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The Human–Artificial Intelligence Dualism in Organisational Learning: A Multiple Case Study Research

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Abstract–English

Artificial Intelligence (AI) is becoming increasingly central to organisational processes, promising to enhance knowledge access, decision-making speed and adaptive capacity. Yet its diffusion brings a paradox: while digital technologies multiply data, insights and recommendations, many organisations still struggle to translate informational abundance into organisational learning and measurable value. Value emerges only when AI-generated signals are interpreted, contextualised and stabilised into repeatable decision-making and operational routines.

This thesis investigates the role of AI in Organisational Learning (OL) with a dual objective: to explain how AI enhances learning–both by improving Knowledge Management Processes (KMP) and by performing autonomous learning functions–and to clarify how these dynamics translate into value creation. The study combines a systematic literature review with a qualitative multiple-case design across ten organisations operating in heterogeneous contexts.

Findings show two complementary pathways. First, AI strengthens human-driven learning by expanding the evidence base, accelerating feedback loops and improving collective sensemaking. Second, under specific conditions, embedded AI systems can perform autonomous learning routines–such as continuous pattern detection, alternative generation and iterative updating–thereby participating in learning cycles as non-human agents. Importantly, value creation is not an automatic outcome of adoption, but results from the interaction between AI outputs and human processes of validation and institutionalisation within Organisational Learning Practices (OLPs). The thesis proposes a grounded process model linking these mechanisms and clarifying the distribution of learning agency between humans and AI, providing a conceptual lens to guide strategic decisions on AI adoption and governance.

Keywords: Artificial Intelligence; Organisational Learning; Organisational Learning Practices; Knowledge Management Processes; Value Creation.

Abstract–Italiano

L'Intelligenza Artificiale (AI) sta diventando sempre più centrale nei processi organizzativi, promettendo di migliorare l'accesso alla conoscenza, la velocità decisionale e la capacità di adattamento. La sua diffusione porta però con sé un paradosso: mentre le tecnologie digitali moltiplicano dati, insight e raccomandazioni, molte organizzazioni faticano ancora a trasformare l'abbondanza informativa in apprendimento organizzativo e valore misurabile. Il valore emerge solo quando i segnali generati dall'AI vengono interpretati, contestualizzati e stabilizzati in routine decisionali e operative ripetibili.

Questa tesi indaga il ruolo dell'AI nell'Organisational Learning (OL) con un duplice obiettivo: spiegare come l'AI potenzi l'apprendimento, sia migliorando i Knowledge Management Processes (KMP) sia svolgendo funzioni di apprendimento autonome, e chiarire come tali dinamiche si traducano in creazione di valore. Lo studio combina una revisione sistematica della letteratura con un disegno qualitativo di multiple-case study condotto su dieci organizzazioni operanti in contesti eterogenei.

I risultati evidenziano due percorsi complementari. In primo luogo, l'AI rafforza l'apprendimento guidato dall'uomo ampliando la base di evidenze, accelerando i cicli di feedback e migliorando il sensemaking collettivo. In secondo luogo, in condizioni specifiche, sistemi di AI possono svolgere routines di apprendimento autonome–come rilevazione continua di pattern, generazione di alternative e aggiornamento iterativo–partecipando ai cicli di apprendimento come agenti non umani. In modo cruciale, la creazione di valore non è un esito automatico dell'adozione: deriva dall'interazione tra output dell'AI e processi umani di validazione e istituzionalizzazione all'interno delle pratiche di Organisational Learning (OLPs). La tesi propone un modello grounded di processo che collega questi meccanismi e chiarisce la distribuzione dell'attore dell'apprendimento tra persone e AI, offrendo una lente concettuale per guidare decisioni strategiche su adozione e governance dell'AI.

Parole chiave: Intelligenza Artificiale; Apprendimento Organizzativo; Pratiche di Apprendimento Organizzativo; Processi di Gestione della Conoscenza; Creazione di valore.

Contents

1 | Introduction

In contemporary organisations, the central challenge no longer lies–or at least no longer only lies–in the scarcity of knowledge, data, or technical skills: many firms already operate under conditions of informational abundance, supported by digital infrastructures, repositories, dashboards, document management systems, and multiple knowledge artefacts (Grant, 1996; Alavi & Leidner, 2001). The crucial issue lies elsewhere, namely in the ability to transform this abundance into organisational value. Without practices that make knowledge interpretable, shareable, reusable and, above all, translatable into action, the availability of data does not automatically generate improvement, innovation, or efficiency; the real bottleneck is therefore not informational but organisational, as it concerns the routines and practices through which signals and evidence are negotiated, stabilized, and incorporated into repeatable changes (Crossan et al., 1999; Zollo & Winter, 2002; Argote & Miron-Spektor, 2011).

AI is situated precisely within this tension: AI-based systems promise to accelerate the transition from information to action by automating cognitive tasks, synthesizing distributed evidence, identifying patterns and weak signals, and supporting collaboration and real-time decision-making (Jarrahi et al., 2023; Rezaei, 2025). However, the more AI is integrated into organisational processes, the more it challenges simplified narratives that frame it as a mere external "support" to human work, because it can reshape how organisations search, interpret, and validate evidence (Sturm et al., 2021; Alavi et al., 2024). From a learning perspective, the question is no longer simply whether AI improves information processing, but where learning actually takes place, how learning outputs become real at the organisational level through practices and routines, and where the agency of learning resides when algorithmic systems continuously generate outputs, recommendations, and dynamically updated representations (Huber, 1991; Crossan et al., 1999; Sturm et al., 2021).

This thesis starts from a practice-centered assumption: AI becomes organisationally relevant when it affects the execution of learning routines, that is, those operational moments in which organisations reflect on experience, interpret signals, make decisions, institutionalize, and reuse knowledge (Huber, 1991; Crossan et al., 1999; Zollo & Winter, 2002). For this reason, the unit of analysis is not "AI adoption" in the abstract, nor knowledge as an asset stored in repositories, but rather the point at which knowledge becomes relevant for the organisation, namely the Organisational Learning Practices (OLPs) and the collective routines through which interpretations and decisions are aligned and translated into stable organisational action (Crossan et al., 1999; Argote & Miron-Spektor, 2011).

The conceptual foundations of the research lie at the intersection of Knowledge Management (KM), Organisational Learning (OL), and AI: KM has progressively evolved into a strategic pillar oriented towards the creation, preservation, access, and dissemination of intellectual capital, with the objective of generating value by effectively mobilizing knowledge among stakeholders (Nonaka, 1994; Grant, 1996; Alavi & Leidner, 2001). At the operational level, it relies on Knowledge Management Processes (KMP), understood as a set of dynamic and interdependent activities that constitute the backbone of organisational knowledge practices (Ale et al., 2014; Al-Emran et al., 2018; Abubakar et al., 2019). KMP are often described as essential for leveraging intellectual resources and transforming tacit and explicit knowledge into measurable value, but such transformation is not automatic: it depends on how organisations structure, coordinate, and integrate these processes within broader routines; in this sense, KMP represent an enabling infrastructure for OL, because they provide structures and routines through which knowledge can be absorbed, shared, and transformed into new capabilities (Nonaka, 1994; Grant, 1996; Alavi & Leidner, 2001).

While KMP emphasize how knowledge is managed, OL describes how organisations evolve through experience: how they interpret what happens, integrate knowledge into decision patterns, and stabilize new ways of operating (Huber, 1991; Argote & Miron-Spektor, 2011). The literature has conceptualized OL as a social and routinized phenomenon in which learning becomes organisational not when individuals "know more," but when new understandings are shared, legitimized, embedded into routines, and made repeatable (Crossan et al., 1999; Zollo & Winter, 2002; Argote & Miron-Spektor, 2011). In parallel, it has introduced Organisational Learning Capabilities (OLC) as enabling conditions that facilitate effective learning; in this thesis, OLC are not treated as abstract or static characteristics, but as operationally significant capabilities that determine what becomes possible within learning practices, how these practices are carried out, and how learning can be stabilized into routines (Jerez-Gómez et al., 2005; Chiva et al., 2007; Alegre & Chiva, 2008). In the context of AI, this is particularly relevant because the issue is not only whether such capabilities exist, but how their content and execution are transformed when AI systems accelerate feedback cycles, broaden the evidence base for sensemaking, and alter the pace and timing of decisions (Sturm et al., 2021; Jarrahi et al., 2023; Alavi et al., 2024).

The relevance of AI for KM and OL has increased rapidly with the evolution and diffusion of different technological paradigms: machine learning and deep learning enable systems to recognize patterns and adapt based on data, while more recent developments such as generative AI (GenAI) and Large Language Models (LLMs) introduce advanced capabilities for accessing and recomposing knowledge, allowing even non-specialists to query complex domains, synthesize information in real time, and generate customized content for organisational needs (Pournader et al., 2021; Alavi et al., 2024; Jackson et al., 2024; Kirchner et al., 2025). From a learning perspective, this shift matters because it changes not only which information can be produced, but also how it can be accessed, shared, and embedded into routines (Alavi et al., 2024; Kirchner et al., 2025).

However, given that OL and KM are intrinsically routinized and social phenomena, the fact that AI increases the availability of informational outputs does not automatically imply that such outputs become "organisational" learning or, even less, value: the conversion depends on the practices through which the organisation interprets, negotiates, and stabilizes these outputs into decisions and repeatable changes (Zollo & Winter, 2002; Argote & Miron-Spektor, 2011). In this sense, the crucial element is not the production of information per se, but the passage from output to institutionalization, that is, the way in which signals, evidence, and recommendations enter OLPs and collective routines (Huber, 1991; Crossan et al., 1999).

This is where the theoretical tension that motivates the research emerges: if, on the one hand, AI appears capable of enhancing knowledge management processes, on the other hand the question remains open as to how this enhancement is actually translated into organisational learning and value creation (Alavi et al., 2024; Rezaei, 2025). The key issue thus becomes whether these outputs remain informational flows or are translated into organisational learning and value through OLPs and collective routines (Crossan et al., 1999; Zollo & Winter, 2002).

It is precisely here that the research gap underpinning this study is located, articulated along two complementary ambiguities. The first concerns the indirect pathway AI $\rightarrow$ KMP $\rightarrow$ OL $\rightarrow$ value, since, although there is consensus that AI improves the execution of KMP, the way in which AI-enabled KMP translate into OL and, subsequently, into value creation remains theoretically underdeveloped and empirically underexplored; there is a lack of convincing explanations of the intermediate mechanisms and of how operational improvements are stabilized into organisational change (Al-Emran et al., 2018;

Alavi et al., 2024; Rezaei, 2025). The second ambiguity concerns the direct influence of AI on OL as a potential learning agent: while AI has traditionally been described as a tool supporting human learning, recent developments suggest that AI-based systems may participate actively in learning cycles by generating representations and insights that the organisation appropriates and stabilizes; the question therefore remains open as to whether AI should be conceptualized exclusively as a facilitator of KMP or whether, in certain contexts, it may perform functions that resemble learning routines at the operational level. There is still no consolidated empirical body or shared conceptual framework that clarifies how these AI-driven mechanisms interact with organisational routines, OLC, and value creation. Consequently, this thesis positions itself in this space by proposing an integrated and mechanistic explanation of the impact of AI on OL and of how such impact can generate value: the contribution does not lie in documenting the "benefits of AI," but in explaining how AI transforms learning practices and how these transformations are converted into value creation through OLPs and routines.

In light of these unresolved issues, the objective of the research is to bridge the missing theoretical link between AI, KMP, and OL in the context of value creation, by explaining how AI enhances OL both indirectly (through its impact on KMP) and directly (through AI-driven learning mechanisms) and how this transformation enables organisations to create value. The thesis is therefore guided by the main research question (MRQ):

"How does Artificial Intelligence enhance Organisational Learning to enable value creation?"

MRQ is then articulated into two sub-research questions (SRQs):

- (SRQ1) **"How does Artificial Intelligence reshape organisational learning practices within organisations, both by augmenting existing organisational learning capabilities and by acting as an organisational learning agent?"**
- (SRQ2) **"How does the combination of AI-driven organisational learning and human-driven organisational learning contribute to value creation?"**.

SRQ1 clarifies how AI transforms learning practices and capabilities, while SRQ2 shifts the focus from learning to value without assuming that value follows automatically from technology adoption, aiming to show how the impact of AI on learning can be translated into plausible mechanisms of value creation; the MRQ synthesizes this logic and extends the reasoning towards implications for competitive advantage, understood not as a measured outcome but as a theoretical implication derived from the identified mechanisms.

To address these research questions, the thesis adopts a qualitative and interpretive approach based on a multiple-case study and a Grounded Theory logic: the aim is not to causally measure performance effects or competitive advantages, but to construct an explanation at the level of processes and mechanisms (Gioia et al., 2013; Yin, 2018). To support the theoretical positioning and the definition of the gap, the study integrates a structured and replicable literature review, designed with a PRISMA-inspired methodology on Scopus, which makes it possible to map the AI–KM–OL domain and synthesize the relevant contributions (Moher et al., 2009). In addition, a bibliometric and keyword co-occurrence analysis supports the understanding of the main conceptual trajectories in the field and of the convergence between technological, learning-oriented, and managerial/cognitive clusters, while highlighting the explanatory limitations in translating improvements in KMP into OL and value creation.

On the empirical side, the multiple-case design is chosen because the phenomenon is contemporary, embedded in real contexts and not controllable by the researcher, conditions under which case studies are particularly suitable for answering "how" and "why" questions (Yin, 2018). Following Yin's replication logic, the research does not construct a statistical sample, but a set of theoretically relevant contexts in which the interaction AI–KMP–OL can manifest in comparable forms. Controlled heterogeneity across cases (sectors, size, digital maturity) is used as a lever to test the explanatory power of the framework in different situations and to identify boundary conditions, pursuing analytic generalisation rather than statistical inference. The sample includes ten organisations represented by senior managers responsible for operations, innovation, IT, or strategy, with cases distributed between Australia and Italy and sectoral variety including manufacturing, food, automotive, and tech; this configuration ensures a perspective that is both strategic and operational, since the interviewees are close to everyday practices and at the same time involved in capability-level decisions. The analytical apparatus combines structured coding and Gioia-style data structuring to build a transparent path from raw data to theoretical categories: coding is treated as a disciplined practice of engagement with the text, while the data structure (first-order concepts → second-order themes → aggregate dimensions) serves as an integrative device for assembling categories into a conceptually coherent whole and constructing a grounded model (Gioia et al., 2013).

Consistent with this setup, the scope of the thesis is deliberately explanatory rather than measurement-oriented: the research does not aim to quantify performance effects or competitive advantages or to test predefined hypotheses, but to build a grounded explanation of how AI transforms OL and how this transformation can be converted into value creation through plausible causal chains rooted in qualitative evidence. This choice follows directly from the focus on practices: a technological perspective that equates AI adoption with value risks overlooking the organisational work required to convert AI outputs into stable change; in the framing of the thesis, value creation emerges when learning does not remain an informational flow but becomes coherent and repeatable organisational action, and this conversion depends on Organisational Learning Practices, that is, discussion and reflection around evidence, decision-learning processes, and the institutional stabilization of insights into interventions and routines (Crossan et al., 1999; Zollo & Winter, 2002; Argote & Miron-Spektor, 2011). Within this scope, the issue of learning agency is central: if AI improves human-led practices by broadening evidence and accelerating feedback, the organisational challenge concerns interpretation, alignment, and institutionalization; if, instead, under certain conditions embedded systems can perform autonomous learning routines (continuous pattern detection, generation of alternatives, iterative updates), the challenge also concerns orchestration, validation, and the definition of the boundaries through which algorithmic outputs enter processes, without implying that AI replaces the social dimension of learning but clarifying how it alters the pace, scope, timing, and quality of evidence and thus the translation of learning into value.

Within this framework, the expected contribution of the thesis is to fill the identified explanatory gap through a grounded model that clarifies which dynamics AI enables, where learning agency resides, and how AI outputs are converted into action and results; this contribution goes beyond generic claims that AI "improves" decision-making or "supports" learning, as it develops an explanation centered on practices and routines, treating value as the outcome of the stabilization and institutionalization of AI outputs. In particular, the contribution unfolds alonglong three complementary directions: first, by connecting AI, KMP, and OL to value and clarifying the indirect path that the literature does not explain, showing how enhancements in KMP translate into learning dynamics and subsequently into value creation (Al-Emran et al., 2018; Alavi et al., 2024; Rezaei, 2025). Second, by addressing the ambiguity related to AI as a learning agent, examining how embedded systems can participate in learning loops and reshape the distribution of agency between people and systems, with implications for orchestration, validation, and governance (Sturm et al., 2021; Gibson et al., 2023; Mancuso et al., 2025). Third, by linking AI-enabled learning to value creation through a process explanation, in which value is not an automatic by-product of AI adoption but the outcome of the interaction between AI-generated learning flows (signals, synthesized evidence, alternatives, recomposed knowledge) and human processes of contextualization, responsible choice, and stabilization into interventions and routines, recognizing the complementarity between AI-driven outputs and human judgement as a central mechanism for converting learning into repeatable action and tangible outcomes. Finally, the thesis develops this logic progressively: after a literature review and the definition of the conceptual framing, it presents the methodological design and the multiple-case study, introduces the empirical context and the qualitative analysis with the related data structure, develops the grounded theory model to answer SRQ1 and articulates the mechanisms through which the interaction between human learning and AI-driven learning produces value in response to SRQ2, concluding with a synthesis of the contributions, a discussion of the limitations, and several directions for future research (Gioia et al., 2013; Yin, 2018).

2 | Literature Review

The following literature review aims to provide a comprehensive understanding of how Artificial Intelligence (AI) interacts with Organisational Learning (OL) and Knowledge Management (KM) within organisational contexts. Its purpose is to identify, classify, and synthesize the main academic contributions that explore the role of AI in enhancing learning processes and knowledge dynamics across firms.

To ensure methodological rigor and transparency, the review was conducted following a structured and replicable procedure inspired by PRISMA guidelines (Moher et al., 2009). This approach allowed for the progressive refinement of the corpus, from the identification of relevant studies to the in-depth analysis of publication trends, leading journals, and conceptual linkages emerging from the keyword co-occurrence network. The process began with a systematic search conducted on the Scopus database through an advanced TITLE-ABS-KEY query specifically formulated to capture studies at the intersection of AI, OL and KM. The exact query used was as follows:

("artificial intelligence" OR "machine learning" OR "deep learning" OR "data-driven" OR "AI tools") AND ("organisational learning" OR "learning organisation" OR "knowledge management" OR "knowledge processes" OR "knowledge creation" OR "knowledge sharing" OR "knowledge storage" OR "knowledge transfer").

This search initially yielded 13,949 records.

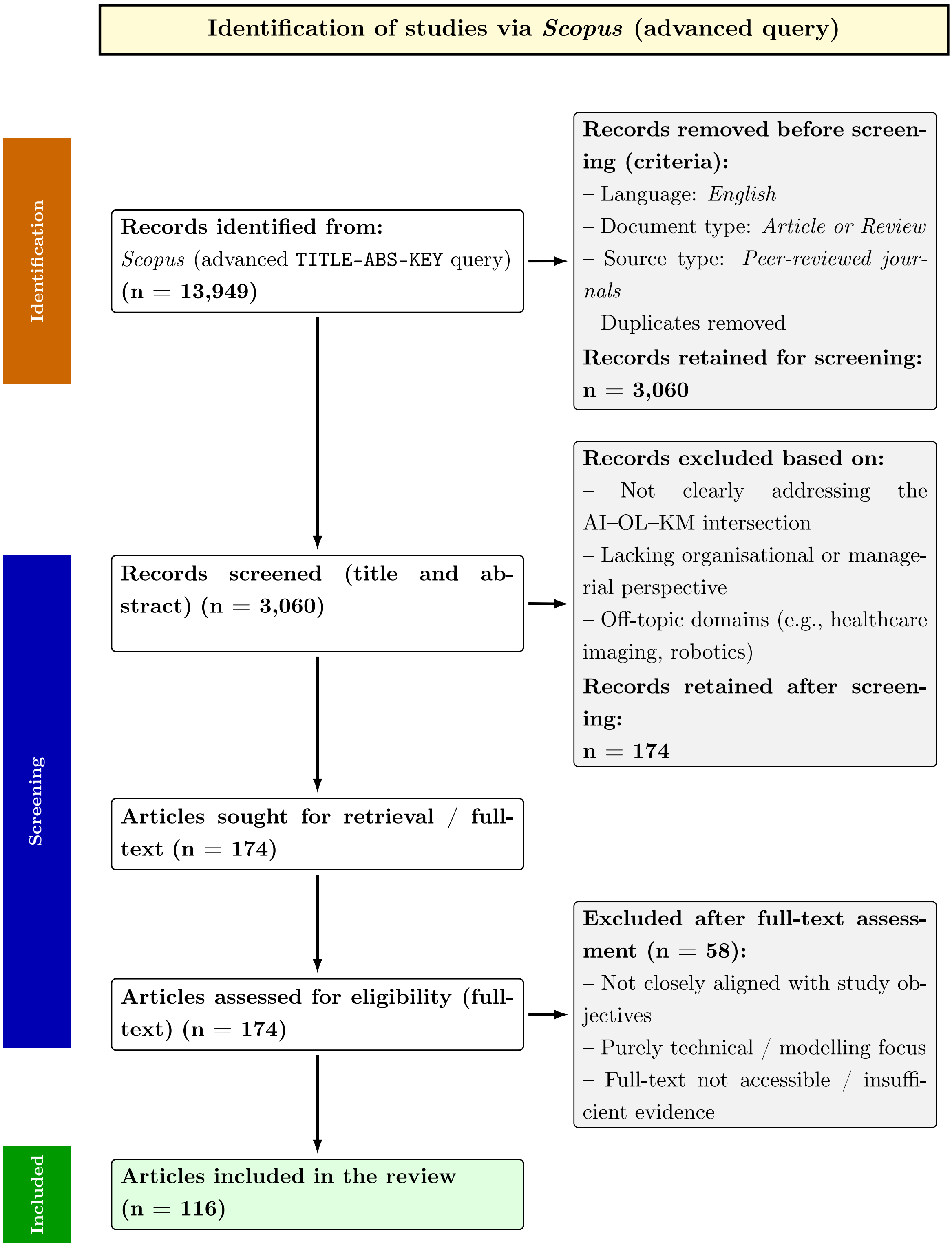
To refine the dataset, several exclusion criteria were applied before screening. Only English-language publications classified as articles or reviews and published in peer-reviewed journals were considered, while duplicates were removed. This resulted in 3,060 records retained for title and abstract screening. During the screening phase, records were excluded when they did not address the AI–OL–KM intersection, for instance, papers focused exclusively on technical or mathematical aspects without organisational implications, or belonging to unrelated fields such as healthcare imaging or robotics. After this step, 174 articles were selected for full-text assessment. Following a detailed eligibility evaluation, additional exclusions were made for studies that were not clearly aligned with the research objectives, lacked a managerial or organisational perspective, or did not provide sufficient theoretical or empirical evidence. The final selection resulted in 116 articles included in the review. This entire process is summarized in *Figure 2.1*, which presents the PRISMA-style flow diagram of the screening and selection methodology.

Following article selection, a descriptive bibliometric analysis was conducted to explore how the topic evolved over time and to identify the most relevant publication outlets. As illustrated in *Figure 2.2*, the publication trend reveals three distinct stages in the development of this research domain. The first stage, spanning from the late 1970s to the early 2000s, was characterized by a limited number of publications primarily focused on defining organisational Learning and Knowledge Management and on establishing the main theoretical frameworks underpinning these concepts. The second stage, starting around the 2010s, coincided with the growing attention toward Digital Transformation and its implications for organisational processes. During this period, the literatures on OL, KM, and digital transformation began to converge, emphasizing the role of knowledge flows and learning mechanisms in supporting digital adoption. Finally, in the most recent years, a marked acceleration can be observed, with a sharp rise in publications exploring the integration of Artificial Intelligence into organisational and learning contexts. These studies highlight how AI is increasingly seen as a key driver of innovation performance and as a technological enabler capable of enhancing organisational learning capabilities through improved knowledge acquisition, transfer, and utilization.

The analysis of publication outlets (*Figure 2.3*) further identified the leading academic journals contributing to this interdisciplinary field. organisation Science (8 articles), Journal of Knowledge Management (6), Journal of Business Research (6), and International Journal of Information Management (5) emerged as the most influential sources, consolidating the intersection between AI, knowledge processes, and learning dynamics within organisations.

Finally, a keyword co-occurrence analysis was performed using VOSviewer (*Figure 2.4*) to uncover the conceptual structure of the reviewed corpus. The resulting bibliometric network revealed three highly interconnected clusters, each representing a distinct yet complementary research dimension. The red cluster, centered on artificial intelligence, machine learning, and explainable AI, reflects the technological foundation of the field. The blue cluster, dominated by organisational learning, learning capability, and exploration/exploitation, captures the learning-oriented perspective, emphasizing how organisations adapt and evolve through knowledge acquisition and feedback mechanisms. The green cluster, structured around knowledge management, knowledge creation, and knowledge sharing, illustrates the managerial and cognitive dimension, focusing on how firms leverage and diffuse knowledge resources.

The interconnections among these clusters highlight a strong conceptual convergence between organisational Learning, Knowledge Management, and Artificial Intelligence, confirming the integrative nature of the research domain. Within this network, organisational learning and knowledge management emerge as central nodes exhibiting the highest link strength, connecting AI-related concepts (e.g., machine learning, AI capability) with organisational outcomes such as innovation performance and learning capability. This structure demonstrates how AI-based tools are increasingly conceptualized as enablers of learning and knowledge dynamics within organisations, acting as catalysts for adaptation, innovation, and the development of new organisational capabilities.



PRISMA-style flow diagram summarizing the search and screening process for the literature review (database: Scopus). Counts reflect the final corpus (n = 116).

Figure 2.1: PRISMA-style flow diagram of the LR screening methodology (Scopus advanced query).

