of a manufacturing ecosystem (Hearn et al., 2023)	Change management skills extending to strategic capabilities like design thinking and environmental scanning, enabling leaders to address emerging processes and technological changes; risk management, scenario planning; ability to understand trends and anticipate future changes; strong communication and problem-solving abilities to communicate the vision of Industry 4.0, emphasizing the role of workers.	Manufacturing leaders must develop comprehensive capability strategies, focusing on more than just technology acquisition. Key areas include on-the-job training, talent attraction through innovation-driven workplace cultures, and fostering strong collaborations with educational institutions.	C – Manufacturing	QUALITATIVE – CASE STUDIES
Embracing the digital shift: Leveraging AI to foster employee well-being and engagement in remote workplace settings in the Asia Pacific region (Aulia & Lin, 2024)	n.a.	Managers should prioritize AI skills training to improve collaboration, ensuring seamless integration of AI tools with a focus on ethics and privacy. Encouraging human-AI collaboration reduces stress and supports decision-making. Regular assessments and effective e-leadership are essential for maintaining alignment and providing support, especially in remote work settings.	GENERAL	QUANTITATIVE – SURVEYS
Exploring the impact of artificial intelligence on curriculum development in global higher education institutions	Knowledge and understanding of AI integration in curriculum development; frequent use of AI tools; institutional support for faculty in AI integration; ability to personalize learning experiences, improve student engagement, and address individual learning needs through AI; real-time feedback and improving teaching materials; promoting critical thinking	Higher education institutions should strategically integrate AI into curricula by focusing on faculty training and support. Ethical concerns and cultural alignment must be addressed, while prioritizing AI's ability to personalize learning and foster critical thinking.	P - Education	QUANTITATIVE – STATISTICAL ANALYSIS

(Abbasi et al., 2025)	and problem-solving; familiarity with current AI tools; ability to address learning gaps and biases in curriculum content.	Continuous learning is essential to keep curricula relevant and aligned with technological advancements.		
From data to decisions: Leveraging AI to enhance online travel agency operations (Surbakti et al., 2024)	A problem-driven approach; ability to conduct cost-benefit analysis; data understanding; top management support; strong collaboration and communication skills; knowledge and skills in relevant areas; operational agility to adapt to changing needs.	Managers in online travel agencies should apply a problem-driven approach, prioritize AI projects with cost-benefit analysis, and secure top management support. Enhancing data understanding and fostering collaboration between technical and business teams are key to improving decision-making. Promoting operational agility and investing in data science team skills will ensure effective problem-solving and quick adaptation to market changes.	J - Information and communication	QUALITATIVE – CASE STUDIES
Human resources for Big Data professions: A systematic classification of job roles and required skill sets (De Mauro et al., 2018)	Business Analyst family requires communication, business process transformation and financial acumen. Data Scientist family requires analytical skills to leverage Big Data methods; they also need to access in corporate data warehouses and write scripts for querying databases. Big Data Developer family skills are coding, expertise in systems management, cloud computing, understanding of database management and corporate data architecture. Big	Functional and HR managers can leverage the study's findings to create structured job descriptions and design career development frameworks aligned with business and industry needs. Educational institutions should focus on developing both technical and soft skills, while business managers can use the "Big Data Job Families	M - Professional, scientific and technical activities	QUALITATIVE – CONTENT ANALYSIS