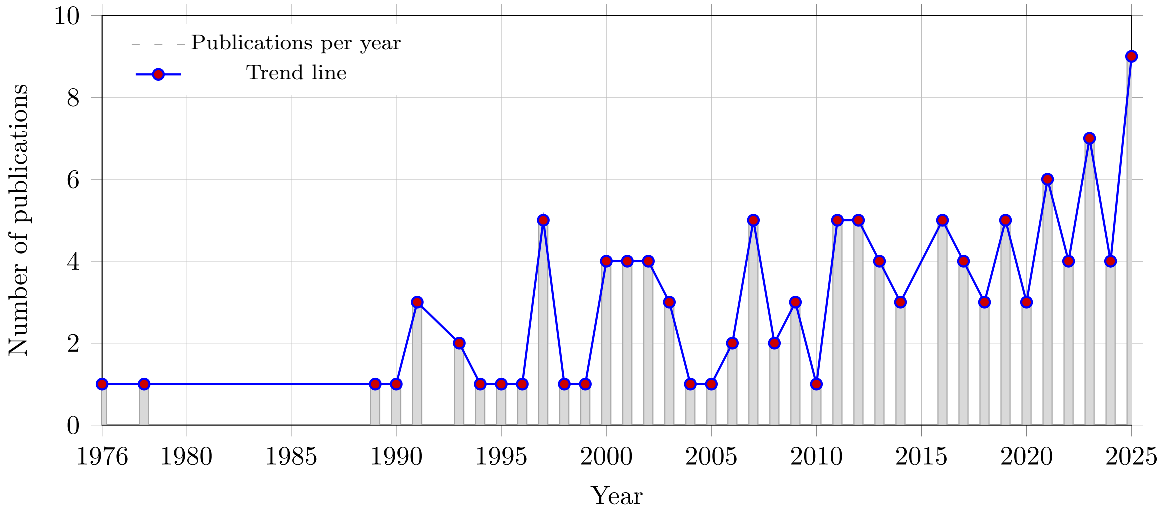
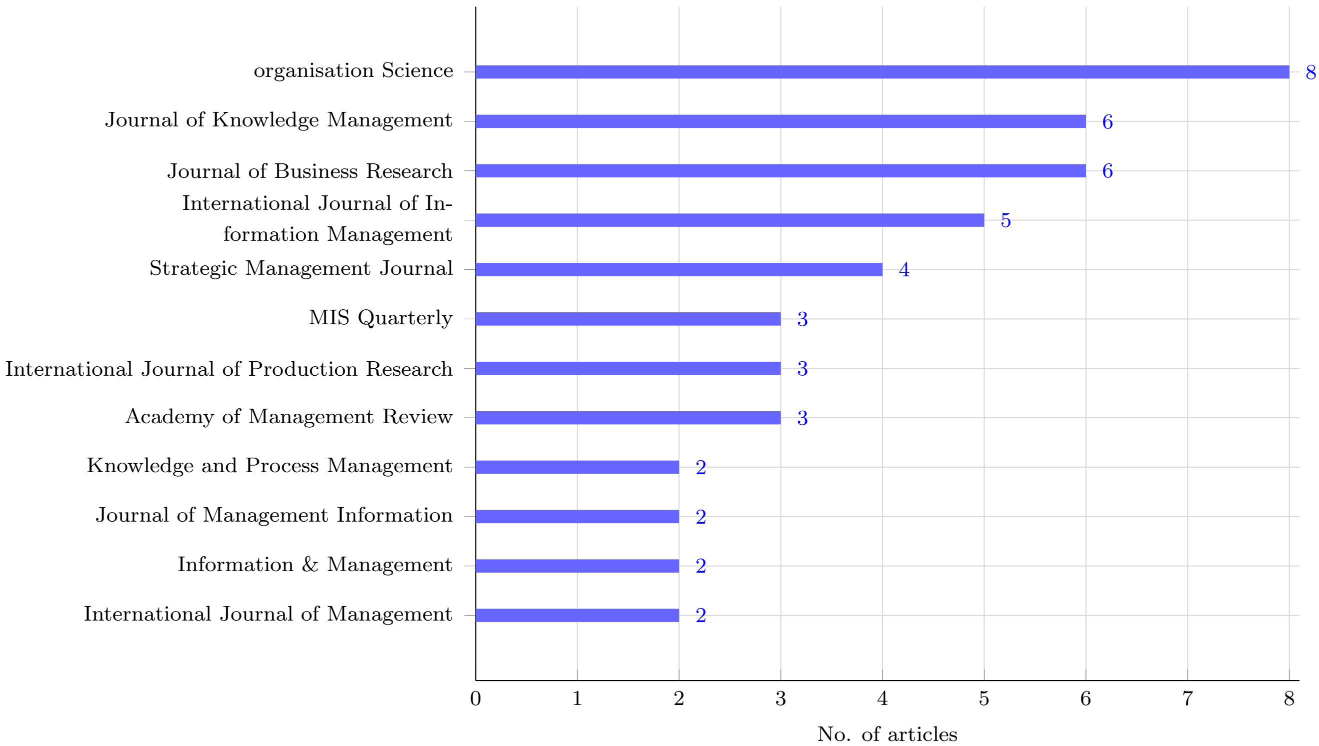


Figure 2.2: Publication trend of the 116 reviewed studies (1976–2025).



Source(s): Created by author.

Figure 2.3: Top journals (venues with $\geq$ 2 articles).

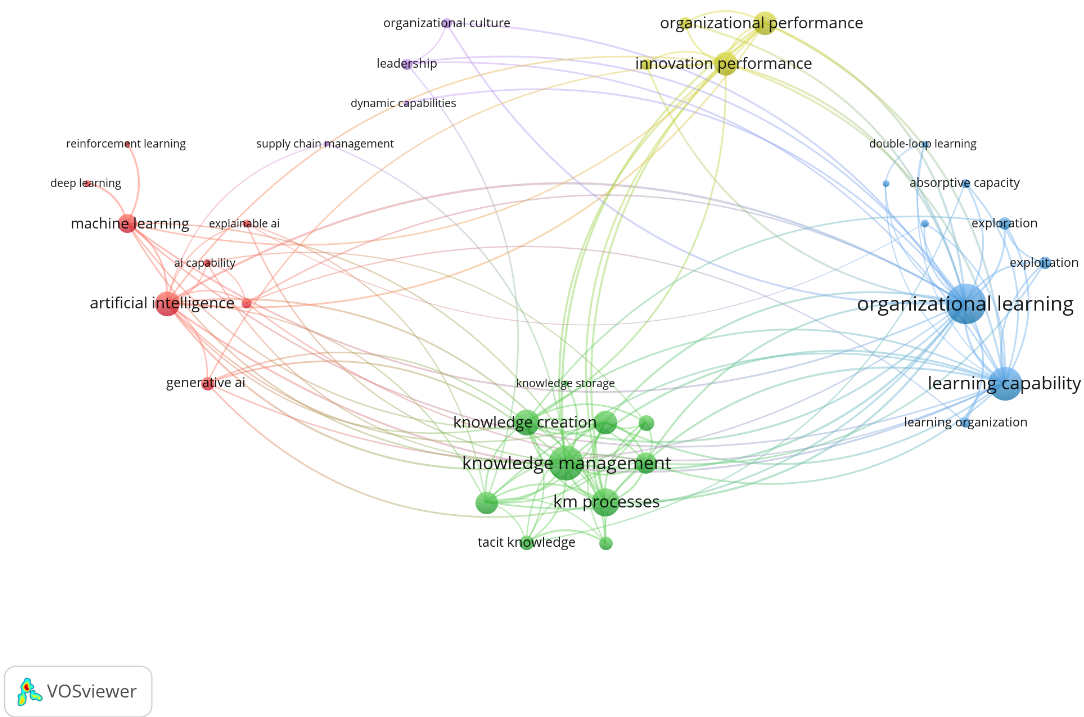


Figure 2.4: Bibliometric network visualization of keywords generated through VOSviewer.(n=35)

2.1. Knowledge Management

Knowledge Management (KM) has increasingly evolved into a strategic pillar of corporate strategy, aimed at overseeing the creation, storage, access, and dissemination of intellectual capital (Ale et al., 2014; Omer et al., 2016; Mohammad et al., 2022). Its ultimate purpose is not simply the administration of information, but the generation of organisational value by ensuring that knowledge is effectively mobilized across internal and external stakeholders (Omer et al., 2016; Mahdi et al., 2019). As Smith (2008) suggests, organisations that learn more rapidly and deploy their knowledge more effectively tend to establish industry leadership, reinforcing the idea that KM is deeply intertwined with competitive positioning.

Far from being a purely technical practice, KM is inherently cross-functional and multifaceted, bridging organisational behavior, human resource management, and information technology (Mohammad et al., 2022). This integration fosters not only institutional learn-

ing and development, but also innovation and long-term organisational success (Lee et al., 2016). At a more operational level, KM serves as a mechanism for capturing, organizing, and reusing knowledge efficiently (Lee et al., 2007), enabling firms to learn from past mistakes and successes, better leverage existing knowledge resources, and promote a long-term focus on developing relevant competencies (Omer et al., 2016).
Crucially, KM rests on KMP, a set of dynamic and interdependent activities that constitute the backbone of organisational knowledge practices (Ale et al., 2014; Mahdi et al., 2019). These processes do not only enhance efficiency, but also represent the foundation through which organisations develop and refine capabilities. In this sense, KM can be interpreted as a precursor of OL, providing the routines and structures that allow knowledge to be absorbed, shared, and transformed into creation of value.

2.1.1. Knowledge Management Processes (KMP)

KMP represent a set of dynamic, reciprocally dependent, and profoundly interconnected activities which are essential for leveraging an organisation's intellectual resources (Wee & Chua, 2013; Ale et al., 2014). Their pervasiveness is demonstrated by the fact that such processes often emerge organically, even in the absence of a formal KM mandate (Wee & Chua, 2013), highlighting their intrinsic necessity for effective organisational functioning. The primary function of KMP is to transform tacit and explicit knowledge into measurable organisational value (Mahdi et al., 2019). However, this transformation is not automatic: it depends on how effectively organisations structure, coordinate, and integrate these processes into broader routines. Although taxonomies regarding the number and sequence of KMP vary among scholars, researchers generally converge upon a core sequence of activities that provides a common ground for analysis.

Systematic reviews identify six key processes that are highly relevant for supporting innovation and organisational learning (Ale et al., 2014; Costa & Monteiro, 2016): **Knowledge Acquisition, Knowledge Creation, Knowledge Storage, Knowledge Codification, Knowledge Sharing/Transfer**, and **Knowledge Application.** Each of these is not isolated, but mutually reinforcing, forming a cumulative cycle through which knowledge flows and evolves. These processes form the operational foundation of organisational knowledge (Lee & Choi, 2003) and are crucial inputs for organisational learning (Liao & Wu, 2010), since they enable organisations not only to connect with information and acquire new insights, but also to integrate and apply them in ways that enhance decision-making and, ultimately, innovation capability (Mahdi et al., 2019).

KMPs	Core Purpose
Knowledge Acquisition	Build the organisation's knowledge base by gathering internal and external knowledge.
Knowledge Creation	Generate new ideas and insights by combining existing knowledge.
Knowledge Storage	Preserve and codify knowledge for future retrieval and reuse.
Knowledge Codification	Convert tacit knowledge into explicit and usable formats.
Knowledge Sharing / Transfer	Disseminate knowledge across individuals and units to enable collective learning.
Knowledge Application	Apply knowledge to decision-making, problem-solving, and innovation.

Table 2.1: Overview of the Six Core Knowledge Management Processes (KMP)

Knowledge Acquisition (KA)

Knowledge Acquisition (KA) constitutes a fundamental organisational capacity, as it allows firms to identify, gather, and source external data and information from diverse channels in order to construct and continuously expand their foundational knowledge base (Ale et al., 2014; Mohammad et al., 2022; Mancuso et al., 2025). Its relevance becomes particularly evident when internal resources are insufficient to sustain innovation efforts, making it necessary to rely on external search and learning activities (Zahra & George, 2002).

In this sense, KA plays a dual role: on the one hand, it compensates for internal limitations by opening the organisation to new ideas, while on the other hand it acts as a trigger for absorptive capacity, enabling firms to recognize the value of external knowledge and integrate it into their own processes. Core mechanisms include directed external search efforts, employee training programs, and experiential learning, all of which strengthen the ability to continuously enrich the knowledge base and create the conditions for organisational learning and innovation to unfold (Hagemeister & Rodríguez-Castellanos, 2019).

Knowledge Creation (KC)

Knowledge Creation (KC) refers to the process through which individuals or organisations generate new knowledge by combining existing information, prior experiences, and cognitive processes (Pinho et al., 2012; Savino et al., 2017). Rather than being a passive activity, it involves deliberate efforts to synthesize ideas, establish novel connections, and foster creative thinking that can address complex problems or emerging opportunities (Wee & Chua, 2013).

This dynamic and complex process is essential not only for the active formulation and internal circulation of organisational knowledge, but also for sustaining long-term adaptability and innovation capacity (Esterhuizen et al., 2012; Abubakar et al., 2019). The seminal SECI model (Socialization, Externalization, Combination, Internalization) provides the primary theoretical foundation for describing how knowledge–particularly tacit knowledge–is converted, shared, and ultimately transformed into new organisational insights (Nonaka, 1994; Nonaka & Takeuchi, 1995).

Traditional methods supporting KC include brainstorming, collaborative problem-solving, and intensive human interaction, yet these practices gain strategic significance when they are embedded into organisational routines, as they become a driver of collective learning and a basis for new capability development. (Esterhuizen et al., 2012).

Knowledge Storage (KS)

Knowledge storage (KS) involves the systematic preservation of knowledge by codifying it into accessible and durable formats. This process often relies on centralised platforms, such as databases and data warehousing technologies (Mohammad et al., 2022; Mancuso et al., 2025). KS's fundamental function is not merely archiving information, but rather institutionalising knowledge assets so they are reliably retained, securely retrievable and readily available to support future decision-making (Raghu & Vinze, 2007).

Knowledge is usually stored through structured research activities, thorough documentation practices, longitudinal trend analysis and identifying knowledge gaps in the current understanding of a phenomenon (Al-Emran et al., 2018). By embedding these practices into organisational routines, KS becomes a critical enabler of organisational learning, ensuring that past insights are not lost, but can be leveraged systematically to inform innovation and capability development.

Knowledge Codification (KCOD)

Knowledge Codification (KCOD) serves as the formalized mechanism through which implicit or tacit knowledge is transformed into explicit, recognizable, and usable formats (McInerney, 2002; Ale et al., 2014). This process often takes the form of drafting manuals, guidelines, or procedural documents, and fundamentally aids in structuring and institutionalizing organisational knowledge (Mahdi et al., 2019).

Beyond its practical value, the active process of codification requires intellectual scrutiny, as it compels individuals to articulate underlying arguments and surface hidden assumptions. This in turn leads to cognitive simplification and the standardization of shared understanding (Zollo & Winter, 2002). Such standardization not only facilitates knowledge diffusion across the organisation, but also reduces ambiguity, enabling more consistent decision-making.

Empirical evidence suggests that converting codifiable tacit knowledge into explicit representations is particularly beneficial for organisations pursuing incremental innovations, as it creates a reliable base of accumulated expertise that can be reused and adapted over time (García-Muina et al., 2009). In this sense, codification acts as a bridge between individual learning and collective capability development, positioning it as a crucial step in the transformation of knowledge into innovation-oriented outcomes.

Knowledge Sharing/Transfer (KST)

Knowledge Sharing and Transfer (KST) defines the set of vital organisational mechanisms through which information, expertise, and know-how circulate among internal and external stakeholders (Nonaka & Takeuchi, 1995; Alavi & Leidner, 2001). Because of its centrality, it is one of the most frequently investigated KMPs in the academic literature (Costa & Monteiro, 2016; Al-Emran et al., 2018), and is widely recognized as a cornerstone for enabling collaboration and collective learning.

While tacit knowledge is often diffused through specialized sub-networks and one-to-one interactions that allow for deeper contextualization (Dyer & Nobeoka, 2000), effective KST increasingly depends on institutionalized mechanisms such as internal social networks, formalized communities of practice, and supportive leadership behaviors (Ale et al., 2014; Le & Tuyen, 2025). These structures not only facilitate the transfer of knowledge but also shape a culture of openness and trust, which are essential preconditions for organisational learning.

From a capability-building perspective, KST is particularly relevant because it transforms dispersed individual insights into collective assets, ensuring that knowledge does not remain localized but is instead mobilized for innovation. In this way, sharing and transfer act as accelerators of organisational learning and as enablers of dynamic capabilities that sustain innovation performance.

Knowledge Application (KAPP)

Knowledge Application (KAPP) represents the execution phase in which acquired or existing knowledge is systematically translated into practical action, implemented in real-world contexts to improve decision-making, address problems, and stimulate innovation (Alavi & Leidner, 2001; Mohammad et al., 2022; Mancuso et al., 2025). Its central role lies in transforming abstract organisational knowledge into tangible and measurable outcomes, thereby exerting a direct and significant impact on organisational performance (Mahdi et al., 2019).

Importantly, KAPP is not a passive end-point but a dynamic process through which knowledge becomes embedded in practices, routines, and strategies. In doing so, it closes the loop of the knowledge cycle and ensures that insights are not only generated and shared, but effectively utilized. Research shows that KAPP frequently mediates the positive relationship between knowledge sharing and a firm's innovation performance (Onağ et al., 2014; Bogale et al., 2025). This mediating role highlights its contribution to capability-building: by institutionalizing the use of knowledge, organisations strengthen their adaptive and innovative capacities, making KAPP a critical lever for fostering organisational learning and the development of new innovation capabilities.

2.1.2. Main Conceptual Frameworks and Model of KM

In addition to processes, several conceptual frameworks and models have shaped the understanding of KM, providing a holistic view of the discipline and its strategic implications. Among these, the *Resource-Based View (RBV)* and the *Knowledge-Based View (KBV)* of the firm represent two fundamental perspectives that consider knowledge as the main strategic resource for achieving sustainable competitive advantage (Grant, 1996). KBV, in particular, extends RBV by emphasizing the role of knowledge as a valuable, rare, inimitable, and non-substitutable (VRIN/VRIO) resource, highlighting how firms are essentially structured around the integration of highly specialized individual knowledge (Barney, 1991). Within this framework, knowledge integration emerges as the essence of organisational capability, representing the key mechanism through which organisations transform dispersed expertise into collective value creation (Grant, 1996). These theories underline the central importance of KM not only for competitive advantage (Holsapple & Singh, 2001) but also for ensuring long-term organisational efficiency (Mohammad et al., 2022).

Building on this strategic foundation, the *SECI* model (Socialization, Externalization, Combination, Internalization), introduced by Nonaka (1994) and further developed by

Nonaka & Takeuchi (1995), provides a complementary lens to explain how knowledge is dynamically created and transformed within organisations. The model illustrates the continuous interaction between tacit and explicit knowledge through four distinct but interrelated phases. In the socialization phase, tacit knowledge is shared among individuals through direct experience and observation; externalization converts tacit insights into explicit concepts by means of dialogue, metaphors, or models; combination integrates different explicit knowledge elements into more complex and systematic sets; and internalization allows individuals to absorb explicit knowledge into their tacit repertoire, often through practice and learning by doing. Rather than a linear sequence, this cycle constitutes a spiral of continuous knowledge transformation that operates across individuals, groups, and organisations. In doing so, the SECI model provides a concrete mechanism for knowledge integration and renewal, reinforcing the KBV perspective that firms derive their competitive advantage from the ability to generate, share, and embed knowledge into organisational routines.

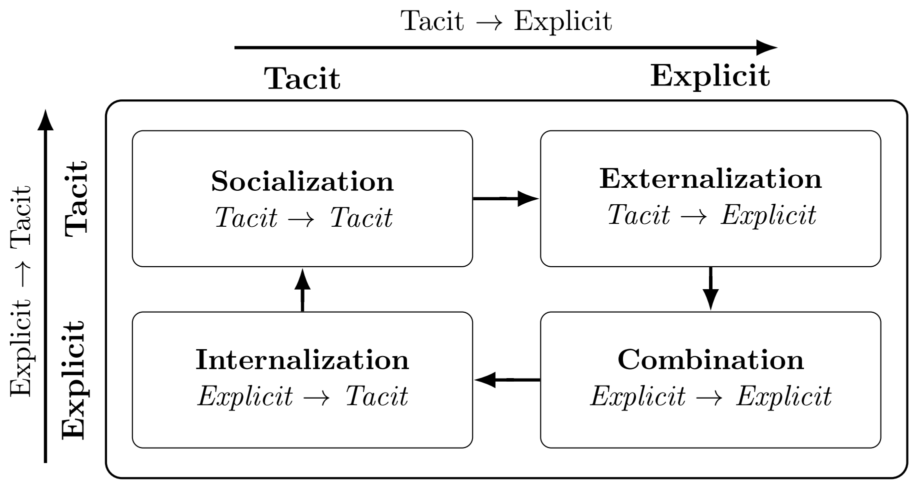


Figure 2.5: SECI knowledge conversion cycle (Nonaka, 1994; Nonaka & Takeuchi, 1995).

2.1.3. Role of Socio-organisational and Technological KM Enablers

The success of KM is intrinsically tied to a combination of *socio-organisational* and *technological enablers* that act as organisational mechanisms to foster knowledge (Ale et al., 2014; Mohammad et al., 2022). They stimulate knowledge creation, protect and facilitate knowledge sharing, and provide the infrastructure necessary to increase the efficiency of knowledge processes (Choi & Lee, 2002).

Socio-organisational Enablers

Organisational culture emerges as a critical factor for the success of KM, as it not only defines which forms of knowledge are valued but also determines which should be preserved to sustain innovative advantage (Lee & Choi, 2003). A collaborative culture built on trust and continuous learning plays a fundamental role, since it enables knowledge sharing and the development of shared understanding among members (Connelly & Kelloway, 2003; Lee & Choi, 2003). Within this perspective, the notion of "care" has been identified as a key relational enabler, fostering environments in which knowledge can be more easily created and shared (von Krogh, 1998). In line with this, a knowledge-centered culture exerts a strong influence on an organisation's learning capability, thereby shaping its ability to renew competencies and innovate (Le & Tuyen, 2025).

Alongside culture, the *organisational structure* also exerts a decisive influence on KM practices. Its dimensions–formalization, centralization, and specialization–can function as both enablers and barriers (Abubakar et al., 2019). Formalization refers to the extent to which decisions, work relationships, and operational routines are regulated by standardized rules and procedures. Centralization indicates the hierarchical level at which decision-making authority is concentrated, while specialization captures how tasks and responsibilities are distributed among employees and teams (Dekoulou & Trivellas, 2017; Abubakar et al., 2019). A cohesive organisational structure that balances these dimensions is essential for ensuring that knowledge can be effectively mobilized and transformed into a source of sustainable value (Abubakar et al., 2019).

Technological Enablers

IT support has long been recognized as a fundamental technological enabler of KM, as it assists in the capture, codification, and distribution of organisational knowledge (Ale et al., 2014). Yet, it is important to acknowledge that technology by itself cannot fully substitute for the human interface and contextual interpretation of knowledge (Robey et al., 2000; Ale et al., 2014). Rather, IT capabilities play a moderating role, influencing the effectiveness of different knowledge evolution strategies on organisational performance (Chen & Liang, 2011). While IT systems can certainly facilitate communication and discourse, they may also, under certain conditions, inhibit organisational learning if they reduce opportunities for social interaction or overly constrain the flexibility of knowledge flows (Robey et al., 2000).

Building upon traditional IT, *AI* has emerged as a critical enabler of KM, automating functions such as information retrieval, content generation, and the categorization of large volumes of knowledge. AI significantly enhances the ability to extract meaning and uncover latent relationships in unstructured data (Barão et al., 2017), while also contributing to safer and more efficient knowledge management practices (Mohammad et al., 2022). In particular, Generative AI (GenAI) and Large Language Models (LLMs) have expanded access to knowledge dramatically, offering robust support for synthesizing complex information, generating ideas, and producing diverse forms of content. By automating repetitive or risky tasks, AI frees human effort for activities that demand creativity, judgment, and empathy (Mohammad et al., 2022; Kirchner et al., 2025).

AI not only improves information processing and cognitive functions but also accelerates knowledge-intensive activities such as data collection, integration, and synthesis, thereby supporting faster and more effective product development (Kirchner et al., 2025). Within this landscape, tools such as data mining, text mining, and Artificial Neural Networks (ANNs) are widely employed to support knowledge creation, acquisition, organisation, dissemination, and application (Ur-Rahman & Harding, 2012; Rogalewicz & Sika, 2016). More recently, prompt engineering has emerged as a novel practice of knowledge creation in the age of GenAI, positioning human-AI collaboration as an increasingly strategic capability (Kirchner et al., 2025).

2.2. Organisational Learning (OL)

Following the comprehensive discussion on KM and its foundational processes (KMP), this section delves into the intricate domain of OL. OL is a critical counterpart to KM, often considered a key outcome or an intertwined process that enables KM to generate strategic value (Antunes & Pinheiro, 2020; Obeso et al., 2020; Idrees et al., 2023). This review will systematically explore the definitions, theoretical underpinnings, measurement complexities, and the crucial relationship between OL, knowledge, and innovation, alongside the factors that facilitate or impede its development within organisational settings. Understanding OL is paramount for this thesis, as it represents the fundamental mechanism through which organisations adapt, innovate, and thrive in dynamic environments, ultimately influencing their ability to leverage advanced technologies like AI.

2.2.1. Definitions and Nature of Organisational Learning

OL is widely recognised in research studies as an active and endogenous process that significantly contributes to organisational behavior and bears considerable influence on overall business performance (Lloria & Moreno-Luzon, 2014; Obeso et al., 2020; Inthavong et al., 2023). Its very fundamental importance is underscored by its status as a prerequisite for survival and enduring success (Huber, 1991; Argote & Miron-Spektor, 2011; Bogale et al., 2025). Early conceptualizations defined OL as the capacity of organisations to modify their actions and procedures as a response to experience and new knowledge (Argyris & Schön, 1978, cited by Zollo & Winter, 2002). Extending this behavioural view, Levitt and March, 1988, cited by Levinthal & March, 1993, emphasised that learning occurs when organisations act inferences into routines that then guide subsequent actions. This adaptive process involves continuously building the organisational knowledge base and strategic acumen, forged through the connection of past actions, perceived effect, and decisions yet to be made (Huber, 1991; Zollo & Winter, 2002).

Moving towards a more formal approach, OL has been characterized as having four related processes: knowledge acquisition, information distribution, interpretation of information, and formation of organisation memory (Huber, 1991). This perspective highlights that OL goes beyond the buildup of private learning, instead becoming collectively embedded in structures and habits (Crossan et al., 1999; Schilling & Kluge, 2009). Building on this process account, scholars developed a multi-level conceptualization such that learning occurred at the individual, group, organisational, and inter-organisational levels, and Nonaka (1994) took the lead with the Knowledge Conversion Cycle (SECI model) to explain how tacit and explicit knowledge were dynamically interacting.

These concepts were then assimilated in the 4I model (Crossan et al., 1999; Vera & Crossan, 2004), which links the different ontological levels through the subprocess of intuiting, interpreting, integrating, and institutionalizing. This model spells out the recursive dynamic between action and cognition, placing OL as fundamentally distinct from KM: whereas KM involves knowledge flows, OL involves the dynamic between interpretation and action as inseparable drivers of learning.

Yet another conceptual differentiation differentiates other studies on OL, which are descriptive and ask about how organisations learn (Tsang, 1997), from the Learning Organisation (LO), which is prescriptive and asks about how organisations should learn (Garvin, 1993). Such a differentiation reflects other common debates over the descriptive versus normative nature of OL studies (Easterby-Smith, 1997; Tsang, 1997). In recent strategic management literature, OL has been fully defined as an explicit or implicit process in which organisations supplement, retrieve, and update memory in order to inform future action (Robey et al., 2000).

Based on this systems perspective, OL is an important dynamic capability enabling organisations to develop strategic flexibility, agility, competitiveness, and innovation capabilities in unstable environments (Hung et al., 2011). For this reason, OL is the central process that transforms KM inputs–knowledge creation, acquisition, and transfer–into beneficial outputs such as innovation (Liao & Wu, 2010; Barão et al., 2017).

2.2.2. Main Theoretical Models of Organisational Learning

The theoretical landscape of OL is multifaceted and diverse, and several influential models offer somewhat divergent but in crucial respects complementary analyses of its many-faceted dynamics. The initial conceptualization is the single-loop and double-loop learning paradigm of Argyris & Schön (1978), which emphasizes the difference between correcting mistakes in tried and tested routines and questioning the assumptions underlying such routines. Basing this on that, March's (1991) groundbreaking exploration-exploitation model defines the conflict between seeking knowledge and describing existing capabilities, a balance which remains central to innovation success.

Another foundation stone is Nonaka's (1994) ontological levels of learning conceptualization and the SECI cycle, demonstrating how tacit and explicit knowledge interact dynamically to generate new organisational knowledge. This focus on knowledge conversion was succeeded by the 4I framework of Crossan, Lane, and White (1999), which clarified OL as a process encompassing four interdependent subprocesses - intuiting, interpreting, integrating, and institutionalizing - operating at different levels within an organisation. More recently, Gibson et al. (2023) offered an integrative three-level model that formally incorporates the role of emerging technologies, providing a contemporary extension of earlier theories and noting the increasing importance of technological enablers in determining OL.

The Single-loop and Double-loop Learning Framework

Argyris & Schön (1978) first made the seminal distinction between *single-loop* and *double-loop* learning, providing a valuable framework with which to evaluate both the depth and the transformational potential of OL. Single-loop learning occurs where organisations detect and correct errors without questioning underlying assumptions, values, or controlling variables, thereby learning within established frameworks. This mode of learning maintains stability but has the consequence of entrenching defensive routines, secrecy, and low feedback, as organisations socialize members not to challenge fundamental norms. Double-loop learning, by contrast, implies a fundamental examination and potential change in such assumptions and values, enabling organisations to re-examine the "how" and the "why" of their activities. It sets the stage for valid information, free and informed choice, and internal commitment, with open inquiry and constructive confrontation. Despite its transformative potential, double-loop learning is difficult to achieve in practice because most organisations and individuals are socialized primarily into single-loop learning, and a shift to deeper levels of learning often requires the presence of crisis or intentional interventions (Argyris, 1976; Argyris & Schön, 1978).

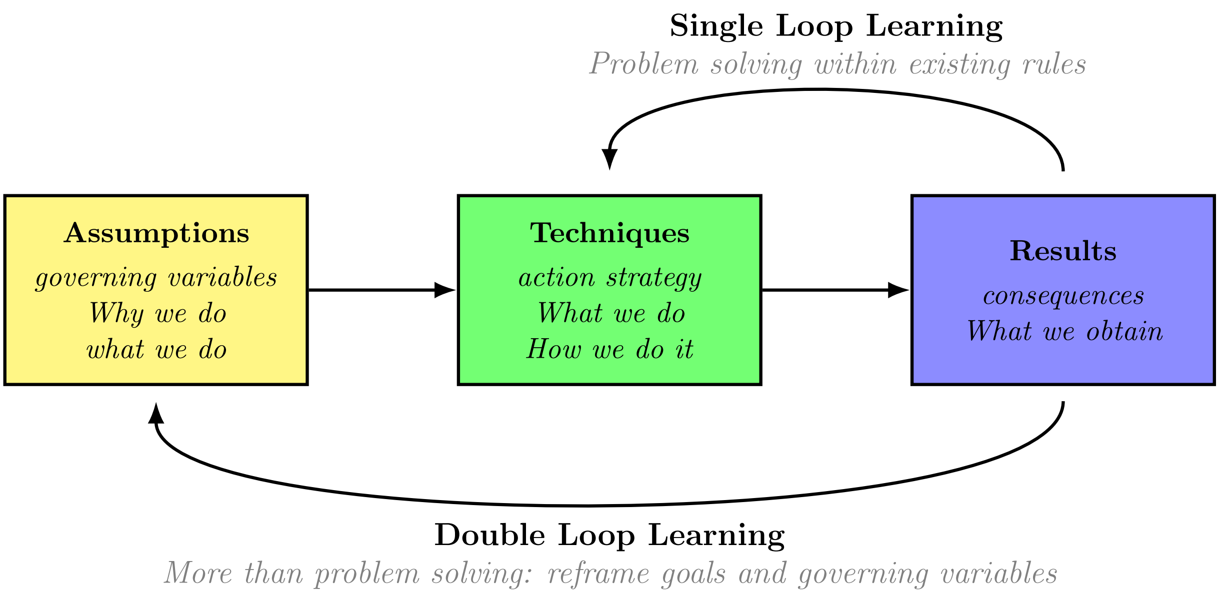


Figure 2.6: Single-Loop and Double-Loop Learning framework (Argyris & Schön, 1978).

Exploration versus Exploitation Model

March's (1991) model gives a general distinction within organisational learning through the contrast of *exploration* and *exploitation* as two interdependent but competing kinds of adaptive behavior. Exploration comprises search, experimentation, risk-taking, variation, play, discovery, and innovation, all of which are aimed at discovering new possibilities. Even though these activities promise substantial ultimate returns, they are uncertain, separated from the present by time, and often costly in the short run (Levinthal & March, 1993). Exploitation, as its name suggests, is the process of using existing knowledge to refine and improve what is already known, through activities like efficiency, production, and implementation, which typically yields more certain, short-term rewards . The crux is that exploration and exploitation are both essential to organisational survival but compete with scarce resources, and accommodation between them is full of trade-offs.

March (1991) points out that over-reliance on exploitation locks organisations into poorer equilibria since expertise at routine tasks is self-sustaining, discouraging experimentation and constraining future adaptability. This syndrome is inextricably bound up with what Levinthal & March (1993) later term "learning myopia", the tendency to prefer short-run, certain gains to uncertain but possibly greater rewards. Conversely, such systems that overemphasize exploration stand the chance of paying experimentation costs without reaping sufficient returns and being left with a wasteland of inadequately developed concepts and a lack of distinctive capabilities.

The model also recognizes the asymmetry in space and time of the two modes: exploitation yields proximate, near-term payoffs, while exploration yields more dispersed, future, and uncertain payoffs. That is why adaptive processes tend to prefer exploitation at the expense of exploration, making organisations successful in the short run but insecure in the long run (March, 1991). March deepens his model with simulations of mutual learning by members and organisational codes, revealing how too rapid convergence on existing norms can suppress beneficial diversity and reduce the long-term knowledge base of the organisation.

Subsequent research has extended this model to the theory of organisational ambidexterity, the capacity to trade off exploration and exploitation in a dynamic way (Vera & Crossan, 2004; Alerasoul et al., 2022). But the underlying dilemma that March still describes is still present: how to sustain exploration in the face of adaptive pressures that naturally prefer exploitation. The tension between the known payoff of exploitation and the uncertain but required payback of exploration continues to define the strategic dilemmas of organisational learning.

However, with the advent of Machine Learning (ML) systems that this theoretical construct has been afforded a new dimension, with AI now being recognized as a novel learning agent that can help balance this fine margin between exploration and exploitation (Kane & Alavi, 2007). Dynamic Capabilities Theory adds further depth to this conversation by proposing that organisations are able to intentionally reconfigure their capabilities in order to cope with shifting surroundings, thus affecting the dynamic relationship between exploration and exploitation (Zollo & Winter, 2002).

The 4I Framework

The *4I* approach is currently a foundational framework in the theory of OL since it conceptualizes learning as a dynamic and recursive process that arises out of four interrelated subprocesses: intuiting, interpreting, integrating, and institutionalizing (Crossan et al., 1999; Vera & Crossan, 2004; Schilling & Kluge, 2009). Each subprocess is embedded in distinct ontological levels–individual, group, and organisation–hence providing a multi-level perspective of learning as it emerges and develops. Intuiting occurs at the individual level and is largely subconscious, wherein new intuition and perception emerge without being consciously created. Interpreting bridges the individual with the group because such insights are expressed and communicated through words, dialogue, and engagement. Integrating moves the process to the organisational and group levels, since groups collaboratively build mutual meanings, coordinate action, and transform individual intuition to collective practice (Crossan et al., 1999; Schilling & Kluge, 2009). Institutionalizing is the final occurrence at the organisational level, where learning is embedded in routines, systems, structures, and strategies and becomes organisational memory, shaping future action.

One of the distinctive features of this framework is its recursive nature, which underscores the continuous feedback loops within and between the layers. This points to the inherent complexity of OL, illustrating how learning flows upward from individuals to groups and organisations but also downward, since organisational routines and norms shape subsequent cognition and action (Crossan et al., 1999; Vera & Crossan, 2004; Lloria & Moreno-Luzon, 2014). By emphasizing this two-way movement, the model illustrates not only how knowledge consolidates and dissipates across levels but also how action and cognition are inseparable in learning (Crossan et al., 1999; Vera & Crossan, 2004).

Despite its expansive scope, there have been academic notes that the 4I model is limited. Its aspiration to combine different perspectives leaves theoretical tensions sometimes on the horizon, and additional refinement is needed to move toward a theory of OL widely recognized (Crossan et al., 1999; Örtenblad, 2017; Alerasoul et al., 2022). Nonetheless, its contribution is foundational: combining processes and levels, the 4I framework still provides one of the most influential and widely employed models for describing organisational learning and transformation.

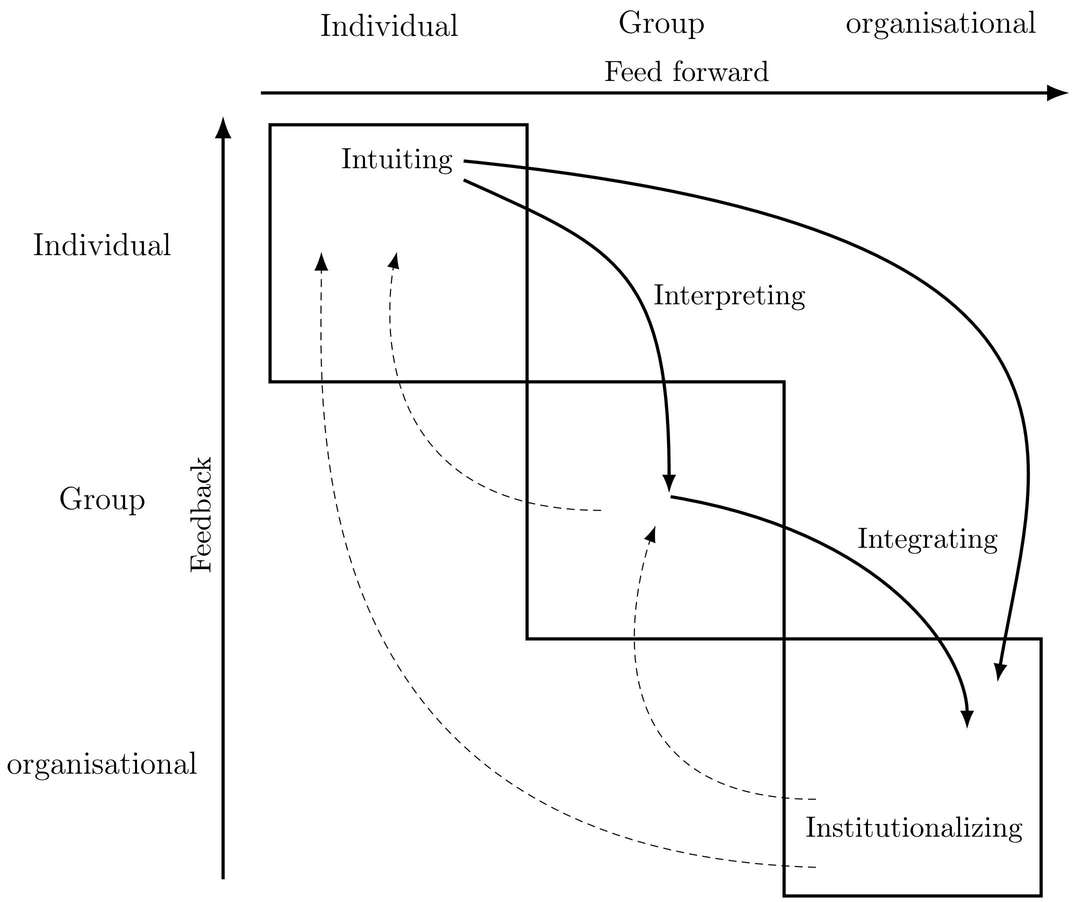


Figure 2.7: Organisational Learning as a Dynamic Process (4I framework; Crossan, Lane & White, 1999).

Generally speaking, these pioneering models collectively place the recursive and multidimensional character of organisational Learning at the center but each of them does so from a distinct theoretical perspective. While Argyris & Schön (1978) stress the intensity of learning through challenging underlying assumptions, March (1991) puts the strategic trade-off between exploration and exploitation in the center. Crossan et al.'s (1999) 4I model integrates these conclusions by putting learning simultaneously both across processes and levels, thereby giving a more systemic perspective. But the persistence of theoretical tensions among these models indicates that OL is not a single theory but rather a pluralistic body of work whereby various lenses illuminate different aspects of the same thing. It is this pluralism that makes OL a fertile ground for extensions in the modern age: by analyzing how emerging technologies such as AI interact with, enable, or complicate these dynamics, we can observe the manner in which OL becomes a strategic advantage that enables innovation and organisational transformation.

2.2.3. Organisational Learning Capability (OLC) and Measurement

While the theoretical frameworks mentioned before (Argyris & Schön, 1978; March, 1991; Crossan et al., 1999) outline the way that organisational learning happens, they do little to resolve the practical question of how to assess the extent to which an organisation is really able to learn. This is where the idea of OLC enters. OLC has been a long-standing creator of sustainable competitive advantage and a key driver of long-term organisational performance (Hult & Ferrell, 1997; Alegre & Chiva, 2008). Although abstract OL models allow low space for concrete practice, routines, or competencies, OLC is a more process-directed idea: it points to the definite organisational and managerial practices, routines, and competencies actively creating the process of learning, ranging from knowledge acquisition and transfer to integration and application (Goh & Richards, 1997; Jerez-Gomez et al., 2005; Onağ et al., 2014). In this sense, OLC is the facilitator between OL theoretical propositions and their empirical, measurable representations.

Dimensions of OLC

With its strategic importance, one of the long-standing issues with OLC is that there has been a paucity of consistency regarding its dimensions. Different studies have conceptualized OLC differently, suggesting anything between four and eleven dimensions. For instance, Chiva et al. (2007) determine five essential dimensions: experimentation, risk-taking, dialogue, participative decision-making, and external interaction.

In their turn, Goh & Richards (1997) emphasize purpose clarity, experimentation, risk-taking, knowledge sharing, and collaboration. On the other hand, Onağ et al. (2014) propose an expanded model consisting of eleven dimensions, including leadership commitment, empowerment, systemic perspective, and knowledge transfer. Such diversity is a reflection of the very nature of OL itself: rather than disqualifying the notion, it reinforces that the capability for learning is context-specific and multi-faceted. Still, the absence of a common template also makes comparison of results across research difficult and operationalization of OLC consistent.

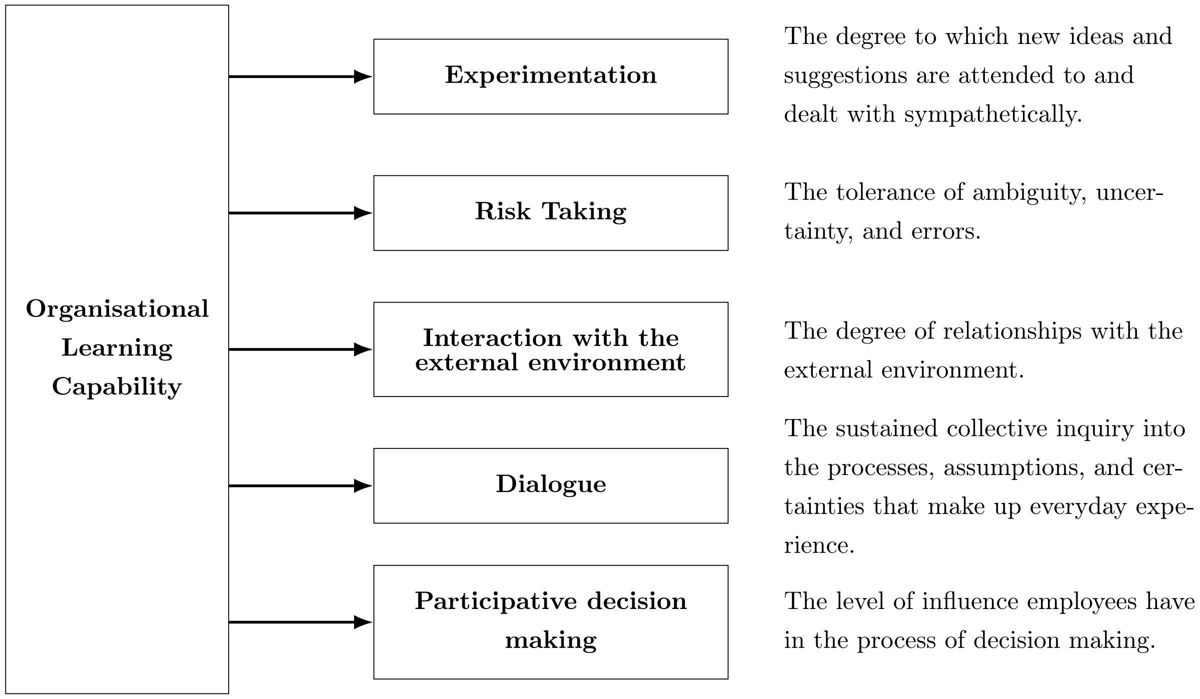


Figure 2.8: Organisational Learning Capability and its core dimensions (Chiva et al., 2007).

Measurement Scales and Reliability

In response to this fragmentation, some scholars have sought to provide integrative measurement tools. Lloria & Moreno-Luzon (2014) developed and validated an 18-item scale organized around five dimensions: ontological levels of learning, modes of knowledge conversion, subprocesses of learning, exploration versus exploitation, and feedback/feedforward flows. Their empirical analysis revealed four coherent factors: the effectiveness of information systems, the existence of a framework for consensus, procedures for the institutionalization and broadening of knowledge, and forms of management and the genesis of knowledge. Similarly, the Organisational Learning Survey (OLS) developed by Goh & Richards (1997) has been widely used to assess managerial and organisational practices that underpin learning. These instruments demonstrate good levels of reliability and validity, yet remain bound to specific conceptual assumptions. They thus represent steps forward but not definitive solutions.

Limitations and Theoretical Debates

Despite these advances, OLC research continues to face conceptual and methodological challenges. First, the lack of a universally accepted definition of OLC leads to persistent fragmentation (Onağ et al., 2014; Lloria & Moreno-Luzon, 2014). Second, as Tsang

(1997) noted, much of the literature conflates the descriptive perspective of OL (how organisations learn) with the prescriptive ideal of the learning organisation (how they should learn), which complicates the design and application of measurement instruments. Moreover, several studies implicitly assume that OLC naturally translates into learning outcomes without sufficiently testing this causal relationship (Alegre et al., 2011).

From a broader perspective, OLC can be interpreted as the operational layer that links theoretical models of OL to organisational outcomes such as innovation and renewal. As Jerez-Gomez et al. (2005) and Alegre et al. (2011) argue, OLC acts as a precursor to absorptive capacity and dynamic capabilities–two constructs widely regarded as foundational for innovation. In this sense, OLC does not merely describe the presence of favorable conditions for learning but also signals the potential of organisations to transform learning into new capabilities. This positions OLC as a natural conceptual bridge toward the next section, where the interplay between OL, knowledge creation, and innovation will be explored in detail.

2.2.4. Enabling Factors and Barriers to Organisational Learning

The effective realization of OL within organisations is a complex outcome stemming from the dynamic interplay between various facilitating factors and impeding barriers. A critical analysis of these elements, encompassing organisational culture, leadership styles, structural configurations, and the role of information technologies (including Artificial Intelligence), is fundamental to understanding how organisations can optimally enhance their learning processes. This understanding provides a crucial context for evaluating the integration of advanced technologies to foster a continuous learning environment.

The Role of organisational Culture

organisational culture plays a significant influence on whether OL is promoted or restricted. organisational culture promoting constructive learning, open communication, and broad knowledge sharing plays a strong role as an organisational learning catalyst (Choi, 2000; Alerasoul et al., 2022). Specifically, an innovation-oriented culture can be built by HR practices that support generating and sharing new ideas in the organisation (Alerasoul et al., 2022; Dombrowski et al., 2007). Likewise, a "knowledge-centered culture" (KCC) increases the relationship between transformational leadership and knowledge-sharing behaviors, thereby increasing the overall learning capacity of the organisation (Rehman et al., 2021).
Culture has also traditionally been seen as a key enabler of KM (Choi, 2000; Gold et

al., 2001; Dekoulou & Trivellas, 2017), which–as noted in the above section–is inherently associated with OL (Idrees et al., 2023; Antunes & Pinheiro, 2020; Obeso et al., 2020). Corporation and academic life evidence confirms that organisational culture provides the underlying norms and values that support cooperation, questioning, and experimentation, otherwise suppressing them (Goh & Richards, 1997; Berson et al., 2006; Dekoulou & Trivellas, 2017).

To this end, culture needs to be seen as not a causal but a key motivator of OL, impacting the factors under which knowledge can be developed, transferred, and transformed into an innovator.

The Impact of Leadership

Leadership is also another essential support column for OL success. Leaders play a crucial role in developing learning environments and enabling employees to develop continuously competencies (Vera & Crossan, 2004; Bogale et al., 2025; Imane & Fatima, 2025). Of the various styles, Transformational Leadership (TL) has been invariably effective in creating OLC, primarily through facilitating proactive knowledge-sharing behavior (Vera & Crossan, 2004; Rehman et al., 2021; Alerasoul et al., 2022). Empirical evidence confirms such an outlook: Noruzy et al. (2013), e.g., demonstrated that TL positively affects OL, KM, organisational innovation, and overall firm performance (Abbasi & Zamani-Miandashti, 2013; Bogale et al., 2025).

Simultaneously, though, it must be understood that not all forms of leadership are enabling. Authoritarian modes or reliance on management-by-exception can indeed inhibit learning by stifling the provision of new ideas and promoting passive conformity with established patterns of behavior (Vera & Crossan, 2004). By contrast, visionary leadership has also been found to be a principal enabler, providing organisations with a sense of future direction that is capable of fuelling collective learning and renewal (Bianchi et al., 2021; Alerasoul et al., 2022).

Together, these results validate that leadership profoundly affects an organisation's learning capacity, affecting not only the behavior and practice of individuals but also the organisational capacity for development and adaptability as a whole (Bogale et al., 2025).

The Configuration of organisational Structure

organisational structure design is a central influence on OL effectiveness, as it should actively facilitate the mechanisms by which organisations acquire, share, and codify new knowledge (Gold et al., 2001; Dekoulou & Trivellas, 2017). Perhaps the oldest debate in the literature is about what structural form is best suited to learning. Conversely, organic structures, characterized by open communication, adaptability, flexibility, and flatter structures, tend to be associated with stronger learning outcomes (Dekoulou & Trivellas, 2017; Örtenblad, 2017). Conversely, in certain circumstances–e.g., in subsidiaries or those dependent on highly standardized processes–bureaucratic and formalized configurations might be more appropriate, less because they can promote learning in itself, but more because they can guarantee the regular application of change efforts resulting from the learning process (Hakala et al., 2016).

Besides the first-order organisational design, secondary forms like project teams, cross-functional departments, or ad hoc networks often shoulder the responsibility of managing inherent tension between exploratory and exploitative learning (Crossan et al., 1999; Vera & Crossan, 2004). Also, central structural dimensions have immediate impacts on KM and OL performance. Formalization reflects the extent to which choices and procedures are subject to open regulation; centralization versus decentralization governs decision-making authority allocation; and specialization determines how work tasks and duties are allocated across individuals and groups (Choi, 2000; Gold et al., 2001; Dekoulou & Trivellas, 2017).

Taken together, these results suggest that there is no one best design. Instead, there must be a context-sensitive and sensitive solution to organizing one that balances the degree of formalization, centralization, and specialization with the particular learning needs of the organisation and strategic environment.

The Role of Information Technologies (IT) and AI

Historically, Information Technologies (IT) were typically understood to be support tools that enabled human learning mechanisms (Robey et al., 2000; Alavi & Leidner, 2001; Argote & Miron-Spektor, 2011). Literature consistently raised the point that IT could either be used as an enabler or a barrier to OL depending on whether or not it was adopted and how it was implemented into the organisational environment (Robey et al., 2000; Al-Emran et al., 2018).

The introduction of AI has drastically changed this perception. Rather than being engineered as a secondary device, AI is now considered a different type of "organisational learning agent" that can learn on its own and directly add to the organisational knowledge store. Here, the AI systems themselves can be regarded as new organisational learners cooperating with human actors in influencing hybrid human–machine learning processes (Argote & Miron-Spektor, 2011; Sturm et al., 2021; Rolf et al., 2023).

More specifically, Machine Learning (ML) innovation–already in the development and training phase, even before productive use–provokes organisational learning by encouraging reflection, accommodation, and generation of new knowledge by human professionals (Sturm et al., 2021; Rolf et al., 2023). ML systems may be employed as tacit knowledge repositories and as tacit knowledge externalization mechanisms, solving one of the perennial problems in KM (Nonaka, 1994; Rolf et al., 2023). Then comes Generative AI (GenAI) and, most significantly, Large Language Models (LLMs), which significantly expand the potential scope of knowledge availability. They facilitate the interfacing of complex information, the generation of personalized content, and the personalization of interactions (Pataranutaporn et al., 2021; Dwivedi et al., 2023; Kirchner et al., 2025).

At the same time, AI supports a wide variety of KMP through advanced analytics, automation, and decision-making support (Pournader et al., 2021; Rolf et al., 2023; Jackson et al., 2024). These effects give evidence that AI is not only a facilitator of OL but also a force multiplier in amplifying the routines and mechanisms through which companies learn and transform knowledge into innovation.