	Data Engineer family skills are data architecture, cloud computing, distribute processing, interacting with databases.	vs. Skill Sets matrix" to improve recruitment and career path strategies.		
Artificial Intelligence Adoption for E-Government: Analysis of Enablers in an Emerging Economy (Fetais et al., 2022)	n.a.	Government managers can use the study to create strategies for AI adoption, prioritizing enablers to guide resource allocation. The study provides a hierarchical structure for the variables related to AI adoption within organizations implementing.	O - Public administration and defence; compulsory social security	QUALITATIVE – CONTENT ANALYSIS
Is non-intervention feasible? How laissez-faire leadership moderates the relationship between AI usage and service employee empathetic creativity	Empathetic creativity: Using emotional intelligence and creativity to interact with customers in ways AI cannot replicate. AI collaboration management: Leveraging AI to handle routine tasks, allowing employees to focus on high-value human interactions. Role clarity in hybrid teams: Defining clear responsibilities when working alongside AI to reduce confusion and improve performance. Leadership-sensitive adaptability: Staying effective and engaged even	Hospitality managers should avoid laissez-faire leadership in AI integration, focusing instead on clear goal setting and support for human-AI teams. Organizations must update performance management systems to prioritize empathetic creativity and recruit candidates with strong interpersonal skills to foster collaboration in AI-driven environments.	I - Accommodation and food service activities	QUANTITATIVE – SURVEYS

(Luo et al., 2025)	when leadership is passive or absent in AI-integrated environments.			
The Review of Chinese Artificial Intelligence Labor Market: Both in Figures and Skills (Pitukhina et al., 2024)	n.a.	To compete in the AI sector, particularly in China, companies should prioritize hiring specialists with advanced degrees and experience in AI-related fields. Educational institutions must tailor curricula to equip students with the necessary AI skills. Strategic planning and financial investment are essential for achieving global leadership in AI development.	GENERAL	QUALITATIVE – CONTENT ANALYSIS
Leveraging STARA competencies and green creativity to boost green organisational innovative evidence: A praxis for sustainable development (Ogbeibu et al., 2021)	Green creativity, the ability to create environmentally sustainable novel ideas; Green expertise, combining green factual knowledge, technical aptitudes, and team talents; Green creativity skills, relevant for generating green creative solutions to environmental issues; Green task motivation, encompassing both intrinsic and extrinsic motivation, driven by challenge, satisfaction, curiosity, or intention to accomplish goals for green-oriented tasks.	Managerial programs should integrate STARA competencies for leadership in green initiatives. Managers must also focus on developing green creativity to boost green expertise and motivation for innovation. It's important to recognize the impact of environmental changes on creativity and Green Innovation Outputs, and mitigate these effects. Organizations should prioritize green creativity skills to drive tangible sustainability outcomes.	C – Manufacturing	QUANTITATIVE – CROSS-SECTIONAL STUDIES

Machines augmenting entrepreneurs: Opportunities (and threats) at the Nexus of artificial intelligence and entrepreneurship (Shepherd & Majchrzak, 2022)	n.a.	Entrepreneurs can leverage AI to enhance services like customer support, finance, healthcare, and education. They can develop emotional AI to adapt to the "feeling economy." By influencing AI governance and keeping humans involved, they can redistribute occupational skills. Entrepreneurs can design AI to enhance skills in opportunity identification and stakeholder interaction. They must also be mindful of AI's potential risks, like bias, and take responsibility for its ethical use.	GENERAL	NOT - DEFINED
Digital Leadership Added Value in the Digital Smart Organizations (Temelkova, 2019)	n.a.	Digital leadership skills are essential for effective business organization and a thriving high-tech economy. Leaders should have interdisciplinary qualifications, the ability to manage international teams, and proficiency in digital tools, strategic management, and leadership behavior. Managerial development programs must focus on developing these capabilities, including skills for leading teams and a strong understanding of digital and information technology.	J - Information and communication	QUALITATIVE – CONTENT ANALYSIS