Yet, a major drawback of research that currently exists is the widespread emphasis on the use of AI-based systems relative to learning dynamics embedded in their design. The perspective neglects the fact that the development, training, and calibration of ML systems themselves establish learning processes within organisations (Alavi & Leidner, 2001; Argote & Miron-Spektor, 2011; Robey et al., 2000). Thus, while the potential of AI as an facilitator of OL is important, the necessity for deeper and broader insights into where and how AI is integrated in the organisational learning system is still urgent (Basten & Haamann, 2018; Rolf et al., 2023).

Barriers to organisational Learning

Apart from these facilitation factors, there are multiple barriers to influence the effectiveness of OL. Schilling & Kluge (2009) classify such barriers into three general categories: *actional-personal*, *structural-organisational*, and *societal-environmental* barriers (Schilling & Kluge, 2009; Bianchi et al., 2021). Some of the most widely referenced barriers are resistance to change as well as the lack of relevant skills in the workforce, both of which inhibit the absorption and embedding of novel knowledge (Alerasoul et al., 2022).

Another and particularly ingrained challenge is "learning myopia", a preference for exploiting familiar knowledge rather than expanding new possibilities (Levinthal & March, 1993; Denrell & March, 2001; Patky, 2020). This exploration-exploitation asymmetry–already noted in March's (1991) initial model–not only constraints learning, but it is also a direct barrier to innovation.

In addition, barriers often emerge because of poor cultural conditions and the absence of participatory or transformational leadership patterns to bring forth collective learning dynamics (Alerasoul et al., 2022; Bianchi et al., 2021). Finally, management of tacit knowledge continues to pose one of the most persistent challenges: its immeasurability (Nonaka, 1994; Rolf et al., 2023) and lack of high-level frameworks for capturing and integrating it (Shahzadi et al., 2024) continue to represent key obstacles to building a systematic and cumulative organisational knowledge base.

2.3. Bridging KM and Innovation: the Central Role of OL

The relationship between KM and OL has been widely recognized as a central mechanism in shaping organisational competitiveness, innovation and broader value creation. OL is widely considered a key outcome or an intertwined process that enables KM to generate strategic value (Antunes & Pinheiro, 2020; Obeso et al., 2020; Idrees et al., 2023).
From a systemic perspective, KM is conceptualized as an essential input, while OL functions as a critical process that ultimately yields innovation and other value-creating outcomes at the organisational level (Liao & Wu, 2010). This view is supported by the recognition that KM practices, inherently focused on knowledge creation and transfer activities, form the operational bedrock upon which OL processes are built (Barão et al., 2017). More broadly, this perspective is consistent with the knowledge-based view of the firm, which regards knowledge as the primary source of competitiveness in contemporary markets (Grant, 1996). Indeed, OL itself is defined as the inherent ability of an organisation to modify its procedures and actions in response to accumulated experiences and newly acquired information, a process that necessitates the continuous development of its knowledge base (Argyris & Schön, 1978).

This interdependence becomes particularly evident when considering KMP–acquisition, creation, sharing, codification, storage and application–which directly support organisational learning dynamics (Esterhuizen et al., 2012; Rolf et al., 2023; Jackson et al., 2024). The SECI model (Nonaka, 1994; Nonaka & Takeuchi, 1995) and the 4I framework (Crossan et al., 1999; Vera & Crossan, 2004; Schilling & Kluge, 2009) exemplify this complementarity, showing how knowledge conversion and recursive learning cycles transform individual and group insights into organisational memory and, ultimately, into coordinated action.
Within this architecture, OL emerges as a fundamental bridge between KM and the development of organisational capabilities that sustain innovation and value creation over time. Empirical evidence consistently positions OL as a critical driver of innovation, since it enables the continuous acquisition, conversion and utilization of new knowledge, thereby

fostering adaptive capacity and creative renewal (Esterhuizen et al., 2012; Idrees et al., 2023; Bogale et al., 2025). Within this broader perspective, innovation capability can be understood as a key mediating construct linking OL with firm performance, competitiveness and value-creation outcomes (Liao & Wu, 2010; Costa & Monteiro, 2016; Bogale et al., 2025). This implies that while KM provides the necessary knowledge inputs, it is through the dynamic processes of OL that these inputs are transformed and integrated, leading not only to innovative outputs and the formation of new capabilities, but also to more general patterns of organisational value creation (Antunes & Pinheiro, 2020).

OLC has therefore been theorised as a critical enabler of absorptive capacity and dynamic capabilities, supporting corporate renewal and long-term adaptation (Jerez-Gomez et al., 2005; Alegre & Chiva, 2008; Alegre et al., 2011). OL itself can thus be understood as a dynamic capability that fosters strategic flexibility, agility and the ability to reconfigure resources in turbulent environments (Hung et al., 2011; Santos-Vijande et al., 2012; Alerasoul et al., 2022).

The integrative view that positions OL as a bridge is not without theoretical debate. Some scholars have argued for a conceptual absorption of OL into KM (Castaneda et al., 2018), portraying it as a subset of knowledge practices. However, frameworks such as the 4I model reaffirm OL's distinctive role in linking cognition and action (Crossan et al., 1999), highlighting that while KM provides the necessary structure and "raw materials", it is OL that drives the actual transformation of this knowledge into organisational change. In this sense, KM can be seen as the provider of inputs, whereas OL functions as the transformative engine that converts these resources into actionable insights and value-creating organisational capabilities–including, but not limited to, innovation capabilities–an aspect that becomes particularly salient in the era of Artificial Intelligence, where AI systems are increasingly regarded as novel organisational learners (Argote & Miron-Spektor, 2011; Rolf et al., 2023).

2.4. Artificial Intelligence (AI)

Building upon the foundational analysis of KM processes and the mechanisms of OL, this section focuses on AI as the pivotal technological paradigm currently reshaping organisational knowledge structures and strategic capabilities (Olan et al., 2022; Jarrahi et al., 2023; Han et al., 2025). The escalating global digital transformation has cemented AI's role, particularly in driving corporate innovation and industrial modernization (Han et al., 2025). Understanding the dynamics of AI adoption, its symbiotic relationship with human capital, and its influence on KM pathways is paramount for comprehending how modern enterprises adapt, develop new innovation capabilities, and secure sustained competitive advantage (Olan et al., 2022; Jarrahi et al., 2023).

2.4.1. Definition and Conceptualization of AI

AI is commonly defined as the capability of a system to interpret external data accurately, learn autonomously from that data, and subsequently apply the acquired knowledge to pursue specific goals through adaptive behaviour (Kaplan & Haenlein, 2019; Pournader et al., 2021). The essence of AI research lies in constructing machines that can reason, learn, and act in ways that emulate aspects of human intelligence (Mohammad et al., 2022; Mancuso et al., 2025). Within the managerial and organisational domains, AI is frequently conceptualized not only as a set of Information and Communication Technologies (ICT) but as a transformative technological paradigm. It is designed to replicate cognitive processes with the objective of enhancing job performance, improving efficiency, and fostering economic growth (Pournader et al., 2021; Olan et al., 2022).

AI systems interact with their environments through multiple modalities–text, video, or audio–by leveraging technologies such as speech recognition, computer vision, and Natural Language Processing (NLP) (Pournader et al., 2021; Cannas et al., 2024). These capabilities are underpinned by advanced computational techniques, including Machine Learning (ML), Deep Learning (DL), and neural networks, which enable organisations to extract patterns from vast and complex datasets, ultimately supporting enhanced predictive and prescriptive decision-making (Pournader et al., 2021; Nakash and Bolisani, 2025).

The literature identifies a set of operational capabilities that define AI's strategic utility: Learning, Perception, Prediction, Interaction, Adaptation, and Reasoning (Samoili et al., 2021; Pournader et al., 2021). Together, these functions position AI as a powerful technological enabler, capable of augmenting and, in some cases, autonomously executing decision-making processes. The ultimate aspiration in organisational contexts is to achieve computational agents with a high degree of autonomy, thereby reshaping not only operational routines but also strategic decision-making and innovation pathways (Gibson et al., 2023).

2.4.2. Impact of AI in organisations: Transformation of Processes, Roles and Practices

The implementation of AI has a profound and pervasive effect on organisations, reshaping processes, roles, and practices across nearly every dimension of activity. Its transformative influence is particularly evident in relation to KMP, decision support, and operational efficiency (Jarrahi et al., 2023; Al Alawi and Al Qumaish, 2024; Cannas et al., 2024). By enabling the large-scale collection, analysis, and interpretation of data–especially in areas that rely on pattern recognition and prediction–AI enhances decision-making and fundamentally redefines the scope and capacity of modern Knowledge Management Systems (KMS). These systems become adaptive and elastic, equipping organisations with the flexibility to respond to dynamic and uncertain market conditions (Barão et al., 2017; Al Alawi and Al Qumaish, 2024).

A closer examination of the six core KMP reveals the specific ways in which AI alters the knowledge landscape:

1. **Knowledge Acquisition (KA)**: AI significantly strengthens acquisition by automating the processing of large and complex datasets. Through Machine Learning (ML), DL, and Natural Language Processing (NLP), organisations can identify hidden patterns, extract critical insights, and even capture tacit elements of knowledge from unstructured sources (Jarrahi et al., 2023; Nakash and Bolisani, 2025). This represents a decisive departure from traditional human-driven acquisition, reducing reliance on individual effort while expanding both speed and scope (Kirchner et al., 2025).

2. **Knowledge Creation (KC)**: AI serves as a powerful accelerator, enabling organisations to analyze vast datasets to identify and accelerate optimal outcomes, directly leading to the generation of new knowledge (Kirchner et al., 2025; Rezaei, 2025). Generative AI (GenAI) augments cognitive functions and information processing, fostering both individual and organisational learning (Alavi et al., 2024; Kirchner et al., 2025). The activity of prompt engineering is recognized as a new, distinct form of knowledge creation facilitated by GenAI, where skilled human input guides the generation of complex content (Kirchner et al., 2025; Zhang et al., 2025).

3. **Knowledge Storage and Codification (KSC)**: AI facilitates the storage and retrieval of knowledge through automated classification, reducing the barriers of volume and complexity (Mohammad et al., 2022; Nakash and Bolisani, 2025). Unlike human memory, AI-based systems retain information without degradation over time, thereby reinforcing organisational memory (Jarrahi et al., 2023). Nevertheless, research investigating the precise relationship between AI applications and storage practices remains underdeveloped, limiting the theoretical and empirical understanding of this linkage (Mohammad et al., 2022).

4. **Knowledge Sharing and Transfer (KST)**: AI enhances the dissemination of knowledge across organisational boundaries, promoting real-time access, secure dis-

tribution, and cross-functional collaboration (Jarrahi et al., 2023; Rezaei, 2025). AI-enabled platforms not only encourage participation in sharing activities (Olan et al., 2022) but also mitigate barriers related to individual motivation and ability, creating alternative mechanisms that substitute or complement human interaction (Kirchner et al., 2025; Standaert & Andreis, 2026). This is particularly valuable in environments where traditional collaboration practices are hindered, offering new opportunities for process innovation.

5. **Knowledge Application (KAPP)**: This phase is significantly enhanced by AI, which supports the translation of knowledge into practice and enables more effective and sophisticated decision-making processes (Mohammad et al., 2022). AI leverages real-time and historical data with minimal human involvement (Cannas et al., 2024; Rezaei, 2025;). The application of predictive data analytics, enabled by AI, transforms organisational knowledge and adds strategic value (Barão et al., 2017; Mancuso et al., 2025).

Importantly, AI's impact is not confined to supporting human-driven learning processes. Recent scholarship increasingly frames AI as an autonomous *organisational learning agent* that operates alongside humans, contributing its own knowledge to the organisational base (Argote & Miron-Spektor, 2011; Sturm et al., 2021; Rolf et al., 2023). The very processes of designing and deploying ML systems act as rich learning contexts, fostering interdisciplinary knowledge exchange and driving collective expertise (Vetter et al., 2023). In this way, AI simultaneously amplifies human learning and generates new organisational knowledge, reinforcing the idea of a hybrid learning environment where humans and machines co-evolve.

From this perspective, AI emerges as more than a technological tool: it becomes a structural enabler of organisational Learning, strengthening individual and team learning capabilities and, ultimately, enhancing Corporate Innovation Performance (CIP) (Han et al., 2025). Its dual role–facilitating KMP while also functioning as an independent learner–positions AI as a catalyst that reconfigures the very mechanisms through which organisations create, share, and apply knowledge.

2.4.3. Relationship between AI and Human Capital

The deep integration of AI into organisational contexts increasingly requires a strategic emphasis on the human–AI partnership, which fundamentally redefines human roles and responsibilities (Olan et al., 2022; Jarrahi et al., 2023). The prevailing view in the literature is that the most sustainable and effective configuration lies not in full automation, but in complementary systems where AI technologies augment, rather than replace, human knowledge processes (Olan et al., 2022). While AI provides unparalleled capabilities in amplifying human cognition and processing capacity (Alavi et al., 2024; Mancuso et al., 2025), human capital remains indispensable, particularly in the complex task of capturing and interpreting Tacit Knowledge (TK). AI may facilitate this process–for example, by externalizing tacit insights through decision trees or other models–but it primarily serves as a stimulus for reflection and articulation, reinforcing the centrality of human interpretation in organisational learning (Jarrahi et al., 2023).

A particularly relevant advancement in supporting this partnership is the rise of Explainable AI (XAI). Unlike traditional "black-box" models, XAI emphasizes transparency, interpretability, and justifiability. These attributes are critical for building trust in AI systems, but more importantly, they enable employees to critically evaluate and integrate machine-generated outputs with their own expertise. In innovation-oriented contexts, XAI provides analytical support, yet human judgment remains the decisive factor in synthesizing decisions and pursuing creative directions (Mancuso et al., 2025). By also addressing limitations in knowledge sharing–such as motivational or cognitive barriers–AI assumes a complementary role in facilitating more effective internal knowledge flows (Standaert & Andreis, 2026).

However, this partnership also brings new demands. The successful deployment of advanced AI systems, particularly Generative AI, requires the development of new competencies within the workforce. Employees are not only expected to interpret and refine AI-generated outputs but must also master practices such as prompt engineering to generate meaningful inputs and critically assess the reliability of results (Kirchner et al., 2025). This underscores that AI adoption cannot be separated from continuous learning initiatives, advanced data-literacy training, and adaptive change management practices (Shahzadi et al., 2024). Moreover, the ethical dimension of this collaboration–ranging from bias awareness to responsible data usage–requires constant attention, further reinforcing the inseparability of technical and human capabilities in shaping organisational learning and innovation (Kirchner et al., 2025).

Taken together, this literature highlights that AI's contribution to organisational learning and innovation is contingent on a symbiotic partnership with human actors. While AI provides scale, speed, and novel modes of knowledge codification, it is ultimately through human oversight, interpretation, and capability development that organisations can fully harness its transformative potential.

2.4.4. Expected and Observed Results, Barriers and Facilitators of AI Adoption

The organisational outcomes of AI adoption are both anticipated and empirically validated to be largely positive. Across the literature, AI is consistently identified as a key driver of corporate innovation and industrial modernization, contributing directly to enhanced competitiveness. Recent empirical evidence confirms a strong positive association between AI adoption and CIP (Han et al., 2025). Particularly in high-tech domains such as Operations and Supply Chain Management (OSCM), AI has been shown to reduce operational costs and lead times, while simultaneously improving service levels, quality, safety, and sustainability (Cannas et al., 2024). More broadly, AI is linked to greater organisational effectiveness, efficiency, and productivity, primarily by identifying redundancies and optimizing the allocation of scarce resources (Mohammad et al., 2022; Olan et al., 2022).

Nevertheless, the translation of this potential into tangible results is far from automatic. The successful implementation of AI is frequently obstructed by a range of barriers that can be broadly categorized as technical, organisational-strategic, human, and financial (Shahzadi et al., 2024). On the *technical* side, AI requires massive volumes of clean, high-quality data for training and testing algorithms, a requirement that many firms struggle to meet. *organisational* and *strategic obstacles* often stem from the absence of a clear AI strategy, insufficient top-management commitment, and industry fragmentation, all of which limit alignment between AI projects and broader strategic priorities (Cannas et al., 2024). *Human barriers* remain particularly salient: there is both a shortage of specialized AI talent and a pervasive lack of trust in algorithmic outputs, which undermines adoption (Shahzadi et al., 2024). *Financially*, firms face the dual challenge of substantial upfront investment in technological infrastructure and skills development, combined with lingering uncertainty about the long-term economic returns of AI initiatives (Cannas et al., 2024).

At the same time, several *facilitating factors* can significantly enhance the effectiveness of AI adoption. Among these, OLC emerges as a crucial moderator, amplifying the positive relationship between AI adoption and CIP (Han et al., 2025). This finding underscores that the mere acquisition of AI technologies is insufficient; their successful integration depends on the degree to which they stimulate and reinforce learning processes across the organisation (Leoni et al., 2022). In other words, AI's transformative potential is only realized when it is embedded within organisational practices that promote KMPs. Additional enablers include strong and committed leadership, robust managerial practices, and an organisational culture that not only supports innovation but is also open to tech-

nological experimentation and change (Olan et al., 2022; Shahzadi et al., 2024).
Taken together, this literature highlights a critical paradox. While the benefits of AI adoption are well-documented, the gap between expected outcomes and realized impact often hinges on the interplay between technological deployment and organisational learning dynamics. This observation reinforces the central argument of this thesis: AI should not be understood merely as a technological tool, but rather as a catalyst that, when combined with strong OLC and supportive contextual factors, enables the emergence of new capabilities for innovation.

2.4.5. Theoretical Frameworks for AI Adoption and Use

The Technology Acceptance Model (TAM) remains one of the most widely applied frameworks to explain technology adoption at the individual level. Developed by Davis (1989), TAM argues that actual technology use is primarily determined by the user's behavioral intention, itself shaped by two key constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (Davis et al., 1989; Legris et al., 2003; King & He, 2006). PU reflects the extent to which individuals believe that technology enhances their work performance, while PEOU refers to the degree to which the technology is perceived as effortless to use. Although TAM has been extensively validated across digital technologies, its explanatory power in the era of Artificial Intelligence is increasingly debated, since AI adoption often entails more complex social, ethical, and emotional dynamics than those captured by PU and PEOU alone.
Addressing the limitations of the previous model, Gursoy et al. (2019) proposed the AI Device Use Acceptance (AIDUA) model, a theoretical advancement specifically conceived to capture the psychological, social, and emotional dimensions that characterize human interaction with AI systems. Unlike traditional frameworks grounded primarily in rational and cognitive evaluations, AIDUA integrates affective and social determinants into a dynamic three-stage appraisal process, thus offering a more comprehensive interpretation of how individuals cognitively assess, emotionally experience, and ultimately decide whether to accept or reject AI technologies. The model's first stage, the *Primary Appraisal*, concerns the individual's initial emotional and social response to AI. Here, constructs such as social influence, hedonic motivation, and anthropomorphism shape the user's intuitive perception of the technology. This phase reflects how individuals interpret AI not merely as a functional tool but as an entity situated within social and symbolic contexts. The *Secondary Appraisal* phase moves toward a more deliberate and reasoned evaluation, where individuals cognitively assess the benefits and demands associated with using AI. It revolves around the constructs of performance expectancy and perceived effort

expectancy, capturing respectively the extent to which AI is believed to improve efficiency and the perceived ease or complexity of its use. This transition from affective to cognitive appraisal is crucial, as it bridges the intuitive and rational dimensions of technology acceptance. The final *Outcome Stage* synthesizes these prior evaluations through the mediating role of emotion. Emotions operate as a central mechanism translating both affective and cognitive appraisals into behavioral outcomes, determining whether individuals develop a willingness to accept AI or, conversely, an objection toward its use. Positive emotional responses–such as curiosity, trust, or enthusiasm–strengthen acceptance intentions, while negative emotions–such as fear, discomfort, or ethical unease–can generate resistance. Empirical testing revealed six critical predictors of AI acceptance: performance efficacy, hedonic motivation, anthropomorphism, social influence, facilitating conditions, and emotion. By integrating cognitive, social, and affective dimensions, AIDUA extends TAM and provides a more comprehensive lens for explaining AI adoption in organisational contexts, where emotional reactions and perceived human-likeness often play a decisive role.

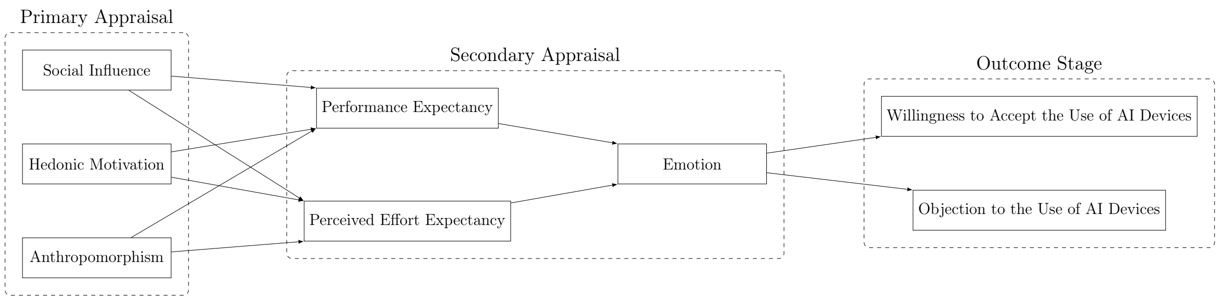


Figure 2.9: AIDUA model (structure only) (Gursoy et al., 2019).

At the organisational level, the Technology-organisation-Environment (TOE) framework (Tornatzky & Fleischer, 1990; Baker, 2011) offers a complementary perspective. TOE conceptualizes AI adoption as a process influenced simultaneously by technological characteristics (e.g., complexity, compatibility), organisational attributes (e.g., culture, managerial commitment, internal capabilities), and environmental pressures (e.g., competition, regulation, market dynamics). More recent applications extend the framework to include explicitly human drivers, acknowledging that workforce skills, leadership quality, and organisational culture are indispensable for the successful integration of AI (Shahzadi et al., 2024; Kirchner et al., 2025). By situating AI adoption within its broader organisational and environmental context, TOE highlights the structural and cultural conditions that either enable or constrain the translation of AI capabilities into strategic value.

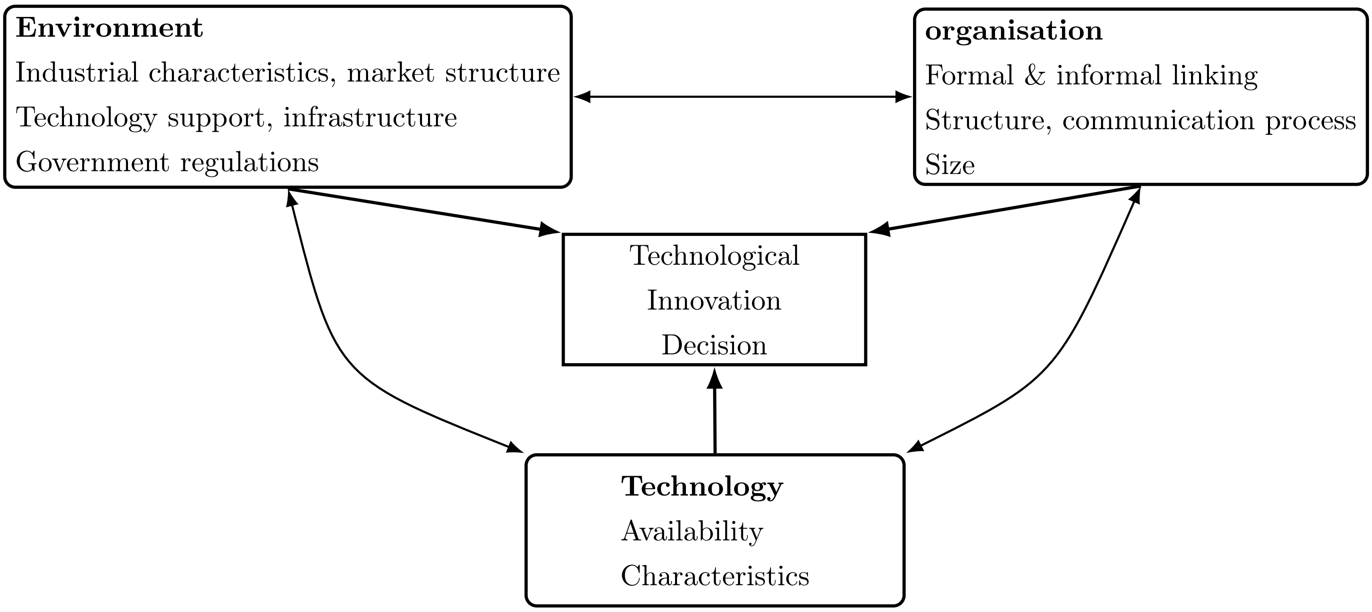


Figure 2.10: TOE framework (Tornatzky & Fleischer, 1990) applied to technological innovation decisions.

Finally, Gibson et al. (2023) advance a three-level model that integrates diverse learning theories to explain how AI can foster learning across scales. The framework differentiates between the micro level (individual learners), the meso level (teams and communities of practice), and the macro level (historical and socio-cultural systems), showing how information aggregates and dissipates across interconnected layers. In organisational contexts, this model underscores AI's potential not only to optimize operational processes but also to catalyze learning and knowledge flows across multiple ontological levels, reinforcing its role as both a technological enabler and a learning agent.

Phases or states of Piaget–Kauffman with Keller dynamics	**The focus of AI systems co-participating in learning processes**
Disequilibration-causes or mediates attention	AI personalized recommendations
Assimilation-causes or mediates relevance	AI learning analytics
Accommodation-causes or mediates confidence	AI pedagogical interventions
Equilibration-causes or mediates satisfaction	AI formative and summative feedback

Table 2.2: Four roles of AI at the micro (individual) level. (Gibson et al., 2023)

Contexts of Bransford et al.	**AI assisting individual team members**	**AI assisting the team or community of inquiry**
Learner: individual entering the community of practice	AI matches individual capabilities to task requirements	AI builds and maintains learner models for each participant
Community: social group defining norms and knowledge sharing	AI supports collaboration and shared understanding	AI unites members and manages human–AI knowledge shaping
Assessment: evaluation from novice to expert	AI provides cognitive feedback and performance guidance	AI manages evidence models and supports automated feedback
Knowledge: shared constructs and disciplinary models	AI enhances problem-solving and knowledge-building roles	AI finds new knowledge links and suggests research directions

Table 2.3: Four role areas for AI at the meso (team or knowledge community) level. (Gibson et al., 2023)

Entities in cultural historical activity theory	**The focus of AI systems co-participating in cultural intelligence**
Artefact: tools, systems, symbols, language and devices	AI intelligent tools generate novel ideas, narratives, and visualizations for learning artefacts
Object: aims or goals mediated by artefacts to achieve community purposes	AI enhances goal-setting and planning to clarify objectives and support achievement
Subject: individual or group learner engaging in knowledge creation and feedback	AI supports meso- and micro-level learning functions across roles and communities
Community: global and multicultural network integrating diverse knowledge fields	AI helps cross-cutting communities form, evolve, and collaborate across disciplines
Roles: specific functions and identities of community members	AI assists members in fulfilling roles such as publishing, reviewing, or mentoring
Rules: norms, values, and entry principles guiding community participation	AI maintains and mirrors algorithms as research test beds for creative exploration

Table 2.4: Six roles of AI at the macro (cultural) level. (Gibson et al., 2023)

2.4.6. Overview of AI Technological Categories

The sophisticated organisational impacts attributed to AI are not the result of a monolithic technology but rather of a diverse set of technological paradigms, each contributing unique capabilities. At the foundation lies **Machine Learning (ML)**, which enables information systems to autonomously detect patterns, build models, and adapt based on data inputs, thereby transforming data into actionable knowledge (Pournader et al., 2021; Vetter et al., 2023). Building on this foundation, **DL** represents a more advanced and specialized subfield, leveraging multi-layered neural networks to process highly complex data structures and uncover intricate relationships that traditional ML methods might overlook (Pournader et al., 2021; Nakash and Bolisani, 2025).

A more recent and disruptive development is **Generative Artificial Intelligence (GenAI)**, which has expanded the scope of AI from predictive modeling to creative production. By learning from vast training datasets, GenAI systems are capable of generating entirely new outputs–ranging from text and images to code and simulations–thereby broadening AI's role from analytical support to co-creation (Alavi et al., 2024; Jackson et al., 2024). Within this evolution, **Large Language Models (LLMs)** have emerged as a particularly transformative category. LLMs drastically enhance knowledge accessibility by allowing even non-specialists to synthesize complex information, query domain-specific knowledge in real time, and produce tailored content for diverse organisational needs (Kirchner et al., 2025; Rezaei, 2025).

Taken together, these technological categories illustrate the progressive layering of AI's capabilities. This trajectory not only underscores AI's versatility but also highlights the increasing integration of AI into organisational learning processes. The implications are critical for this thesis: while ML and DL enhance data-driven learning and decision-making, GenAI and LLMs redefine how organisations create, share, and apply knowledge, thereby acting as potential enablers of new innovation capabilities.

3 | Research Direction and Conceptual Framing

Building on the theoretical foundations established in the previous section, this chapter defines the research direction by synthesizing the relationships between KMP, OL, and organisational Value Creation (VC). Collectively, these constructs describe a sequential and interdependent framework in which organisations acquire, create, store, share, and apply knowledge to stimulate continuous learning, which in turn underpins the emergence of innovation, improved performance, and, more broadly, organisational value creation. Within this conceptual model, AI emerges as a transformative technological enabler that redefines how knowledge is generated, interpreted, and utilized. By automating cognitive tasks, identifying hidden patterns, and facilitating real-time collaboration, AI has been shown to enhance the efficiency and quality of each KMP, thereby strengthening the foundation upon which learning and value creation are built.

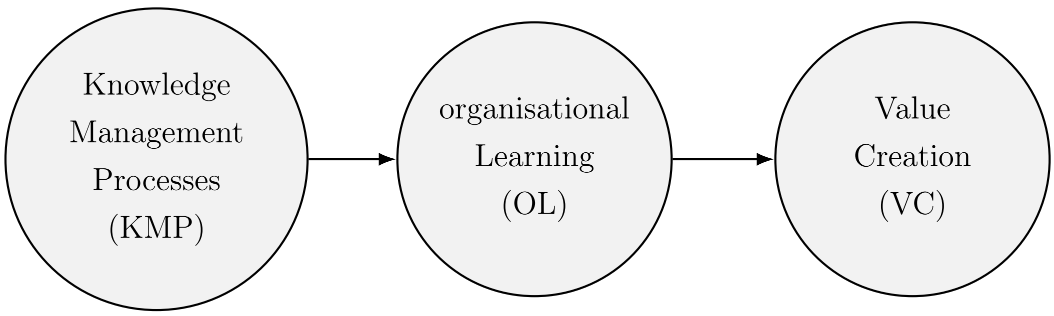


Figure 3.1: Framework linking KMP, OL and VC.

Despite this conceptual alignment, however, the literature remains fragmented in explaining the mechanisms through which AI contributes to organisational Learning and, ultimately, to organisational value creation. Existing studies largely converge on the assumption that AI improves the execution of Knowledge Management Processes across organisational levels, but these contributions are predominantly examined in isolation, emphasizing operational enhancements without tracing the subsequent learning dynamics and value-creation mechanisms that these improvements may activate. As a result, while the role of AI in optimizing knowledge processes is relatively well established, the indirect pathway through which AI-enabled KMP translate into enhanced organisational Learning and, in turn, into more robust patterns of organisational value creation remains theoretically underdeveloped and empirically underexplored.

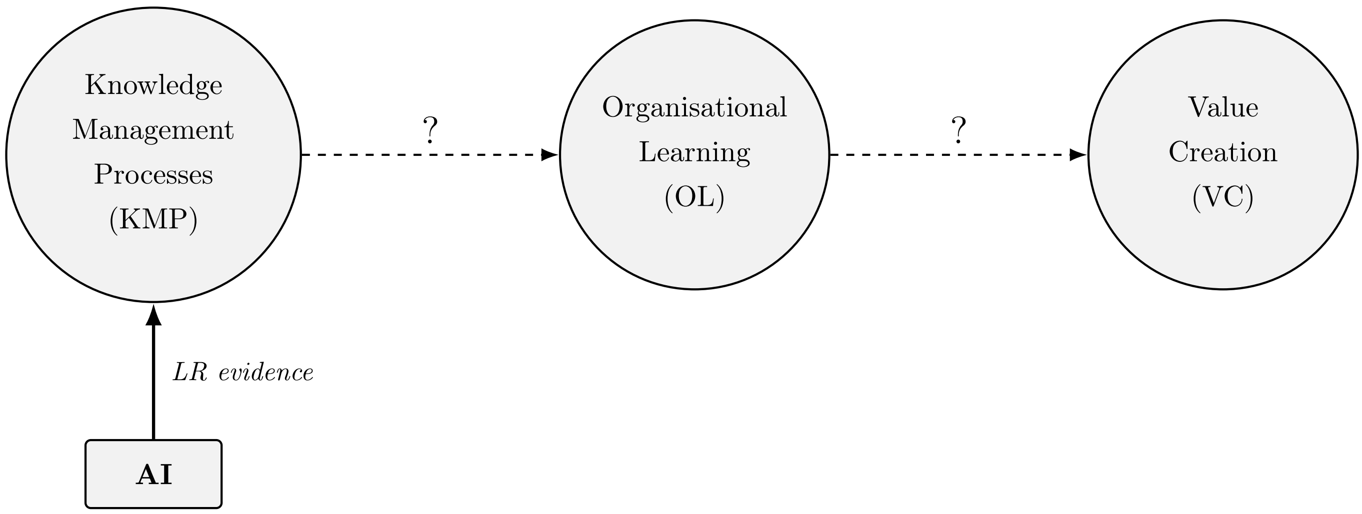


Figure 3.2: First Research Gap

In parallel, a second ambiguity concerns the possibility of a direct influence of AI on organisational Learning itself. Although AI has traditionally been framed as a technological tool supporting human learning through improved knowledge flows, recent debates suggest that AI systems may also participate more actively in learning loops by generating insights, recommendations, and novel representations that organisations can appropriate, contest, and refine. From this perspective, AI may not only support existing learning routines but also contribute to the emergence and strengthening of specific organisational Learning Capabilities that reshape how organisations sense, interpret, and exploit knowledge.

Yet, the literature provides no consolidated empirical evidence or shared conceptual framework explaining how these AI-driven learning mechanisms interact with organisational learning routines, nor how such interactions translate into more effective value-creation dynamics and competitive positioning. It therefore remains theoretically unclear whether AI merely facilitates learning through enhanced knowledge management or whether it can itself become an active agent of organisational Learning, potentially reshaping the foundations through which organisations evolve and create value.

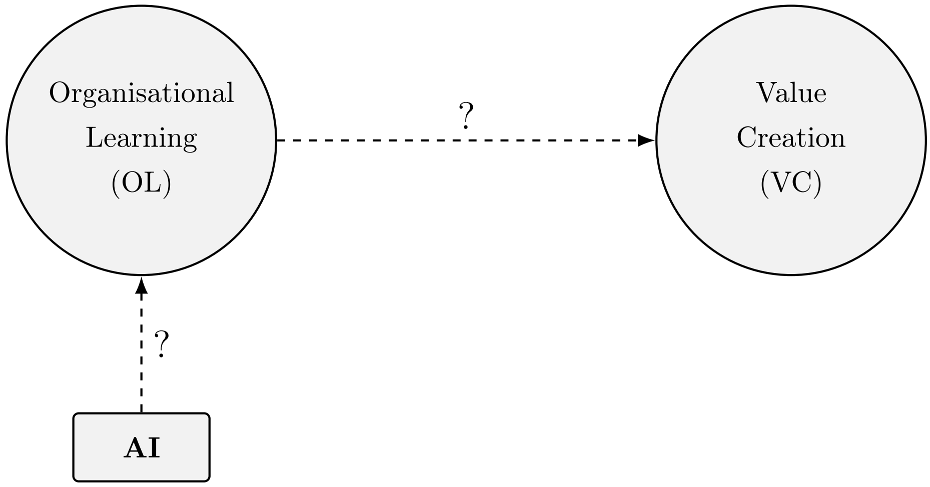


Figure 3.3: Second Research Gap

In light of these unresolved issues, this research aims to bridge the missing theoretical link between AI, KMPs, and OL in the context of organisational VC. Accordingly, the research objective is to explain how AI enhances OL, both directly and indirectly through its impact on KMPs, and how this learning transformation enables organisations to create value.

Accordingly, this study is guided by the following Research Question:

How does Artificial Intelligence enhance Organisational Learning to enable value creation?

To address this question, the empirical analysis adopts a multiple-case study design, examining how organisations practically deploy AI in their knowledge processes, how these deployments reshape organisational Learning dynamics, and how they are perceived to contribute to value creation within increasingly intelligent and adaptive environments.

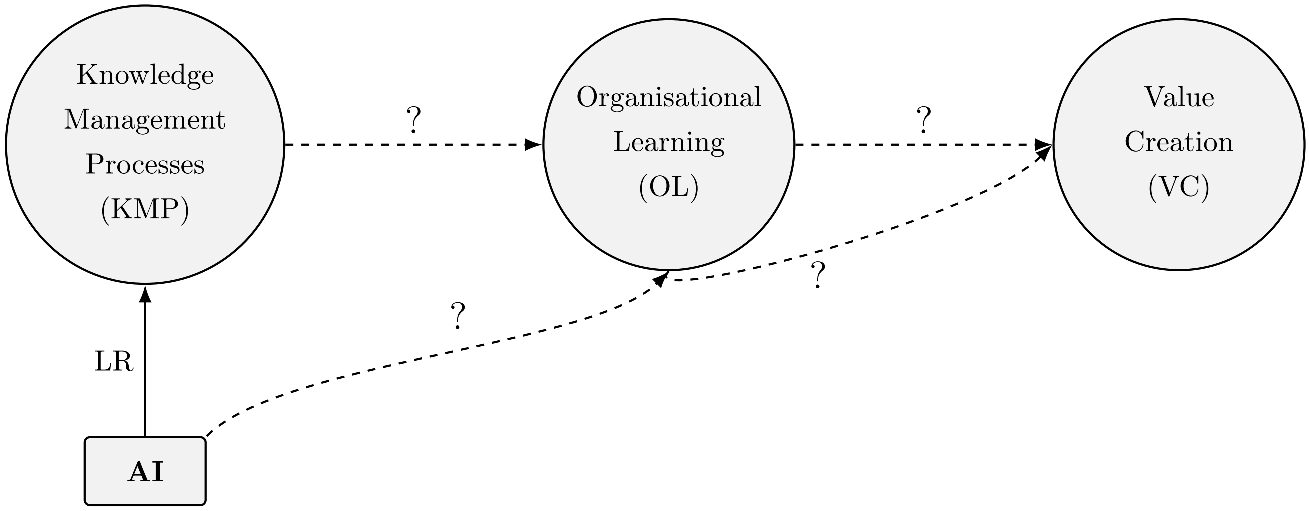


Figure 3.4: Final Framework for Research Thesis

4 | Methodology

4.1. Methodological Positioning and Rationale

This study adopts a qualitative approach based on multiple case studies, founded on the methodological principles of Yin's (2018) approach to theory building. This approach responds to the need to explore in depth a complex and still little-investigated phenomenon: how *AI* can enhance *OL*, both directly and through its impact on *KMP*, thereby enabling organisational value creation. This is a topic that requires in-depth qualitative analysis, capable of capturing the underlying interactions, meanings and dynamics rather than simply measuring correlations between variables.

As mentioned in the previous section, the main research question guiding the study is as follows:

How does Artificial Intelligence enhance Organisational Learning to enable value creation?

To unpack this overarching question and guide the research design and data collection protocol, the study addresses two sub-research questions:

SRQ1: How does Artificial Intelligence reshape organisational learning practices within organisations, both by augmenting existing organisational learning capabilities and by acting as an organisational learning agent?

SRQ2: How does the combination of AI-enabled organisational learning and human organisational learning contribute to value creation?

According to Yin (2018), the case study approach is particularly suitable when answering "how" and "why" questions, in situations where the researcher cannot exercise any control over the behaviour of the actors and the phenomenon under investigation is contemporary and rooted in its real context. In such circumstances, the case study method allows complex phenomena to be investigated in their entirety, simultaneously analysing the relationships between variables and the contextual elements that influence them. This approach is perfectly consistent with the objectives of this research, which aims to understand how the adoption of AI solutions intertwines with the organisational processes of knowledge creation, sharing and use, why these processes lead to different outcomes in terms of learning and value creation, and how these effects contribute to organisational competitiveness.

The qualitative nature of the study derives from the need to explore these dynamics in depth, which cannot be isolated or fully understood through quantitative tools. The objective is not to measure variables or verify predefined hypotheses, but rather to construct theoretical knowledge from empirical data, following an inductive and iterative process of analysis and reflection. In this sense, the qualitative approach allows the experiences and perceptions of the interviewees to be voiced, highlighting the cognitive, cultural and relational dimensions that determine the success or failure of AI-enhanced learning processes. The research, therefore, aims to build a holistic and contextualised understanding of the phenomenon, consistent with the logic of analytic generalisation proposed by Yin, according to which the objective of a case study is not to statistically generalise the results, but to develop concepts and theoretical mechanisms that can be transferred to other similar contexts.

The choice of the qualitative method is motivated by several converging reasons. First, the phenomenon under study has not yet been extensively explored in empirical literature: there are no established contributions that simultaneously examine the links between AI, knowledge management and organisational learning, and their implications for organisational value creation. Secondly, learning and knowledge processes are inherently social and cognitive in nature and require interpretative tools capable of capturing the meanings attributed by actors to their own experiences and practices. Thirdly, the complexity of interactions between technology, people and organisational structures implies the need for a holistic perspective capable of integrating technological, managerial and cultural dimensions. Added to this is the desire to conduct an in-depth rather than broad but superficial investigation, favouring the wealth of information and quality of data over the size of the sample. Finally, the scarcity of concrete empirical cases in the literature and in the industrial world further justifies the choice of an exploratory approach, aimed at generating new theoretical and operational evidence useful to both the scientific community and managerial contexts.

From an epistemological point of view, the research adopts a pragmatic and interpretative perspective, which integrates Yin's realistic and systematic logic with the constructivist sensibility typical of the Gioia Methodology. This orientation recognises that organisational reality is partly objective–since there are observable structures, processes and

results–but at the same time it is socially constructed through the perceptions, interpretations and interactions of the subjects involved. In this view, knowledge is not discovered in a neutral way, but rather co-constructed in dialogue between researchers and participants. The pragmatic approach also reflects the purpose of the research: to understand the mechanisms through which AI promotes learning and value creation, not only for theoretical purposes, but also to generate useful implications for organisational practice.
This epistemological position allows us to reconcile two seemingly opposing requirements: on the one hand, the procedural rigour and logical clarity of Yin's model, which ensures consistency in the definition of units of analysis, the construction of the protocol and the management of the chain of evidence. On the other, the interpretative depth and emergent openness characteristic of qualitative-inductive research, which allow the perspectives of participants to be valued and new theoretical categories to emerge from the data.
The combination of a realistic-analytical framework and an interpretative perspective results in a hybrid approach, in which research proceeds through an iterative process of abduction between theory and data: theoretical concepts guide the collection of evidence, while empirical insights feed, refine and, in some cases, redefine the initial conceptual frameworks.
In this perspective, the researcher takes on the role of co-interpreter rather than mere observer. The authors conducted the interviews themselves, interacting with participants in a reflective and adaptive manner to stimulate the production of authentic and situated knowledge. The ability to dynamically adapt follow-up questions during the dialogue and to capture tacit or implicit elements–such as language, values and decision-making logic–made it possible to collect rich and contextualised data, which is essential for understanding AI-mediated learning and value-creation processes. This active role of the researcher is consistent with the pragmatic-interpretivist approach: understanding of the phenomenon arises from the continuous interaction between empirical data and theoretical reflection, rather than from the mere application of predefined schemes.

In summary, the methodological positioning of this research reflects a balance between rigour and interpretation. Following the systematic logic of Yin's case study design, the study aims to construct an empirically grounded but conceptually sound theory capable of explaining how and why Artificial Intelligence can generate organisational learning processes and support organisational value creation. This approach provides the basis for the research design presented in the next section, which illustrates in detail the stages of data preparation, collection and analysis, together with the validity and reliability criteria adopted.

4.2. Research Desing

The methodological design of this research was constructed following the principles of multiple-case holistic design proposed by Yin, with the aim of investigating in depth how the adoption of Artificial Intelligence technologies intertwines with organisational learning practices and capabilities, as well as with related knowledge processes, in a limited but theoretically significant number of organisations. In line with the epistemological positioning outlined above, the design lies at the intersection between realistic-analytical rigour and interpretative and pragmatic sensitivity: on the one hand, it aims to ensure clear logical consistency between the research questions, the empirical evidence collected and the conclusions developed; on the other, it recognises the socially constructed nature of organisational phenomena, valuing the meanings and narratives produced by the actors involved.

Within this framework, each organisation was treated as a distinct case, analysed in its entirety. The unit of analysis is therefore the enterprise considered as a holistic system, in which practices, routines, managerial roles, digital infrastructures, and decision-making processes jointly contribute to defining the capacity to learn and innovate. Although the interviews explored different dimensions–from the adoption of AI solutions to knowledge management processes, organisational learning dynamics and impacts on innovation and value creation–the analysis was not fragmented into formal sub-units, such as individual departments or specific projects. For this reason, the design is configured as a multiple-case holistic design rather than a set of embedded cases: the focus remains on the overall organisational level and not on internal sub-units.

The choice of a multi-case design responds to the need to strengthen the theoretical soundness of the results through the logic of theoretical replication, as proposed by Yin. In this perspective, cases are not selected to constitute a representative sample in a statistical sense, but as contexts in which the phenomenon of interest–the interaction between AI, knowledge and learning processes–is believed to manifest itself in relevant and comparable forms. The aim is to observe whether and how the mechanisms conceptualised in the light of the literature on AI, KMP and OL emerge in organisations that differ in terms of sector, size and level of digital maturity, while verifying which conditions favour or hinder their activation. In this sense, the controlled heterogeneity of the cases is a strength of the design: the presence of different contexts allows us to test the explanatory power of the AI–KMP–OL theoretical framework in multiple organisational situations, strengthening the analytical generalisation of the results and allowing us to better articulate the conditions surrounding the mechanisms observed.

Consistent with Yin's approach, the multi-case design is not limited to list a series of company stories, but is constructed in such a way as to facilitate a systematic comparison between cases. Each organisation is analysed as a single case, but is conceived from the outset as part of a larger whole. In this sense, the research design is inherently comparative: the value of individual cases lies not only in their descriptive richness, but also in their ability to confirm, extend or contrast the patterns emerging from other cases, thus contributing to the construction of a more robust theoretical framework of Organisational Learning in the AI era.

To ensure that this design maintains an adequate level of methodological rigour, the research was developed with Yin's four quality criteria for case studies in mind: construct validity, internal validity, external validity, and reliability.
In translating these general principles to the specific context of the research, the authors paid particular attention to construct validity, i.e., the consistency between the theoretical concepts used and the empirical evidence collected. In practice, this translated into the combined use of different sources of information, while maintaining semi-structured interviews as the core of the empirical corpus. In addition to the narratives provided by the managers interviewed, supporting company materials, such as public documents, reports, presentations, or descriptions of AI initiatives available online, were sometimes consulted in order to contextualise the statements and verify specific elements that emerged during the conversations. More importantly, the authors constructed and maintained a clear "chain of evidence" linking the research question to the interview guide, transcripts, coding stages and subsequent construction of the data structure according to the Gioia Methodology. Each step was systematically documented to make the path from theory to data and from data to interpretation as transparent and traceable as possible. The ability to trace back from the final aggregate dimensions to the original quotes and, in turn, to the logic behind the formulation of the interview questions is a key element through which construct validity was pursued in the daily practice of research.

With regard to internal validity, the authors adopted an analytical approach combining pattern matching and explanation building, with a view to constructing credible and consistent explanations of the phenomenon under investigation. In operational terms, this means that the patterns emerging from the interviews are compared both with each other and with the theoretical expectations derived from the literature review. When multiple cases show similar configurations of conditions, mechanisms, and outcomes, the authors interpret these recurrences as evidence of a common underlying mechanism, which is progressively made explicit and articulated. At the same time, possible alternative explanations are also considered, which may strengthen or weaken the initial interpretation.

This work follows an iterative logic of back-and-forth between theory and data, typical of abductive reasoning: theoretical concepts guide the reading of the evidence, but the evidence, in turn, leads to a review, refinement or sometimes reformulation of the interpretative hypotheses. In this way, the proposed relationships between AI, KMP, OL and value creation are not simply stated, but constructed and verified step by step in light of the stories that emerged from the cases.

External validity was addressed by accepting from the outset that the purpose of the research was not to statistically generalise the results to a population of companies, but rather to construct plausible theoretical mechanisms that could be transferred to other similar contexts. The choice of a heterogeneous multiple-case design, which includes organisations from different industrial sectors and characterised by different levels of digital maturity, was guided precisely by the need to test the AI–KMP–OL conceptual framework in various situations, rather than in a homogeneous context. The underlying idea is that if certain patterns emerge in multiple cases with different characteristics, it will be more credible to argue that these mechanisms do not depend exclusively on a single situation. In this sense, the systematic comparison of cases serves not only to describe differences, but also to identify theoretical configurations that can be used as a reference by other organisations facing similar challenges in integrating AI into their knowledge and learning practices.

Finally, the reliability of the study was pursued by establishing procedures that were as stable and replicable as possible for conducting and managing interviews and data. All interviews were guided by the same question list, divided into consistent thematic blocks, so as to ensure that, while allowing for the flexibility necessary to follow the flow of the conversation, the key areas of research were addressed in a comparable manner in each case. The methods of contact, presentation of the project, request for consent to record and start of the interview were kept consistent between interviews, as far as the specific characteristics of each interviewee allowed. Once completed, the interviews were all recorded using the same platform, transcribed using similar procedures and stored in a case-structured database, which also included notes and memos written by the authors. This archiving system makes it possible for a hypothetical external researcher to reconstruct the main steps of the work carried out, verify how the raw data was used to arrive at the codes and theoretical categories and, in principle, replicate the analytical process by following the same steps. In this way, reliability is not understood as mechanical repetition, but as the possibility of clearly tracing and understanding the methodological choices that led to the results presented.

Overall, these four criteria–construct validity, internal validity, external validity and reliability–systematically guided the entire research design process, defining both how cases were selected and compared and the procedures through which data were collected, organised and analysed. In the following paragraphs, these principles are translated into specific operational activities, illustrating in detail the stages of field preparation, the processes of participant recruitment, the structuring of the interview guide, and the methods of conducting and managing the interviews that made it possible to construct the empirical corpus on which the analysis is based.

4.3. Preparation and Fieldwork Setup

The process of preparation and fieldwork setup was a central phase of the research, in which the methodological choices outlined at the design stage were translated into concrete operating procedures. From the outset, the authors felt it necessary to clearly structure their approach to accessing companies, interacting with potential participants and conducting interviews, so as to ensure consistency between cases while maintaining the flexibility essential for exploratory qualitative research. In this sense, field preparation involved both the definition of a proper "case study protocol", largely coinciding with the question list and the shared rules for conducting interviews, and the design of recruitment strategies, the management of ethical aspects, and the construction of an interview guide consistent with the AI–KMP–OL theoretical framework.

An important preparatory element concerned the creation of the interview guide and, more generally, the protocol used to conduct all interviews in a consistent manner. The question list was not created purely for pragmatic reasons, but was developed directly from the theoretical models and key concepts that emerged from the literature review on AI, Organisational Learning and Organisational Learning Capabilities, with attention to related Knowledge Management Processes as well. Starting from these models, the authors identified the conceptual areas considered fundamental to understanding how Artificial Intelligence interacts with knowledge management processes and organisational learning dynamics, translating each area into blocks of open-ended questions formulated mainly in the form of "how" and "why" questions, so as to stimulate rich narratives, concrete examples and operational descriptions. Abstract theoretical concepts, such as "knowledge sharing", "double-loop learning" or "AI-enabled capabilities", were thus transformed into questions capable of generating accounts of episodes, practices, decisions and business routines, preventing the answers from remaining purely declarative or prescriptive.

The case study protocol was built around this list of questions, which served as a reference document for all interviews. Although not formalised in a voluminous manual, the protocol included a clear set of shared elements: a short standard introduction to be used at the beginning of each meeting, the general structure of the conversation, the preferred order of the thematic blocks and some implicit rules on how to manage time and the level of detail in the answers. Each interview began with a presentation of the researchers, their academic background and the collaboration between the University of Melbourne and the Politecnico di Milano, followed by a brief explanation of the research objectives and the central question, expressed in a conversational manner to facilitate immediate understanding by the interviewee. Already in this introductory phase, the expected duration of the interview, generally between thirty and forty minutes, and the ethical aspects related to recording, the confidentiality of the information shared and the anonymisation methods that would be applied in the analysis phase and in the writing of the thesis were clarified.