Navigating circular economy: Unleashing the potential of political and supply chain analytics skills among top supply chain executives for environmental orientation, regenerative supply chain practices, and supply chain viability (Bag & Rahman, 2024)	Political skills; Ability to cultivate strong relationships with influential people at work; Ability to create a comfortable and positive work environment; Capacity to identify hidden agendas; Innate sense of how to influence others through the right words and actions; Supply chain analytics skills; Abilities required for the efficient analysis of data and information pertaining to the firm's environmental performance; Ability to pinpoint supply chain improvement opportunities to meet sustainability goals.	Top supply chain executives should enhance their political and analytical skills to improve the firm's environmental orientation, promoting regenerative supply chain practices. Managers can conduct sustainability assessments to identify opportunities for regenerative practices and set clear goals for environmental performance. They should develop a regenerative supply chain strategy that aligns with these goals. Additionally, managers should foster an AI-driven big data analytics culture by investing in infrastructure, building a data-driven culture, and implementing data governance policies, while measuring and communicating impact.	C – Manufacturing	MIXED – SEQUENTIAL EXPLANATORY DESIGN
Optimizing Romanian Managerial Accounting Practices through Digital Technologies: A Resource-Based and Technology-Deterministic	New abilities in data analysis and interpretation; Competencies in data interpretation, technological tools, and strategic analysis to remain relevant in the evolving landscape; Ability to analyze financial data, forecast trends, and support strategic decision-making; Digital literacy; Agile mindset; Design-thinking skills related to management control competency.	Companies should strategically plan digital implementations to mitigate resource constraints and capitalize on opportunities for sustainable growth and competitive advantage. Business leaders can use the report's recommendations to optimize the potential of digital technology.	N - Administrative and support service activities	QUANTITATIVE – STATISTICAL ANALYSIS

Approach to Sustainable Accounting (Pantea et al., 2024)		Researchers can use the report to guide future studies in this area.		
Partnering with Al: How organizations can win over skeptical managers (Kolbjørnsrud et al., 2017)	Ability to manage by fact, which means that managers must be able to manage with more information than before, not only by gut feeling; Ability to balance human judgment with machine-generated advice; Ability to collaborate with smart machines; Creativity; Hypothesis-testing; Good judgment; Social intelligence; Digital shrewdness.	Executives should engage managers from different levels in AI experimentation to familiarize them with its potential. Managers should help train AI systems by providing input on preferences and skills. Organizations need clear AI use parameters and ensure ethical and legal compliance. Leaders must recruit and train workers with soft skills like collaboration, creativity, and judgment, balancing experience with social intelligence and digital skills.	K - Financial and insurance activities; J - Information and communication; M - Professional, scientific and technical activities; N - Administrative and support servic	MIXED – CONCURRENT TRIANGULATION DESIGN

			e activities.	
Civil servants' readiness for ai adoption: the role of change management in Morocco's public sector (Barodi & Lalaoui, 2025)	n.a.	Public sector managers should focus on developing digital skills, invest in technology, and address resistance to change. They should communicate AI's role in enhancing, not replacing, jobs, and use tailored change management to increase confidence. Addressing bureaucratic resistance and digital infrastructure gaps is key for AI adoption in Morocco.	O - Public administration and defence; compulsory social security	QUANTITATIVE – SURVEYS
Rise of the Machines: A Critical Consideration of Automated Leadership Decision Making in Organizations (Ken et al., 2016)	n.a.	Managers should use AI to improve decision-making by eliminating biases and enhancing transparency. They need to balance quantitative targets with qualitative values and address social leadership aspects. Defining human veto power and considering the ethical implications of AI leadership decisions is crucial, with a "logged" veto system as a potential solution.	GENERAL	QUALITATIVE – CONTENT ANALYSIS
Robot Adoption and Profitability: The Opportunities	Digital upskilling for intelligent automation; ability to apply digital tools in new and existing processes; digital leadership awareness at the managerial level; knowledge of	Firms should invest in digital skills and leadership training to support intelligent automation and business model innovation.	C – Manufacturing	QUANTITATIVE – LONGITUDIN