The structure of the conversation followed a relatively stable pattern, which formed the backbone of the protocol. After the introduction, the interviewee was asked to briefly describe their role and the organisational context in which they operated, in order to gather information on the company's positioning, its degree of exposure to AI and the participant's responsibilities. The conversation then moved on to a series of thematic blocks consistent with the theoretical framework of reference: a first block focused on knowledge management processes, with open-ended questions on how knowledge is created, shared, stored and used within the organisation, as well as questions aimed at recounting examples and situations that have occurred within the organisation; a second block dedicated to organisational learning and organisational learning capabilities, exploring how the company learns from past experiences, projects, mistakes and experiments, and how such learning is incorporated into routines, processes or structural changes; a third block focused on learning practices and its relationship with the creation of value, with attention to mechanisms, routines and enabling factors; finally, a specific section on the adoption and use of Artificial Intelligence, with questions on concrete use cases, perceived impacts on learning and decision making, and links to knowledge and organisational learning processes, including the possible role of AI as a learning agent. The interview ended with a moment of thanks and, where appropriate, a brief feedback on the potential value of the results for the companies involved. Although this structure was shared and replicated in all cases, the authors maintained a flexible approach: the sequence of questions could be adapted to the flow of the conversation, especially when the interviewee spontaneously anticipated topics that were planned for later sections, and in some cases questions were added or omitted to take into account the specific nature of the business context or the time available.

The preparation phase also included defining how the results would subsequently be reported. Already at this stage, the authors were clear that the companies would be presented anonymously, through brief descriptive sheets outlining their sector, size, approximate level of digital maturity and the role of the interviewee, using generic labels such as Company A, Company B, and so on. This choice, consistent with the ethical requirements of the University of Melbourne, allowed the confidentiality of the participating organisations to be preserved, without sacrificing the minimum information needed for the reader to understand the variety of contexts analysed. Similarly, participants would also be referred to anonymously, with reference to their role (e.g. “Head of Operations”, “Head of Innovation”) and the case to which they belonged, but omitting proper names and other potentially identifying information.

A crucial element of the field preparation involved defining recruitment strategies for companies and participants. In the first phase, the authors leveraged the existing contacts of the principal supervisor and, more generally, the University of Melbourne, which has a well-established network of relationships with the Australian industrial fabric. With the support of the supervisor, a first draft of the contact email was prepared and carefully reviewed to ensure a respectful, clear and professional tone appropriate for addressing managerial and executive figures. The text introduced the two students, the universities involved, the role of the supervisor, the research objectives and the general theme of the interview, emphasising that this was an academic study and not an inspection or audit. It specified the approximate duration of the conversation, the method of conduct (mainly via Microsoft Teams) and the fact that the interview would be recorded with prior consent, with subsequent anonymisation of the data. This standard message was then used to contact several companies suggested by the supervisor or other lecturers; in some cases, the organisations refused to participate or did not respond, while in others they agreed to schedule an interview, thus contributing to the initial core of cases.
At the same time, a second line of recruitment was activated based on direct contacts via LinkedIn. The authors selected profiles of managers and executives who, based on their role description, previous experience and skills, were involved in areas relevant to the study, such as innovation, AI, operations, knowledge management or digital transformation. After requesting a connection, a private message was sent to potential participants, with a text very similar to that used in the emails: a brief presentation of the researchers and universities involved, a summary description of the subject of the study, a clear indication of the duration and nature of participation, and a polite request for availability to take part in an interview.
A third component of the recruitment strategy involved the use of professional databases

such as Apollo and AMTIL, which provide up-to-date information on companies and key contacts in various industrial sectors. Using these archives, the authors filtered potential contacts based on sector (e.g. food industry, automotive, manufacturing), company size and the role held by the person. Priority was given to profiles with managerial or executive responsibilities, particularly those whose title or job description suggested direct involvement in innovation projects, digital transformation initiatives or knowledge management practices. Again, each selected contact was sent a standard message, adapted in terms of name and company, but essentially identical in content and tone.
Finally, the personal professional network of the researchers was leveraged to contact and arrange interviews with italian companies as well. In this way, the logic of selection and initial approach to potential participants remained consistent, while combining different recruitment channels (academic contacts, LinkedIn, professional databases, personal network).

When a company or manager expressed interest in participating, a practical negotiation phase began to set up the interview. Subsequent exchanges generally took place via email, where the date, time and preferred mode–in person or online, according to the company's willingness and availability–were agreed upon, taking into account the needs of the interviewees. When confirming the interview, the relevant ethical documents (plain language statement and consent form) were shared along with the link to the meeting, so that participants could review the conditions of participation before the call.

The preparation of the field was not limited to organisational aspects, but also included a complex ethical approval process at the University of Melbourne. The authors completed a structured application form, which described the research project in detail: objectives, theoretical context, research questions, proposed methodology, participant characteristics and recruitment methods. The form also required an assessment of the potential risks to participants and the expected benefits, a description of the types of data collected, storage methods and archiving times, as well as detailed information on the researchers involved, academic supervisors in Australia and Italy, and their experience in conducting ethical studies with human participants. A significant part of the application was devoted to informed consent procedures, anonymisation measures and confidentiality management, as well as the technical characteristics of the tools used, such as the Microsoft Teams platform for recording interviews.
The approval process involved several exchanges with the ethics committee, which requested clarifications and changes on specific points. In some iterations, for example, we were asked to specify in more detail the terms and conditions of use of Microsoft Teams, how the recordings would be downloaded, stored and protected, and the expected time

frame for their deletion. On other occasions, it was necessary to clarify the content of the plain language statement or recruitment material to ensure that potential participants received clear, complete and understandable information about the project before deciding whether to participate. This review process led to the definition of a consistent and robust set of ethical documents: a plain language statement explaining the purpose of the study, the type of questions that would be asked, the expected duration of the interview, the voluntary nature of participation, and the right to withdraw at any time; a consent form formalising consent to participate and to have the conversation recorded; and a description of the recruitment material, which essentially coincided with the standard emails and contact messages used to invite companies to participate.
In preparation for the interviews, these documents were sent to participants in digital format, attached to the call confirmation messages. When interviews took place in person, the authors brought paper copies of the plain language statement and consent form with them: at the end of the initial explanation, they left the plain language statement with the interviewee and collected the signed consent form, which was then filed according to the ethics committee's instructions. In all cases, at the beginning of the interview, it was again explicitly stated that the conversation would be recorded, that the data would be used exclusively for research purposes, and that the company and the participant would be anonymised in the reports and thesis. Only after obtaining clear and informed consent the authors began recording.

In summary, the preparation and fieldwork setup phase allowed us to transform the general methodological design into a concrete set of practices: a shared interview protocol, a multilevel recruitment strategy, a solid ethical framework with clear consent and anonymisation procedures, and an interview guide built in strict adherence to the AI–KMP–OL framework. This forms the basis for the next phase of the methodology, dedicated to the detailed description of data collection procedures, the operational management of interviews, and the methods used to transform the conversations into a systematic analytical corpus.

Protocol Element	Summary Content
Research Focus	• *Main RQ:* How does AI enhance OL to enable value creation?
Interview Guide Structure	• Introduction and warm-up. • Knowledge Management Processes. • Organisational Learning and Organisational Learning Capabilities. • KMP $\rightarrow$ OL $\rightarrow$ Value Creation. • AI and Digital Technologies.
Sources of Evidence	• Semi-structured interviews. • Company documents (when available). • Researchers' notes. • Anonymised transcripts.
Operational Workflow	• Recruitment: Unimelb contacts, LinkedIn, AMTIL/Apollo, personal network. • Interview execution: two researchers; MS Teams recording. • Transcription: manual revision and anonymisation. • Archive: case folders with transcripts, notes, materials.
Expected Outputs	• Clean anonymised transcripts. • Structured case folders. • First-order codes, second-order themes. • Aggregate dimensions; Gioia data structure.

Table 4.1: Case Study Protocol Overview

4.4. Data Collection Procedures

The collection of empirical data represented the moment when the design choices described in the previous sections were translated into concrete interactions with participants and into analysable material. Starting from the defined methodological framework and the preparatory work, the authors constructed a data collection process which, while rooted in Yin's guidelines for case studies, was strongly shaped by the practical needs and characteristics of the phenomenon under investigation. The intent was not merely to "conduct interviews" but to build, through each encounter, a dense, coherent and comparable empirical base capable of credibly supporting the subsequent stages of coding and interpretation.

All interviews were conducted jointly by the two authors, without exception. The simultaneous presence of both responded to a twofold need. On the one hand, it allowed for better oversight of the different dimensions of the conversation: while one of the two conducted the interaction more directly, asking questions and following up, the other could concentrate more on listening, picking up on nuances, contradictions or implicit elements and taking notes when necessary. On the other hand, joint participation encouraged a form of interpretative "cross-checking": during the interview, the two authors could exchange signals and, subsequently, impressions, reducing the risk that the meaning of what the interviewee said would be filtered through a single perspective. Although there were no formalised roles, both actively intervened with questions, requests for clarification and comments, alternating naturally according to the flow of the conversation.
The interviews were conducted entirely in English for the Australian companies and in Italian for the Italian ones, using a register appropriate for interlocutors with managerial and technical responsibilities. The vocabulary used reflected both the professional terminology typical of business contexts–referring, for example, to processes, roles, information systems, innovation projects–and the more conceptual lexicon related to literature on AI, knowledge management and organisational learning. This linguistic choice made it possible to create continuity between the empirical and theoretical levels: the terms used in the scientific articles that inform the reference framework could, when appropriate, be taken up and reformulated during the interview, facilitating the translation of abstract concepts into concrete examples. At the same time, the use of open-ended questions in the form of "how" and "why" shifted the focus of the conversation from simply stating opinions to describing processes, stories, episodes and decision-making logic, a crucial element for a study focused on the mechanisms through which AI impacts learning, capabilities and knowledge flows.

From an interactive point of view, the interviews did not follow a rigid pattern but developed as guided conversations. The authors started with a sequence of predefined questions, built around the thematic blocks of the question list, but intentionally left themselves the possibility to deviate from the script when the interviewee opened up interesting digressions or provided examples that suggested potentially relevant interpretative avenues. In many cases, when answering questions about knowledge management or how the company learns from experience, interviewees spontaneously brought up the topic of AI, describing solutions, projects or systems introduced in the company. In these cases, the authors preferred to follow the natural flow of the narrative, exploring the topic in depth immediately and then returning to the unanswered questions later. The underlying idea was that the value of qualitative data lies in the richness of the stories and the depth of the insights, rather than in strictly following a script. Only when the conversation strayed too far from the focus of the research did the authors gently bring the interviewee back to the original "track", rephrasing a question or introducing a new one from the question list.
In addition to the planned questions, the authors frequently added additional prompts, generated on the spot based on what emerged from the responses. These "follow-up" questions were not present in the preparatory documents, but arose from active listening and an attempt to grasp the mechanisms underlying the situations described, in line with the abductive logic already discussed in the methodological positioning.

The collection process did not end with the interview. In many cases, immediately after the call, or at least on the same day, the authors discussed their impressions, the elements they found most interesting and any critical issues encountered. These debriefings were informal and were not transcribed or systematised in specific documents, but they served an important function of mutual clarification: they allowed the researchers to verify whether they had interpreted key passages in the same way, to discuss any inconsistencies or ambiguities, and to begin to consider how a particular case compared to others already collected. In addition, these discussions helped to guide the reading of the transcripts in the following days and, in some cases, suggested minor changes to the interview guide for future sessions, such as introducing a more explicit question on a topic that had emerged as crucial or rephrasing a question that had proved unclear to participants.

The transformation of the recordings into analysable textual data took place through a complex process. The authors first used the automatic transcription provided by the platform, which was downloaded and imported into a Word document. However, this first version of the transcript was considered only a starting point: a manual review phase then began, during which the authors listened to parts of the audio again to correct recognition

errors, reconstruct broken sentences, integrate missing words and resolve lexical ambiguities. During this phase, marginal elements that were not relevant to the analysis were also removed, such as prolonged greetings, technical problems ("can you hear me?", interruptions due to connection difficulties) or purely social digressions, while retaining everything that helped to shed light on the interviewee's reasoning on the subject in question.
In parallel with linguistic cleansing, the authors proceeded to carefully anonymise the transcripts. Names of people, customers, products, proprietary technologies, or overly specific references to projects were replaced with generic labels, which preserved useful information (e.g., the interviewee's role or the type of initiative) but removed any recognisable details. In this way, the transcripts retained their wealth of information and context, but were compatible with the confidentiality requirements established during the ethical approval phase. When the authors felt it was useful to highlight a particularly dense passage, they added comments in the margins of the Word file, without modifying the original text, in order to begin building a first outline of the future coding work.

Once the review of each transcript was complete, the file was saved with a standardised nomenclature–usually "Company X-Role of Interviewee"–and placed in a folder dedicated to the corresponding case. These folders also contained notes taken during the interview and, where available, additional documents or materials shared by the company. Although the file names did not explicitly indicate the date, duration, or mode of the interview, this information remained accessible through the metadata of the recordings and the Teams meeting logs, allowing the timeline of the fieldwork to be reconstructed if necessary. The organisation into case folders facilitated the construction of a coherent empirical database: for each organisation, the authors had an easily accessible "package" of evidence, which would form the basis for subsequent within-case analysis.

Overall, therefore, the data collection procedures were not limited to recording and transcribing interviews, but aimed to build a structured, traceable and conceptually dense empirical corpus. The joint presence of the two authors, the use of open-ended questions to encourage rich narratives, the attention to balancing structure and flexibility in conducting interviews, real-time annotations, informal debriefing, careful review of transcripts, systematic anonymisation, and organised archiving by case represent, taken together, the practical translation of the principles of rigour discussed in the previous sections. On this basis, the next phase of methodological work will be initiated, dedicated to qualitative data analysis procedures, in which the interviews will undergo a systematic coding process inspired by the Gioia Methodology and the guidelines on qualitative coding found in the literature.

4.5. Analytical Procedures

The analytical strategy adopted in this research combines qualitative coding techniques with the Gioia Methodology in order to provide a rigorous, transparent and conceptually generative framework for interpreting complex organisational phenomena. Within this overall perspective, coding constitutes the fundamental operation through which raw textual material is transformed into analytically tractable evidence. In its most basic sense, coding involves identifying meaningful segments of data–sentences, paragraphs, or narrative episodes–and assigning to each a concise label that captures its core meaning in relation to the research focus (Linneberg & Korsgaard, 2019). This operation has a dual function. On the one hand, it performs data reduction, condensing extensive narratives into more compact units that render the empirical corpus manageable without erasing its diversity. On the other hand, coding initiates early analysis, because every coding decision already implies an interpretive act: the researcher must decide what is salient, how to delimit analytic units, and how to express their meaning in conceptual shorthand. Coding thus occupies an intermediate space between data and theory: it is no longer "raw" empirical material, but not yet fully fledged theory. It requires continuous judgement, sensitivity to context and reflexive awareness of how one's interpretations shape the representation of the phenomenon.

A useful way to conceptualise coding is to distinguish between cycles of coding rather than imagining it as a single, linear pass through the data. In a first coding cycle, the emphasis lies on staying close to the empirical material and mapping its diversity without prematurely forcing it into a narrow set of preconceived categories (Linneberg & Korsgaard, 2019). At this stage, the researcher typically employs code types that preserve proximity to informants' accounts and provide an overview of "what is in the data". Descriptive coding assigns labels that summarise the topic or issue addressed in a given segment, for example a decision, a routine, or a particular interaction. In vivo codes retain informants' own wording, capturing the specific terms, metaphors and expressions through which managers and professionals articulate their experiences. Process-oriented codes, often formulated as verbs or gerunds, highlight actions, routines and sequences and are well suited to phenomena such as learning cycles, knowledge transformations and capability development. The outcome of this first coding cycle is typically a relatively large and at times unwieldy list of codes. However, this initial proliferation is not a weakness but a precondition for rigorous inductive and abductive analysis: one must first allow the data to "speak" in many different voices before attempting to synthesise them into more abstract conceptual categories.

As familiarity with the data grows, the analytic focus gradually shifts from capturing diversity to identifying patterns, relationships and underlying structures. This marks the beginning of second-cycle coding, where codes become more explicitly analytical in character. In this phase, researchers engage in various forms of pattern coding and categorisation: conceptually similar first-cycle codes are clustered into more abstract units that begin to resemble themes, and tentative families of related codes are formed (Linneberg & Korsgaard, 2019). At this point, researchers ask questions such as: which situations or practices recur across different interviews or cases? Which conditions tend to co-occur? What processes or mechanisms might explain the observed regularities? Conceptual resources from existing literature can be used as sensitising devices, suggesting dimensions along which codes might be grouped, while an abductive stance encourages the analyst to move back and forth between data and theory, revising or extending prior concepts in light of what the material reveals. Through these iterative moves, the coding structure evolves from a broad descriptive inventory into a more integrated set of analytical categories capable of addressing the research questions.

The coding literature also highlights certain pitfalls that can compromise analytic quality if left unaddressed. One recurrent risk is that coding fragments the data to such an extent that the broader context of each case or narrative becomes obscured. Linneberg & Korsgaard (2019) therefore stress the importance of periodically revisiting full transcripts, case narratives and contextual notes alongside coded segments, in order to preserve a holistic understanding of situations and to test emerging interpretations against the wider empirical background. Another concern relates to the inherently interpretive nature of coding decisions: different researchers might emphasise different aspects of the same segment or choose alternative labels. Rather than seeking to eradicate such variation, contemporary perspectives treat it as an opportunity for reflexive dialogue. When more than one researcher is involved, collaborative coding and subsequent comparison of coding choices can help make implicit assumptions explicit, identify blind spots and refine the coding scheme through discussion. The goal is not mechanical convergence for its own sake, but enhanced depth and trustworthiness of the analysis.

Building on these foundations, the Gioia Methodology provides a structured and widely recognised framework for organising the transition from empirical codes to theoretical constructs in inductive research (Gioia et al., 2013). At the heart of this methodology lies the construction of a data structure, a visual and conceptual representation of how first-order concepts, second-order themes and aggregate dimensions are related. The first-order level is explicitly informant-centric: it retains the distinctions and terms used by participants, often incorporating in vivo codes, and aims to represent as faithfully as possible the variety of ways in which informants describe their experiences and practices. In this sense, first-order concepts can be seen as an elaborated, theoretically sensitive extension of first-cycle coding. They preserve richness and nuance by avoiding premature collapse into a small number of categories; as a result, it is not unusual for a Gioia-style analysis to produce several dozen first-order concepts in its early stages.

The second-order level marks the point at which the analysis becomes overtly researcher-centric. Here, the question is no longer simply "what did informants say?", but "what theoretical story can be told that plausibly accounts for what informants said?". The researcher seeks to interpret the array of first-order concepts through a more explicitly theoretical lens, drawing on existing literature where appropriate, but also allowing for the emergence of new constructs that extend or challenge prevailing understandings. Through iterative comparison and re-grouping, first-order concepts that appear to reflect a similar underlying mechanism, condition or process are clustered into second-order themes. This often involves asking how categories relate to one another: for instance, whether some appear as antecedents, consequences, enabling conditions, forms of response, or manifestations of broader patterns. In methodological terms, this stage plays a role analogous to axial reasoning, in that it emphasises connections among categories and moves from description toward explanation, but it is explicitly embedded within the three-level data structure characteristic of the Gioia approach.

Once a sufficiently robust and parsimonious set of second-order themes has been developed, the analysis proceeds to consider whether these themes can be further integrated into a smaller number of aggregate dimensions. Aggregate dimensions represent higher-order conceptual territories that capture the overarching patterns running across several themes, for example, categories such as "organisational responses to digital innovation", "learning from failure", or "reconfiguring knowledge infrastructures" in other applications of the methodology. The resulting three-level data structure–first-order concepts, second-order themes, aggregate dimensions–serves multiple functions. It documents the interpretive journey from raw data to theory, making explicit which empirical material supports which conceptual claims. It offers a compelling visual representation of the analysis that allows readers to assess plausibility and coherence at a glance. And it provides a scaffold for subsequent theorising, for instance when articulating process models, identifying configurations, or specifying mechanisms.

A distinctive contribution of the Gioia Methodology is its explicit linking of qualitative rigour to transparency in the movement from data to theory. Rather than presenting final categories as if they emerged automatically from the empirical material, the approach requires researchers to show "how they got there" (Gioia et al., 2013). This transparency does not imply that there is only one valid way of reading the data; instead, it invites readers to see the path by which the particular interpretation offered was constructed and to judge its credibility in light of the evidence presented. At the same time, Gioia and colleagues caution against treating their framework as a rigid template or checklist. The methodology is best understood as a flexible orientation toward inductive concept development: certain core principles–such as distinguishing informant-centric and researcher-centric levels of analysis, building a data structure, and grounding higher-order constructs in rich empirical evidence–are essential, but there remains room for adaptation in light of the research context, design and epistemological commitments.

Taken together, the coding framework outlined by Linneberg & Korsgaard (2019) and the Gioia Methodology (Gioia et al., 2013) form a coherent analytical architecture for qualitative case-based research. Coding offers a disciplined, stepwise apparatus for engaging closely with empirical material, ensuring that analytical categories are grounded in systematic examination of texts and supported by documented interpretive choices. The Gioia data structure then provides a higher-order integrative device that assembles these categories into a theoretically meaningful whole. The combined use of these procedures supports an abductive logic in which the researcher oscillates between the richness of the data and the demands of conceptual coherence, allowing for both fidelity to informants' experiences and the development of novel theoretical insights. Moreover, the structured outputs of this analytical work–first-order concepts, second-order themes and aggregate dimensions–create the conditions for subsequent development of a grounded theory model.

4.6. Analytical Logic for Cross-Case Comparison

In a multiple-case study, the analytical work does not conclude with the development of codes, themes and aggregate dimensions within each individual case. A core contribution of this type of design lies in the possibility of systematically comparing and contrasting cases in order to refine emerging explanations and strengthen the robustness of theoretical insights. In Yin's terms, multiple cases are treated as a series of "replications" rather than as elements of a statistical sample, and the cross-case analysis becomes the arena in which replication logic is actually enacted (Yin, 2018). The goal is not simply to show that similar phenomena occur in different settings, but to understand under which conditions particular patterns hold, how they vary across organisational contexts, and what this implies for the theoretical propositions that the study seeks to advance. Cross-case analytical procedures therefore play a crucial role in moving from rich, context-specific narratives to more general conceptual claims, while remaining faithful to the underlying qualitative logic of analytic generalisation rather than statistical inference.

Within this perspective, cross-case synthesis can be understood as the systematic juxtaposition of case-level findings with the aim of identifying convergences, divergences and structured variations across cases (Yin, 2018). Whereas within-case analysis focuses on constructing a coherent account of how phenomena unfold in a specific organisational setting, cross-case synthesis asks whether similar mechanisms or configurations can be observed in other settings and how they may be shaped by contextual conditions. In practice, this often involves the construction of comparative displays–such as matrices, summary tables or synthetic narratives–in which key themes, processes or outcomes are aligned across cases along common dimensions. These analytical devices do not replace detailed case descriptions, but provide a higher-level lens through which the researcher can discern patterns that would be difficult to perceive by reading the cases sequentially. The emphasis is on preserving the integrity of each case while at the same time using variation across cases as a source of analytic leverage, in line with the logic of replication outlined by Yin.

Pattern matching represents one of the central techniques through which cross-case synthesis contributes to explanation building in case study research. At its core, pattern matching involves comparing empirically observed patterns with one or more theoretically derived patterns in order to assess the degree of correspondence between them (Yin, 2018). A "pattern" in this sense can take different forms: it may be a set of conditions that are expected to co-occur, a temporal sequence of events, a configuration of practices or an association between processes and outcomes. The researcher develops, on theoretical grounds, an expected pattern that encapsulates a tentative explanation of the phenomenon under study, and then examines whether the pattern observed across cases conforms to, deviates from, or partially overlaps with this expectation. The strength of the explanation increases when the same theoretically derived pattern is observed consistently in multiple cases, especially when these cases differ in other respects, because this suggests that the pattern may capture a more general underlying mechanism rather than an idiosyncratic local configuration. Conversely, systematic mismatches between theoretical and empirical patterns invite refinement of the initial propositions or even the construction of new explanatory accounts.

Closely related to pattern matching is the process that Yin calls explanation building. While pattern matching highlights correspondences and discrepancies between expected and observed patterns, explanation building focuses on the progressive elaboration of a coherent explanation of how and why a phenomenon unfolds as it does (Yin, 2018). In a multiple-case context, explanation building typically proceeds iteratively across cases. An initial, relatively general explanatory proposition is formulated, often drawing on existing theory and early insights from within-case analysis. This proposition is then confronted with the empirical material of the first case, leading to refinements, qualifications or partial reformulations. The revised proposition is in turn compared with the second case, and so on, until a version is reached that offers a plausible account of the phenomenon across all cases examined. At each step, the researcher assesses not only whether the proposition "fits" the data, but also whether alternative explanations could account for the same evidence. In this sense, explanation building is both cumulative and critical: it builds on insights gained from previous cases while remaining open to revising or even discarding them if they are not supported by subsequent evidence.

Within such a framework, the themes and aggregate dimensions produced by the coding procedures and the Gioia Methodology do not remain confined to the level of individual cases, but become the primary building blocks for cross-case comparison and explanation building. Once first-order concepts have been organised into second-order themes and aggregate dimensions within each case, these constructs can be compared across cases along several axes. The researcher may ask, for example, whether the same aggregate dimensions are present in all cases, whether they take similar or different forms, and whether particular combinations of themes tend to appear together in cases that exhibit certain types of outcomes. In certain instances, cross-case analysis may reveal that some themes are specific to particular contexts, while others are more robust across organisational settings. In other instances, it may show that themes that appeared distinct within individual cases can in fact be integrated into broader explanatory patterns when considered across cases. In this way, cross-case analysis serves as a testing ground for the stability, scope and explanatory power of the concepts developed during within-case analysis.

Another important aspect of cross-case analytical logic in Yin's framework is the consideration of potential rival explanations. A rival explanation is an alternative theoretical account that could, in principle, explain the same empirical patterns as the primary explanation advanced by the researcher (Yin, 2018). From a methodological standpoint, the deliberate search for rival explanations is a safeguard against confirmation bias: rather than accepting the first plausible explanation that fits the data, the researcher asks whether different interpretations might also be consistent with the observed evidence. In practice, this may involve reflecting on whether observed patterns could be attributed to other factors, for example, organisational size, sectoral characteristics or broader environmental conditions, rather than to the mechanisms foregrounded by the primary explanation. In the context of exploratory, abductive case study research, rival explanations do not necessarily take the form of fully articulated alternative models; instead, their consideration can remain more implicit and iterative, serving to “stress-test” emerging explanations by checking whether they remain credible when confronted with plausible alternative logics. The analytical procedures are thus designed to remain open to the identification and assessment of rival explanations where they arise from the data, without requiring their formal specification in advance or their systematic treatment as separate analytical outputs.

Ultimately, the purpose of cross-case analysis in a multiple-case design is to support analytic generalisation (Yin, 2018). Unlike statistical generalisation, which infers characteristics of a population from a sample, analytic generalisation involves generalising from empirical case findings to theoretical propositions. Cross-case synthesis, pattern matching, explanation building and the careful consideration of rival explanations all contribute to assessing the scope and robustness of these propositions. When patterns and explanations hold across multiple cases that differ in certain respects, the researcher gains confidence that the theoretical claims may have relevance beyond the specific organisations studied. Conversely, when substantial variation appears, cross-case analysis can help delineate the boundary conditions under which particular mechanisms operate. In both situations, the outcome is not a statement about “how many” organisations in a statistical population display a given pattern, but a more precise and empirically grounded understanding of “how” and “under what conditions” certain processes unfold in organisational settings.

These cross-case analytical procedures complete the methodological framework of the study. Taken together with the epistemological positioning, research design, preparation and fieldwork setup, data collection and within-case analytical procedures, they define the overall logic through which empirical material will be transformed into conceptual contributions. The next chapter moves from methodological considerations to the empirical context, introducing the participating companies and outlining the organisational settings in which the subsequent analysis is situated.

5 | Case Description

This chapter introduces the empirical context of the study by providing a descriptive overview of the organisations and interviewees included in the multiple-case sample. The aim is to outline the key structural characteristics of the cases, in terms of sector, firm size, geographic location, and respondent role, in order to set the background for the subsequent cross-case analysis. Table 5.1 summarises the main profiles of the ten interviewees and their respective organisations (Company A–L), which form the empirical basis of this research.

Interview code	**Company Code**	**Interviewee's role**	**Company's sector**	**Company's size (# employees)**	**Country**
I_01	Company A	Managing Director	Manufacturing and Steel Fabrication	Small: 11–49	Australia
I_02	Company B	Head of Operations	Food and Beverages	Global: 5K+	Australia
I_03	Company C	Managing Director	Electronic Manufacturing	Small: 11–49	Australia
I_04	Company D	Head of Innovation	Food and Beverages	Global: 10K+	Australia
I_05	Company E	Quality Manager	Automotive	Global: 500+	Australia
I_06	Company F	CEO	Marketing and Design	Medium: 50–249	Italy
I_07	Company G	IT Director	Insurance and Financial Services	Global: 10K+	Italy
I_08	Company H	CEO	Architecture and Urban Planning	Small: 11–49	Italy
I_09	Company I	BDM	Technology and industrial manufacturing	Global: 1K+	Australia
I_10	Company L	CEO	Insurance and Financial Services	Small: 11–49	Italy

Table 5.1: Interviewee and Company Profiles

As summarised in the table presented at the beginning of this chapter, the empirical sample consists of ten organisations, each represented by a senior manager with direct responsibility for operations, innovation, IT or overall business strategy. The cases span a broad range of sectors, including manufacturing and steel fabrication, food and beverages, automotive components, engineering and automation solutions, product development services, creative and communication services, architecture, and insurance and financial services. Firm sizes range from small and medium-sized enterprises with a few dozen employees to large global groups with several thousand employees in the relevant business unit. The interviewees include managing directors and CEOs of smaller firms, heads of operations and innovation in large industrial and food companies, IT and unit managers in a global insurance group, and a business development manager in a multinational engineering and automation division. This configuration provides a vantage point that is both strategic and operational: respondents are close enough to day-to-day practices to describe how knowledge, learning and AI are actually used, while at the same time holding roles that require them to think about capabilities and innovation at organisational level. Geographically, the sample is concentrated in Australia, complemented by four Italian organisations in creative services, architecture and insurance, which adds variation in institutional and market context without sacrificing comparability in terms of the phenomena under study.

In terms of knowledge management, all of the organisations combine some form of digital infrastructure for storing and retrieving information with more informal, people-centred repositories of know-how, but the balance between these components differs markedly across the cases. In several industrial and manufacturing firms, the backbone of knowledge storage is provided by enterprise systems. Company A, for instance, relies on an integrated ERP solution that supports the entire order-to-delivery process, from estimating and tendering through to shop-floor scheduling and delivery, complemented by specialised software for health and safety compliance and full 3D CAD modelling and programming of CNC equipment.
In this case, technical specifications, process routings, training matrices and compliance documentation are codified to a significant extent, even though tacit expertise on how to manage complex, bespoke jobs remains critically important on the shop floor.

In Company B, knowledge related to operations is highly formalised and governed. Standard operating procedures, work instructions, quality and safety standards, maintenance plans and troubleshooting guides are maintained in structured document management systems, with clear ownership, version control and audit trails.
Global and regional playbooks, as well as category-specific templates, define “the official way” of carrying out many core activities, and local sites are expected to align with these

standards while retaining some room for adaptation. Here, explicit storage of knowledge and the standardisation of practices are particularly advanced, especially for domains that touch product quality, safety and regulatory requirements.

Company G represents an even more advanced stage of digitalised knowledge management in certain areas. The IT and finance unit has been deliberately investing in a "content domain", that is, a curated knowledge base in which technical and functional documentation is organised by application area and made accessible through a conversational interface powered by generative AI.
This initiative reflects a strategic intent to reduce dependency on individual experts, to accelerate onboarding and problem solving, and to support distributed teams in navigating a complex application landscape. Alongside this, the organisation also runs more traditional data warehouses and reporting systems, and a separate data and analytics function under the Chief Data Officer is responsible for building and governing business-oriented models and use cases.

Other organisations combine medium-to-high levels of formalisation with more emergent practices. Company C, for example, has accumulated a large portfolio of projects over the years and has started to systematise this history in a searchable internal wiki, supported by revision-control tools such as GitLab for software.
However, a substantial portion of the older project knowledge is not yet integrated, and AI tools are explicitly being explored as a way to transform legacy documents into structured, reusable entries. In Company E context, process knowledge is codified through process flow charts, control plans, and structured methods such as FMEAs, supported by quality management and ISO/IATF documentation.
Similarly, Company I emphasises data warehousing and data-driven maintenance of production lines, with extensive use of data lakes and analytics to inform decisions on servicing and reliability of equipment.
In these cases, there is a deliberate effort to capture process knowledge and performance data in structured systems, while at the same time recognising that problem solving often requires the combination of codified information and the experience of seasoned engineers and technicians.

By contrast, in more craft- and project-based environments, knowledge remains predominantly embedded in people, relationships and portfolios of work rather than in formal repositories. Company F, for instance, explicitly describes its activity as "people-intensive", with knowledge originating from the skills and professional trajectories of its staff, from client-provided data and briefs, and from decades of experience in specific domains such as fundraising and retail communication. While the agency does accumulate market research, campaign results and client materials, a large share of its know-how resides in teams' accumulated judgment about what "works" in different channels and markets, and this knowledge must be continuously refreshed as consumer behaviour evolves. Company H likewise emphasises apprenticeship-based learning: young graduates join as interns, learn by working alongside more experienced architects, and progressively take on responsibility, later becoming mentors themselves. Documentation exists in the form of project files, drawings and regulatory submissions, but the capability to design and deliver complex projects is primarily acquired and transmitted through practice, discussion and iterative critique rather than through formal knowledge systems.

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Organisational learning practices reflect these different configurations. In several industrial cases, learning from operations is structured around continuous improvement routines. In Company B, performance dashboards are used not only for monitoring but as triggers for structured problem-solving, with some issues escalated into formal A3 projects when they recur or have significant impact.
Company D adopts a similar logic: daily calls focus on understanding "what went wrong" and "what went right" the previous day, with particular attention to safety incidents, equipment downtime and yield losses; learning from these discussions feeds both immediate adjustments and more formal improvement initiatives.
In Company E, root-cause analysis methods and control-plan updates ensure that lessons from specific incidents are captured and used to prevent recurrence in similar processes.
Company I also stresses the importance of using real data, rather than opinion, to drive

learning about machine reliability and maintenance strategies, drawing on experience accumulated across decades and across multiple sites.

In smaller firms and professional-services environments, learning is often more tightly coupled to projects and client engagements. Company C must rapidly build understanding of new clients, industries and technologies, starting a new project roughly every week; this creates a strong pressure to learn quickly and to reuse insights from past projects, even if the codification of this knowledge is still a work in progress.
Company F and Company H both highlight the role of "learning by doing" and of iterative refinement: teams experiment with campaign formats or design solutions, observe market or client responses, and adjust their approaches accordingly. In the architecture case in particular, the firm deliberately structures career paths around mentoring, with more experienced architects training younger colleagues on both technical and contextual aspects of projects, while also receiving stimulus from younger staff who bring in knowledge of contemporary trends and references.
Across these cases, there is less emphasis on formal post-mortems or lessons-learned documents, and more on continuous dialogue and socialisation.

Overall, across the ten organisations, the spectrum ranges from strongly continuous-improvement-oriented settings, where structured feedback loops and problem-solving routines are embedded in daily management, to more reactive or ad hoc patterns of learning, where reflection is triggered primarily by major incidents, client feedback or project milestones. Even in the more mature cases, there is recognition that the "use" of available knowledge is uneven: people may not always consult repositories or precedents before developing new solutions, particularly under time pressure. This tension between the existence of codified knowledge and its effective mobilisation in decision-making is a recurring theme that the subsequent analytical chapters will explore in more depth.

The state of AI and digitalisation across the cases is equally heterogeneous, and the ten organisations can be seen as occupying different positions along an AI maturity curve. At one end of the spectrum are contexts where AI is present but plays a marginal or experimental role in core organisational processes. Company H, for example, makes limited use of AI tools: generic conversational systems are occasionally consulted for information, and a specialised image-manipulation tool is used to modify renderings (for instance, changing weather conditions or lighting in visualisations), but AI is not trusted for core technical design tasks, given the risks and responsibilities associated with structural and regulatory compliance.

A second group of organisations can be characterised as being in an intermediate stage,

where AI is beginning to be integrated into specific processes but remains relatively circumscribed. Company A has engaged external providers to run workshops on AI and is piloting tools to support email drafting, meeting transcription and the capture of shop-floor discussions into structured action lists.
Management is also exploring AI-assisted drafting and design tools, although current solutions are not yet at the level required for complex custom work. In Company C, AI systems such as ChatGPT, Gemini and Claude are used to accelerate requirements capture, background research on new technologies, drafting of policies and structuring of project documentation, while remaining subject to human review and contextualisation. In Company E, data from production processes are systematically captured and monitored, and while the transcript foregrounds classical statistical and control-plan methods, the broader digital infrastructure provides a basis for more advanced analytics and AI-enabled optimisation. In these cases, AI supports knowledge work and operational tasks, but its use is still selective, and organisations are actively experimenting to identify robust, value-adding applications.

At the more advanced end of the spectrum, several large organisations in the sample are already deploying AI in multiple, interrelated use cases, particularly at the intersection of operations, knowledge work and decision-making. Company B has begun to explore AI-related pilots in areas such as predictive maintenance, quality analytics and planning optimisation, building on an existing layer of performance management systems and advanced analytics.
Company D, while more cautious in the way it presents AI explicitly, collects and uses large volumes of operational data and is actively reflecting on "what insights are there and what can we do with them", indicating a fertile ground for AI-enhanced learning from data.
Company G is further along in terms of AI for knowledge work: in addition to chatbots and virtual assistants that support agents in interacting with customers, it has launched a portfolio of use cases to support the software development lifecycle (for example, code assistants) and to enable natural-language access to a curated knowledge base through the aforementioned content domain.
Finally, Company I leverages sophisticated data platforms to monitor machine behaviour, inform maintenance strategies and support global manufacturing lines, and it is embedded in a corporate environment that is actively investing in Industry 4.0 and data-driven decision-making.

Across the sample, AI use cases can broadly be grouped into three categories. First, AI and advanced analytics are used to improve operational efficiency: scheduling and capacity planning, predictive or condition-based maintenance, quality control and waste reduction are all areas where data-driven approaches are being pursued. Second, AI increasingly supports knowledge work: generative models assist in drafting documents, structuring policy texts, preparing presentations and summarising meetings; domain-specific tools are considered or deployed to help with requirements engineering, background research and the triage of large volumes of project information. Third, in some organisations AI is beginning to act as a trigger for new roles, routines and governance mechanisms. The creation of central teams for data and AI, the definition of content domains and curated knowledge bases, the introduction of AI-augmented development pipelines and the establishment of structured steering and prioritisation processes for AI projects all indicate that AI is not just a tool, but a catalyst for rethinking how knowledge is organised, accessed and governed.

Cultural attitudes towards AI are nuanced rather than polarised. In several organisations, senior leaders report having been initially sceptical or apprehensive, particularly around issues of reliability, control and the risk of eroding hard-won expertise, but describe a gradual shift towards more active experimentation after exposure to peer experiences and structured workshops. Generational differences are present but not deterministic: younger staff tend to be more comfortable with experimenting with new tools, while more experienced employees bring domain knowledge and a stronger awareness of risks; effective learning often occurs when these perspectives are combined. In domains with high stakes in terms of safety, regulatory compliance or structural integrity, such as architecture, automotive and insurance, caution is particularly pronounced, and AI is framed as an assistant rather than as an autonomous decision-maker. At the same time, there is widespread recognition of the potential benefits of AI in reducing cognitive load, improving access to information, speeding up routine tasks and enabling more systematic reuse of knowledge.

Taken together, the ten cases thus offer a deliberately heterogeneous picture of how knowledge management, organisational learning and AI currently intersect in practice. They range from small, craft-based organisations in which capabilities are deeply grounded in human experience and manual skills and where AI remains ancillary, through medium-sized firms that are actively experimenting with AI-supported knowledge work and operational tools, to large enterprises where AI is progressively embedded into formal systems, roles and routines. This chapter has provided a descriptive, comparative introduction to these cases, positioning them along key dimensions of sector, size, knowledge practices and AI maturity. In the following chapters, the analysis will move from this contextual overview to a more fine-grained examination of how AI interacts with knowledge management processes and organisational learning routines across the cases, and how these interactions contribute to the development of new innovation-related capabilities.

6 | Data Analysis

In this chapter, we present the empirical data structure that emerged from the qualitative analysis and show how the raw interview material was progressively transformed into first-order concepts, second-order themes and aggregate dimensions. The goal of this chapter is deliberately descriptive: we focus on how the data were organised and which higher-level empirical patterns surfaced from the coding process, rather than on fully theorising their implications. The interpretive, theory-building work is then developed in the subsequent chapter.

The analysis is aligned with the constructivist and interpretivist stance discussed in Chapter 4. Organisational reality is treated as socially constructed, and interviewees are considered "knowledgeable agents" who can meaningfully articulate how AI, OL and VC are experienced and enacted in their specific contexts. Following the Gioia methodology, we build our data structure by moving from informant-centric, first-order concepts to researcher-centric second-order themes, and finally to higher-level aggregate dimensions. This structure provides the empirical backbone for addressing our main research question:

How does Artificial Intelligence enhance organisational learning to enable value creation?

and, more specifically, SRQ1:

How does Artificial Intelligence reshape organisational learning practices within organisations, both by augmenting existing organisational learning capabilities and by acting as an organisational learning agent?

Across the ten semi-structured interviews, we identified 167 distinct first-order concepts capturing concrete experiences, practices and reflections related to AI use, learning routines, knowledge management and innovation. In the present chapter we therefore concentrate on the subsequent analytical steps: the construction of second-order themes, the clustering of these themes into six aggregate dimensions, and the presentation of the overall data structure that will be used to develop our grounded theory model in Chapter 7.

6.1. From raw interview material to second-order themes

A first, important step was to recognise that many first-order concepts clustered around a limited number of learning arenas. Some codes gravitated around cycles of problem detection, deviation analysis, lessons learned and experimentation. Here, AI was presented as a component of continuous improvement work: it helped surface anomalies worth investigating, supported more structured reflection on root causes, and made it easier to try out changes and observe their effects. Other codes were clearly future-oriented, focusing on predictive capabilities, anomaly detection and early warning. In these accounts, AI expanded the organisation's sensing capacity and enabled learning that anticipates issues instead of merely reacting to them. A third group of codes revolved around the organisation's knowledge base: how data, documents and experiences were captured, organised and made accessible, and how AI helped turn heterogeneous or under-used information into something that could be actively reused for insight generation. A fourth set of codes focused on collective sensemaking and decision processes: they described how AI-generated outputs entered conversations, how they were discussed, questioned or relied upon, and how they interacted with human judgement and contextual understanding. Another family of codes concerned the behaviour of AI systems themselves: interviewees talked about models learning from data, improving with use, producing new patterns and representations, and raising specific questions in terms of trust, bias and alignment. Finally, a group of codes pointed to cultural, leadership and governance conditions that made it easier or harder to experiment with AI, to learn from its outputs, and to embed it in organisational routines.

These learning arenas were intertwined with more transversal lenses regarding what AI actually did in practice and where learning seemed to reside. Across cases, AI alternately appeared as a monitoring and signalling device, an analytical and forecasting engine, a simulation and experimentation environment, a structuring and retrieval layer for organisational memory, a reflection companion in conversations, and a learning system in its own right. At the same time, the material suggested different levels of learning: in some accounts, the emphasis was on how individuals and teams learned to work differently with AI; in others, on how the organisation as a whole institutionalised new routines and capabilities; in others still, on how AI systems themselves adapted as they were trained, tuned and used. These cross-cutting lenses–learning arenas, AI functions, levels of learning and perceived contributions to value (efficiency, reliability, speed, innovation, risk management)–provided the conceptual scaffolding for grouping first-order concepts into second-order themes without losing sight of the empirical richness from which they emerged.

6.2. The Creation of the Aggregate Dimensions

Once a set of second-order themes had stabilised through iterative comparison, it became evident that they did not form a random collection, but tended to align around a smaller number of broader empirical territories. These territories correspond to the six aggregate dimensions that structure the remainder of the chapter, and their construction was guided by the need to capture, in a parsimonious yet faithful way, how AI reshapes organisational learning capabilities and acts as a learning agent, under specific cultural and governance conditions.

6.2.1. AI-enabled continuous improvement and experimentation

The first territory coalesced around the idea of *AI-enabled continuous improvement and experimentation*. Here converged themes in which AI was tightly interwoven with routines of problem solving, error analysis and trial-and-error learning. The underlying logic of aggregation was that, despite differences in context, the codes and themes in this area all described configurations where AI amplified the organisation's ability to notice deviations, reflect systematically on what went wrong or could be improved, and run experiments more rapidly and with better feedback. In other words, they pointed to an AI-shaped learning capability centred on learning from problems, deviations and attempts, making continuous improvement more data-driven and iterative.

6.2.2. AI-augmented sensing and anticipatory learning

A second empirical territory was defined by *AI-augmented sensing and anticipatory learning*. Themes in this area captured how AI extended organisational sensing beyond immediate experience, for instance by analysing large streams of operational data to identify emerging anomalies, by forecasting future states, or by highlighting weak signals that might otherwise go unnoticed. The rationale for grouping these themes together was that they all described a shift in the temporal orientation of learning: instead of waiting for events to occur and then learning from them, organisations were depicted as learning ahead of time, using AI to explore what might happen and to adjust courses of action before issues fully materialised. The resulting aggregate dimension encapsulates an anticipatory learning capability grounded in AI-enabled sensing.

6.2.3. AI-augmented sensemaking and decision-making

A third territory centred on *AI-augmented sensemaking and decision-making.* The themes grouped within this dimension focused on how AI outputs were woven into interpretive and decision processes, and how managers balanced algorithmic insights with contextual judgement, experience and strategic intent. In these accounts, AI appeared as an intelligence layer that pre-processed information, highlighted options or simulated scenarios, but its contributions were always discussed, questioned and reframed within broader conversations about risks, priorities and organisational goals. Interviewees described AI both as a decision support and as a reflection companion that could challenge assumptions, while also emphasising the need for human guardrails to manage bias, uncertainty and accountability. The aggregation into a single dimension reflects the idea of an organisational learning capability in which learning emerges through the iterative interplay between AI-generated insights and human deliberation. Rather than locating learning solely in human reflection or in algorithmic computation, this capability captures how organisations progressively refine their interpretations and decisions by combining data-driven intelligence with situated sensemaking.

6.2.4. AI-enabled organisational memory and knowledge sharing

A fourth cluster of themes formed around *AI-enabled organisational memory and knowledge sharing.* Across different settings, these themes described how AI-supported tools were used not only to reorganise dispersed data and documents, but to build a more coherent and mobilisable memory base for the organisation. Interviewees recounted how search, recommendation, summarisation and chatbot systems helped classify, connect and surface information that had previously remained buried in archives, personal inboxes or local expertise. At the same time, several themes pointed to how tacit and localised know-how could be captured, translated and made available beyond the original holders, enabling wider access to critical insights and experiences. In this sense, AI did not simply improve storage, but actively supported the sharing and circulation of knowledge across teams, functions and sites. The logic of aggregation here was to capture an organisational learning capability that goes beyond technical knowledge management practices: an AI-enabled capacity to preserve, structure and share organisational knowledge in ways that make it more accessible for dialogue, reflection and day-to-day problem-solving, thereby strengthening the organisation's ability to learn collectively from its own experience.

6.2.5. Embedded algorithmic learning systems as organisational learning agents

A fifth set of themes gave rise to the dimension of *embedded algorithmic learning systems as organisational learning agents*. What distinguished this territory from the previous ones was the focus on AI systems' own learning dynamics. Themes here traced how models changed over time as they were exposed to new data and feedback, how they generated new patterns and solution proposals, and how their internal representations of processes or environments evolved. At the same time, they pointed to specific risks and constraints, such as drift, bias or misalignment with organisational goals. The aggregation logic rested on the recognition that these themes were not primarily about AI as a support for human learning, but about AI as a learning subsystem embedded in organisational life, with its own cycles of data, model and output.

6.2.6. Culture and governance for AI-enabled organisational learning

Finally, a sixth territory, more contextual in nature, brought together themes related to *culture and governance for AI-enabled organisational learning*. The codes and themes in this area emphasised how psychological safety, norms around experimentation and error, leadership sponsorship for AI initiatives, and governance and compliance arrangements shaped the possibilities for AI-enabled learning to take root. The decision to treat these as a separate aggregate dimension reflected the fact that they did not describe an AI-mediated learning capability in themselves, but the conditions under which such capabilities could emerge, be sustained and contribute to value creation. They define the backdrop against which all other dimensions operate.

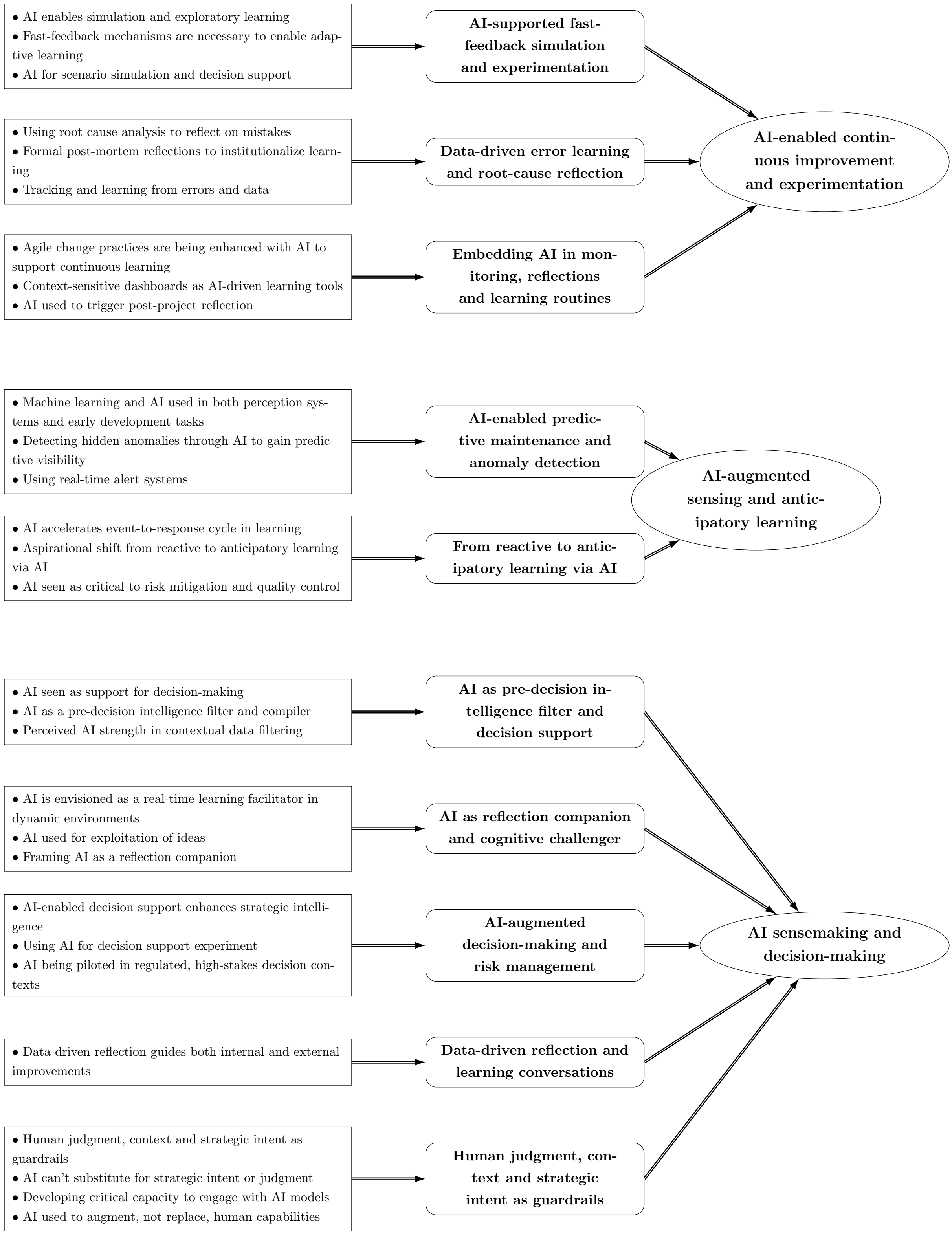
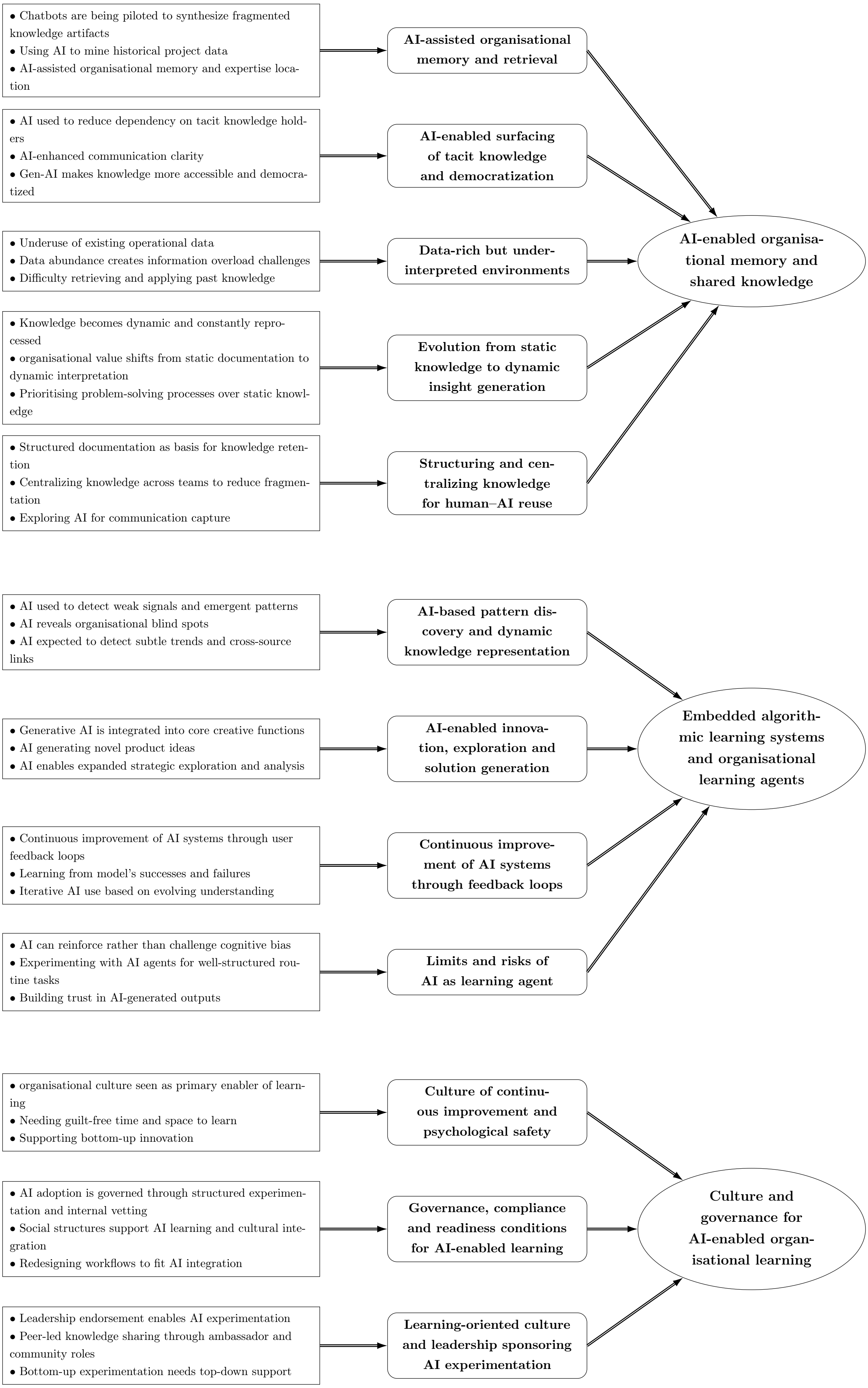