and Challenges Ahead (Y. Chen et al., 2024)	business model innovation; understanding of end-to-end activity systems and value creation within the ecosystem.	Upskilling enables human-robot collaboration and helps manage the shift from cost leadership to market differentiation.		AL STUDIES
The impacts of artificial intelligence on managerial skills (Giraud et al., 2023)	Managerial skills likely to be augmented by AI include communication; recruitment; complex decision-making; innovation; time management; knowledge of jobs and business; and coping with pressure. Managerial skills likely to be replaced by AI include information gathering and simple administrative decision-making. Managerial skills unlikely to be replaced by AI include leadership and imagination. Technical skills that optimize the use of AI include basic AI knowledge and the ability to define needs and business cases. Non-technical skills that optimize the use of AI include judgement and ethical decision-making; multidisciplinary collaboration; organisational change management; open-mindedness; and risk taking.	Most managerial skills will be augmented by AI, requiring managers to collaborate more closely with it. Development programs should include both technical and non-technical training to optimise AI use. Managers should anticipate evolving roles and upskill accordingly. Organisational structures may need to be redesigned to better align with the AI–HRM interface.	GENERAL	QUALITATIVE – INTERVIEWS
Developing a digital transformation model to enhance the strategy development process for leadership in the South African	Data management, including collection, storage, analysis, reporting, and usage of data as a strategic asset; understanding of the role of CIOs, data scientists, and analysts in managing data and building predictive models; digital capability, such as proficiency in cloud computing and the ability to lead digital transformation across generations; fostering innovation, entrepreneurship, and a model-driven	CEOs must lead digital transformation by prioritizing data management and empowering the CIO. They should understand digital connectivity to reduce risks and improve ROI. Cultural change is needed to support learning and a data-driven mindset. Investing in	C – Manufacturing	QUANTITATIVE – SURVEYS

manufacturing sector (Gaffley & Pelser, 2021)	culture; strategic development skills, including risk-taking, ethical data governance, and awareness of social media and e-commerce impact; human capital management, involving cultural change, intergenerational leadership, digital learning promotion, and skill retention strategies.	complementary technologies can help close the digital transformation gap.		
The Adoption and Implementation of Artificial Intelligence Chatbots in Public Organizations: Evidence from U.S. State Governments (T. Chen et al., 2024)	n.a.	Public managers should adopt chatbots based on their advantages and ease of use, while considering external influences like citizen needs and vendor input. Fostering innovation, building a strong knowledge base, addressing skill gaps, and ensuring financial support are key. Cross-agency coordination and managing stakeholder expectations are essential for successful implementation.	O - Public administration and defence; compulsory social security	QUALITATIVE – CASE STUDIES
The Future Property Workforce: Challenges and Opportunities for Property Professionals in the Changing Landscape (C. L. Lee et al., 2024)	Technology proficiency and ability to apply digital tools in development and construction; understanding of AI use and the importance of regulatory frameworks in the property sector; strong communication skills, especially among new graduates; capacity for collaboration between academia and industry to support skill development in future property professionals.	Property professionals should bridge the gap between digital skills and practical application, while regulators must ensure proper AI oversight. Universities and industry must collaborate to strengthen communication skills and provide applied learning experiences. ESG factors should be integrated into valuation practices, and managers should prepare teams for globalisation by	L - Real estate activities	QUALITATIVE – INTERVIEWS

		developing local and international market awareness.		
The critical role of HRM in AI-driven digital transformation: a paradigm shift to enable firms to move from AI implementation to human-centric adoption (Fenwick et al., 2024)	Culture that fosters innovation and adaptability; leadership that sets strategic vision and promotes AI adoption; workforce skill development to bridge gaps in AI readiness; organizational AI principles for ethical and sustainable use; and familiarity with AI tools (hardware and software) to support practical implementation and improved decision-making.	HRM should work with leadership to align AI adoption with strategic goals, educate on AI's potential and risks, and promote human-centered, ethical AI use. It should engage leadership with employee concerns, support well-being, and help define tools and policies aligned with organizational values and skills.	GENERAL	NOT - DEFINED
Towards sustainable business in the automation era: Exploring its transformative impact from top management and employee perspective	n.a.	Automation strategies should be tailored to both employee and employer perspectives, addressing concerns like job security and skill relevance. Training and development must be integrated into automation programs, supported by transparent communication and shared involvement in implementation. A holistic, empathetic approach is essential to ensure	GENERAL	QUANTITATIVE – SURVEYS

(Gómez Gandía et al., 2025)		automation enhances the work environment and supports employee growth.		
Training in new forms of human-AI interaction improves complex working memory and switching skills of language professionals (Wallinheimo et al., 2023)	n.a.	Language professionals should upskill in interlingual respeaking to strengthen working memory and switching abilities, essential for accurate performance. Organisations should invest in training that enhances these cognitive skills to improve real-time human–AI language interaction.	M - Professional, scientific and technical activities	QUANTITATIVE – EXPERIMENTS
Transforming Architectural Programs to Meet Industry 4.0 Demands: SWOT Analysis and Insights for Achieving Saudi Arabia's Strategic Vision (Alnaser et al., 2024)	Sustainability for the Built Environment; Innovation and Creativity; Digital Applications in the Built Environment; Entrepreneurship /Venture Engineering and Leadership.	Educational institutions and policymakers should align architectural education with industry needs and tech trends. Curricula should integrate sustainability, innovation, digital tools, and entrepreneurship in line with Vision 2030. University standards must reflect labor market demands, and stronger industry collaboration through internships and practical learning is essential.	F - Construction	QUALITATIVE – CASE STUDIES
Unlocking the value of artificial intelligence in	Knowledge of AI capabilities and limitations: managers must understand what AI can and cannot do to align its use with business goals and reengineer	The AI capability framework helps HRM assess organizational readiness for AI adoption by identifying	M – Professional, scienti	QUALITATIVE – CONT

human resource management through AI capability framework (S. Chowdhury et al., 2023)	HR processes accordingly. Business application of AI; the ability to interpret AI outputs, apply them to real HRM contexts, and oversee AI-enabled decision-making processes. Leadership for AI integration: strategic orientation to allocate resources, define AI adoption goals, and communicate effectively with teams. Fostering collaborative culture: promoting innovation, risk-taking, and adaptability within a supportive environment for AI-human collaboration. AI-human integration management: clarifying roles, involving employees in AI adoption, and building trust to enhance engagement and productivity. Knowledge management: creating, sharing, and applying AI-related knowledge to develop collective intelligence and support innovation.	required resources. Managers should promote coordination, collaboration, and knowledge sharing across teams, supported by clear communication on AI strategy, job impacts, and expectations. Key areas include digital readiness, process changes, team composition, governance, and fostering a data-centric culture through agile methods and inclusive development practices.	fic and technical activities	ENT ANALYSIS
What does it mean to be a responsible AI practitioner: An ontology of roles and skills (Rismani & Moon, 2023)	n.a.	Business leaders can use ontology to build responsible AI teams, while educators can apply the competency framework to shape AI ethics curricula. Organisations should promote interdisciplinary learning and responsible AI awareness. AI leaders must hire talent capable of cross-disciplinary thinking and provide incentives, resources, and clear	M - Professional, scientific and technical activities	QUALITATIVE – CONTENT ANALYSIS

		communication to embed responsible AI practices.		
Will AI ever sit at the C-suite table? The future of senior leadership (Watson et al., 2021)	Digital know-how, including awareness of AI developments and their integration with technologies like cloud computing, data analytics, blockchain, 5G, and robotics; data-driven focus, with the ability to make decisions based on real-time AI-generated insights; networking, combining communication, social networking, and interpersonal skills to build strong internal and external connections; ethics, with awareness of issues like bias, prejudice, and privacy in AI use; agility, with the capacity to quickly assess situations, plan strategically, and respond effectively to emerging challenges and opportunities.	Senior leaders must stay updated on emerging technologies, prioritize data-driven decision-making, and develop strong networking, ethical awareness, and agility. They should lead cultural change, promote reskilling, manage resistance, and support intrapreneurship. Continuous, empathetic change management and roles like head of knowledge governance are key to long-term competitiveness.	GENERAL	QUALITATIVE – INTERVIEWS

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