Figure 6.1: From First Order Codes to Aggregate Dimensions


• Chatbots are being piloted to synthesize fragmented knowledge artifacts
• Using AI to mine historical project data
• AI-assisted organisational memory and expertise location
AI-assisted organisational memory and retrieval
• AI used to reduce dependency on tacit knowledge holders
• AI-enhanced communication clarity
• Gen-AI makes knowledge more accessible and democratized
AI-enabled surfacing of tacit knowledge and democratization
• Underuse of existing operational data
• Data abundance creates information overload challenges
• Difficulty retrieving and applying past knowledge
Data-rich but under-interpreted environments
AI-enabled organisational memory and shared knowledge
• Knowledge becomes dynamic and constantly reprocessed
• organisational value shifts from static documentation to dynamic interpretation
• Prioritising problem-solving processes over static knowledge
Evolution from static knowledge to dynamic insight generation
• Structured documentation as basis for knowledge retention
• Centralizing knowledge across teams to reduce fragmentation
• Exploring AI for communication capture
Structuring and centralizing knowledge for human–AI reuse
• AI used to detect weak signals and emergent patterns
• AI reveals organisational blind spots
• AI expected to detect subtle trends and cross-source links
AI-based pattern discovery and dynamic knowledge representation
• Generative AI is integrated into core creative functions
• AI generating novel product ideas
• AI enables expanded strategic exploration and analysis
AI-enabled innovation, exploration and solution generation
Embedded algorithmic learning systems and organisational learning agents
• Continuous improvement of AI systems through user feedback loops
• Learning from model's successes and failures
• Iterative AI use based on evolving understanding
Continuous improvement of AI systems through feedback loops
• AI can reinforce rather than challenge cognitive bias
• Experimenting with AI agents for well-structured routine tasks
• Building trust in AI-generated outputs
Limits and risks of AI as learning agent
• organisational culture seen as primary enabler of learning
• Needing guilt-free time and space to learn
• Supporting bottom-up innovation
Culture of continuous improvement and psychological safety
• AI adoption is governed through structured experimentation and internal vetting
• Social structures support AI learning and cultural integration
• Redesigning workflows to fit AI integration
Governance, compliance and readiness conditions for AI-enabled learning
Culture and governance for AI-enabled organisational learning
• Leadership endorsement enables AI experimentation
• Peer-led knowledge sharing through ambassador and community roles
• Bottom-up experimentation needs top-down support
Learning-oriented culture and leadership sponsoring AI experimentation

Taken together, these six aggregate dimensions offer a structured view of how the diverse first-order concepts and second-order themes align around a small set of AI-enabled learning capabilities and contextual enablers. The aggregation was driven not by a desire to fit the data into preconceived categories, but by the recurrent ways in which AI's functions, learning practices, levels of learning and value implications coalesced into recognisable configurations across the material. In this sense, the movement from raw interview segments to first-order concepts, from concepts to themes and from themes to aggregate dimensions can be read as a progressive clarification of the core story emerging from the field: organisational learning in the AI era unfolds through a hybrid landscape in which existing learning capabilities are reshaped by AI, new algorithmic learning processes are embedded in organisational systems, and culture and governance critically condition whether these developments translate into value creation. In the following chapter, these aggregate dimensions are taken forward and combined with our empirical findings and theoretical reasoning to develop the grounded model and the broader interpretive discussion.

7 | Grounded Theory Model: Organisational Learning in the AI Era

7.1. Introduction to the Grounded Theory Model

This chapter presents the Grounded Theory Model developed from the empirical study to address SRQ1: *How does Artificial Intelligence reshape organisational learning practices within organisations, both by augmenting existing organisational learning capabilities and by acting as an organisational learning agent?*
Building on the inductive analysis of the case evidence, the chapter articulates a coherent explanatory model of organisational learning in the AI era, describing how learning routines are transformed when AI becomes embedded in day-to-day processes, decision cycles, and knowledge infrastructures. In doing so, the chapter provides the conceptual bridge between the empirical insights generated through the Grounded Theory approach and the broader research objective of the thesis.

Positioning SRQ1 within the overall research logic, the model presented here specifically explains how AI reshapes organisational learning at the level of capabilities, routines, and mechanisms. This chapter therefore lays the foundations for MRQ by clarifying the learning dynamics through which AI-enabled change unfolds. The downstream implications for value creation are then examined in the subsequent chapter, where the model's learning mechanisms are connected to organisational outcomes and strategic consequences.

The grounded theory model conceptualises AI-enabled organisational learning through two complementary layers that operate in parallel and continuously influence one another. Layer 1 captures the ways in which AI reshapes human-centred organisational learning capabilities, strengthening and reconfiguring how individuals and teams detect problems, reflect on performance, share knowledge, and make decisions. In this layer, AI does not replace organisational learning; rather, it modifies the conditions under which learning oc-

curs by accelerating feedback cycles, expanding the scope of evidence available for reflection, and supporting more structured knowledge reuse. This layer is represented through four aggregate dimensions: AD1 (AI-enabled continuous improvement and experimentation), AD2 (AI-augmented sensing and anticipatory learning), AD3 (AI sensemaking and decision-making), and AD4 (AI-enabled organisational memory and shared knowledge). Together, these dimensions describe how AI becomes intertwined with routines of improvement, sensing, interpretation, and memory, thereby shaping the organisation's capacity to learn.
Layer 2 introduces a distinct but interconnected dynamic: embedded algorithmic learning systems functioning as organisational learning agents. Rather than focusing on AI as a tool that supports human learning, this layer highlights that certain AI systems can themselves enact learning routines–such as identifying patterns in operational data, detecting anomalies, updating predictive representations, generating alternative solutions, or improving performance through iterative feedback. This layer is represented by AD5 (Embedded algorithmic learning systems as organisational learning agents) and reflects an emergent form of organisational learning agency grounded in algorithmic adaptation. Importantly, the model treats this algorithmic agency as organisationally embedded: it becomes consequential for learning only insofar as it is connected to organisational routines, interpretive processes, and feedback loops through which outputs are evaluated, corrected, and integrated into practice.
Across both layers, the model emphasises the pivotal role of AD6 (Culture and governance for AI-enabled organisational learning) as a contextual enabler and constraint. Culture and governance shape whether AI-enabled learning dynamics result in constructive organisational learning or in fragile, misaligned, or compliance-constrained forms of adoption. Learning-oriented leadership, psychological safety, and openness to experimentation condition the willingness to engage with AI-generated insights and to revise established routines. At the same time, governance arrangements–such as accountability structures, compliance requirements, data stewardship, and readiness for responsible AI–set the boundaries within which AI can be deployed, trusted, and improved. AD6 therefore modulates not only the effectiveness of AI in augmenting human-centred learning capabilities, but also the legitimacy and sustainability of algorithmic learning systems acting within the organisation.

At a high level, the grounded model is anchored in a Gioia-inspired data structure that culminated in six aggregate dimensions (AD1–AD6) supported by coherent second-order themes. These dimensions are not presented as independent pillars; rather, they form an integrated system in which learning emerges from the interaction between improved organisational capabilities, algorithmic learning routines, and the sociotechnical context that governs their use. The model thus reframes AI-enabled organisational learning as a dynamic configuration: AI strengthens and reshapes capability-based learning processes while also introducing new forms of learning agency that must be orchestrated, interpreted, and governed.

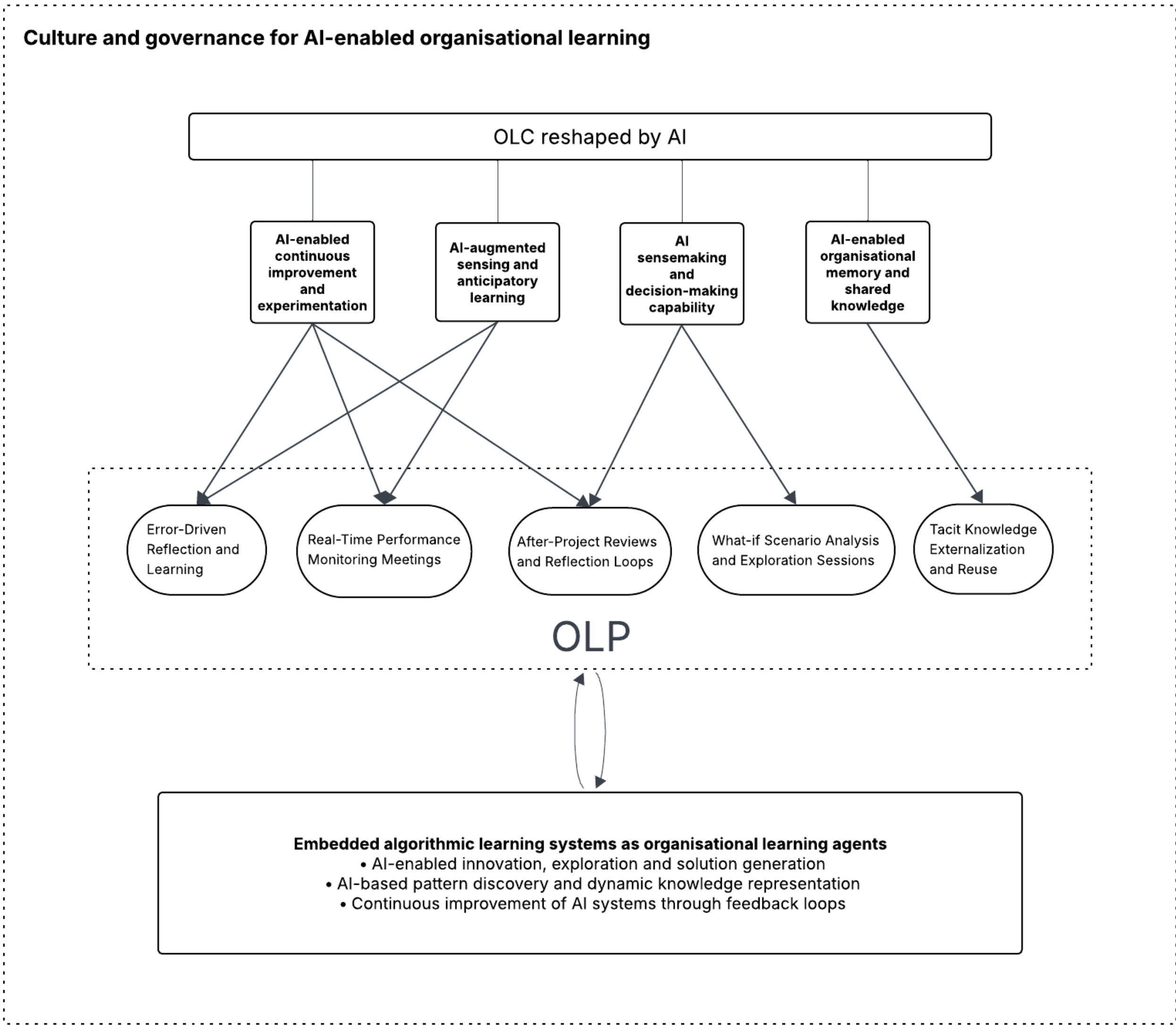


Figure 7.1: Organisational Learning in the AI Era

7.2. Overview of the "Organisational Learning in the AI Era" model

This section introduces the overall architecture of the grounded theory model and clarifies the logic through which its components connect. It provides the reader with a "map" for the remainder of the chapter by explaining how the model is organised into two analytical layers, how these layers are connected through a set of organisational learning practices, and how the entire configuration operates within an overarching cultural and governance context. The model figure is inserted in this section and will serve as the reference point for the chapter's detailed discussion of the six aggregate dimensions.

7.2.1. Model Architecture and Logic

The model is structured around a clear separation between two forms of learning in the AI era. The upper layer captures AI-shaped organisational learning capabilities, represented by AD1–AD4, which describe how AI reshapes human-centred learning processes within organisations. The lower layer captures embedded algorithmic learning systems as organisational learning agents, represented by AD5, which reflects how AI systems can enact learning routines through adaptive, data-driven mechanisms. Between these two layers, the model places a set of organisational learning practices as the central connective element: practices represent the concrete routines through which learning is carried out and through which the effects of both layers materialise in day-to-day organisational life. Surrounding both layers and the practices, the model depicts AD6 as an overarching contextual boundary that conditions how the entire system operates.

A critical feature of the model is that the connection between layers is practice-mediated, rather than framed as a fully recursive, layer-to-layer learning loop. In other words, the model does not assume that "capabilities" in the upper layer and "algorithmic learning systems" in the lower layer continuously feed into one another as abstract constructs. In this architecture, the upper layer primarily follows a capability-to-practice logic: AD1–AD4 shape how learning practices are enacted by altering the quality, speed, granularity, and continuity of reflection, sensing, sensemaking, decision-making, and knowledge reuse routines. The model therefore treats practices as the operational arena in which AI-shaped organisational learning capabilities become visible and actionable–namely through changes in how teams monitor performance, diagnose problems, learn from outcomes, explore alternatives, and share or reuse knowledge.

By contrast, the lower layer introduces an explicit bidirectional dynamic between AD5 and organisational learning practices. Embedded algorithmic learning systems can augment and automate learning routines by performing pattern discovery, anomaly detection, iterative improvement through feedback, and exploration through simulation. Through the routines embedded in practices–such as structured reflection, review, monitoring conversations, and scenario exploration–organisations evaluate model outputs, identify misalignments, feed back corrections, decide whether and how systems should be updated, and define the boundaries within which algorithmic learning is legitimate and useful. For this reason, the model locates its main recursive dynamic in the AD5-OLP loop, rather than across the entire two-layer structure.

Within this architecture, AD6 does not belong to a single layer. Rather, it functions as an overarching socio-technical context that encloses the entire model, conditioning the effectiveness, legitimacy, and sustainability of both AI-shaped learning capabilities and embedded algorithmic learning systems, as well as the organisational learning practices that connect them. In practical terms, AD6 captures the cultural and governance conditions that determine whether AI-enabled learning becomes a robust organisational capability or remains fragile, contested, or constrained. Cultural elements such as psychological safety, openness to experimentation, and leadership sponsorship shape whether individuals and teams feel able to question outputs, surface errors, and engage in reflective learning rather than compliance-driven adoption. Governance elements shape whether algorithmic learning can be improved safely and whether its outputs can be trusted and integrated into organisational routines. This contextual boundary therefore modulates both the capability layer (how learning practices are enacted) and the AD5-OLP loop (how algorithmic learning is steered and stabilised).

7.2.2. Theoretical Positioning of the Model

The upper layer of the model is theoretically anchored in the OLC perspective, and particularly in the framework developed by Chiva et al. (2007), which conceptualises learning capabilities as organisational conditions that enable learning to occur. In that view, dimensions such as experimentation, risk-taking, interaction with the external environment, dialogue, and participative decision-making collectively support the organisation's ability to adapt and improve through learning. The grounded theory model builds on this tradition by retaining the core idea that organisational learning is enabled by capabilities embedded in routines, relationships, and organisational context. At the same time, the model argues that the AI era introduces learning dynamics that require the OLC framework to be extended in order to account for AI-enabled mechanisms and the emergence of algorithmic learning agency within organisations. This repositioning is necessary because AI reshapes the environment in which learning capabilities operate. It changes the scale and immediacy of information flows, increases the feasibility of continuous monitoring and rapid feedback, and introduces new forms of representation and prediction that can alter how organisations detect issues, interpret signals, and evaluate options. It also changes how learning agency is distributed: while human actors remain accountable for judgement, intent, and contextual interpretation, AI systems increasingly participate in the learning process by generating signals, synthesising patterns, and updating predictive representations that influence organisational action. The grounded model responds to these shifts by offering a two-layer perspective that integrates both the reshaping of human-centred learning capabilities and the organisational implications of embedded algorithmic learning systems. The model's theoretical contribution can be clarified through a high-level what–how–who lens, used here as an interpretive device rather than as a rigid template. In terms of what remains stable, the model preserves the fundamental purpose of organisational learning capabilities: enabling reflection, experimentation, dialogue, participative engagement, and the transformation of experience into improved routines. What is expanded, however, is the scope and temporal structure of learning: learning becomes less episodic and more continuous, less reliant on manual sensemaking alone and more intertwined with dynamic insight generation and retrieval processes. In terms of how organisational learning capabilities are reshaped, the model emphasises AI-enabled mechanisms such as prediction and anomaly detection, simulation and what-if exploration, retrieval and reuse of codified and externalised knowledge, continuous monitoring, and fast feedback loops that can accelerate learning cycles and alter how organisational routines are conducted. Finally, in terms of who participates in learning, the model highlights a shift toward distributed learning agency: humans remain responsible for contextual interpretation, value-laden judgement, and strategic intent, while AI systems increasingly contribute to learning routines by performing adaptive, data-driven learning functions. This shift is most explicit in AD5, where embedded algorithmic learning systems are conceptualised as organisational learning agents whose learning becomes meaningful only through their integration into organisational practices and governance arrangements.

7.2.3. OLP in the Model

Within this thesis, we defined organisational learning practices as recurring organisational routines in which reflection, interpretation, knowledge reuse, and adaptation are carried out in a relatively structured way. They represent the observable "sites" of learning through which the organisation converts information into shared understanding, revised decisions, and changed routines. In the empirical context of this multiple-case study, these practices emerged inductively from the data as recurring learning routines that organisations rely on to diagnose performance issues, interpret signals, explore alternatives, and institutionalise knowledge for future reuse. The model incorporates five practices as its operational backbone: **Error-Driven Reflection and Learning**, **Real-Time Performance Monitoring Meetings**, **After-Project Reviews and Reflection Loops**, **What-if Scenario Analysis and Exploration Sessions**, and **Tacit Knowledge Externalization and Reuse**. These practices are depicted in the model as the connective element between the two layers because they translate abstract capabilities and algorithmic learning mechanisms into organisational action. At the same time, to preserve analytical clarity, the chapter focuses on the primary linkages between practices and aggregate dimensions, while acknowledging that minor overlaps can exist without elaborating them in detail. Conceptually, the practices serve two complementary roles in the model. First, they are the arenas where AI-shaped organisational learning capabilities (AD1–AD4) become enacted in everyday work. Changes in sensing, experimentation, decision-making, and organisational memory do not remain at the level of "capability"; they materialise as modifications in how monitoring meetings are conducted, how errors are discussed and learned from, how project reviews capture and reuse insights, how scenario exploration is performed, and how tacit knowledge is surfaced and made reusable. Second, the practices are the sites where the model's explicit recursive dynamic is operationalised–namely, the AD5-OLP loop. Through practices, human actors evaluate and steer algorithmic learning, providing feedback, corrections, and governance decisions that shape how embedded AI systems are refined, trusted, and embedded into subsequent learning cycles.

7.3. AD1–AI-enabled Continuous Improvement and Experimentation

Across the cases, continuous improvement emerges not as a background activity, but as a learning process that is increasingly reshaped by the presence of Artificial Intelligence. AD1 refers to the capability through which AI strengthens organisational learning by supporting faster, more evidence-based, and more iterative improvement cycles. Rather than acting as a standalone analytical tool, AI becomes consequential insofar as it reshapes how organisations enact learning through practice–most notably within Error-Driven Reflection and Learning, Real-Time Performance Monitoring Meetings, and After-Project Reviews and Reflection Loops. It is through these routines that improvement becomes less episodic and more continuously embedded in organisational work.

What distinguishes AD1 from more traditional accounts of continuous improvement is a shift in how learning unfolds over time. Improvement is no longer confined to moments of disruption, formal audits, or periodic reviews, but becomes a recurring feature of everyday operations. The basic logic of organisational learning remains familiar: discrepancies are surfaced, causes are examined, alternatives are tested, and routines are updated. However, AI alters the execution of these steps. Deviations are detected with greater speed and granularity, reflection is supported by a broader and more systematic evidence base, and experimentation becomes less costly to initiate. As a result, organisations can cycle more fluidly between observation, diagnosis, action, and renewed learning, reinforcing improvement as an ongoing rather than exceptional activity.

One way in which this capability becomes visible is through changes in how organisations learn from errors. Empirical concepts indicate a growing emphasis on structured root-cause analysis, formalised post-mortem reflection, and systematic tracking of errors and performance data. AI contributes by making deviations more visible and traceable across time and contexts. Instead of relying primarily on retrospective narratives or local interpretations of failure, learning from error becomes anchored in operational signals such as anomalies, recurring patterns, and cross-event linkages that may be difficult to reconstruct manually. This does not imply that diagnosis is delegated to algorithms. Rather, AI increases the legibility of errors, enabling organisational actors to engage in deeper and more comparative analysis.

The implications of this shift are particularly evident within Error-Driven Reflection and Learning practices. When deviations can be reconstructed with greater precision, reflective discussions move beyond anecdotal accounts toward more diagnostic inquiry. This distinction is critical: effective error learning depends not only on recognising that something went wrong, but on understanding why it happened, whether similar patterns recur elsewhere, and which underlying assumptions or process features require revision. In this way, reflection supported by AI-generated evidence facilitates institutionalisation, allowing lessons to be codified into procedures, decision rules, or control mechanisms rather than remaining tacit or context-specific. Such dynamics resonate with established views of organisational learning as a process of detecting and correcting error through reflective inquiry.

Related dynamics unfold within After-Project Reviews and Reflection Loops. Retrospective learning practices are often vulnerable to hindsight bias, selective memory, and over-attribution to salient events. AD1 suggests that AI strengthens these routines by providing a more robust evidential basis for reconstructing outcomes and tracing causal chains across project phases. Data-supported reflection helps organisations sustain a more disciplined learning posture, supporting critical examination of how decisions, assumptions, and process configurations shaped results. At the same time, the socio-technical nature of learning remains central: evidence does not speak for itself, and learning still depends on collective interpretation, debate, and commitment to change. AI enhances the quality and discipline of reflection without replacing the organisational work of sensemaking.

Beyond retrospective learning, AD1 also encompasses how AI becomes woven into monitoring and learning routines, reducing reliance on exceptional events to trigger improvement. Empirical concepts highlight the use of context-sensitive dashboards as learning artefacts, the reinforcement of agile change practices through AI-supported feedback, and the use of AI to prompt reflection activities. Through repeated enactment, these mechanisms routinise learning: improvement becomes something organisations repeatedly do, rather than something they periodically intend.
This embedding effect is particularly visible in Real-Time Performance Monitoring Meetings. When teams engage with AI-enhanced dashboards that foreground deviations, trends, and emerging issues, monitoring discussions tend to shift in character. Rather than focusing on reporting or opinion-sharing, conversations centre on diagnosis, prioritisation, and coordinated action. Learning becomes more tightly coupled with real-time evidence, enabling quicker escalation of issues and more systematic assessment of whether interventions achieve their intended effects. Importantly, learning speed increases not because decisions are rushed, but because the distance between noticing a deviation, discussing its implications, and testing an adjustment is reduced.
Embedding AI within monitoring routines also reshapes the temporal rhythm of learning. Reflective inquiry, which is often postponed until after outcomes are realised, can be initiated earlier and more frequently. Automated or semi-automated triggers may signal when review is warranted, making reflection less discretionary and more systematically integrated into organisational routines. In this sense, AD1 captures how AI contributes to the infrastructure that sustains learning over time, reinforcing continuity rather than episodic improvement.

A further dimension of AD1 concerns experimentation and fast feedback. Empirical concepts point to the use of AI for simulation, scenario exploration, and adaptive learning, enabling organisations to explore alternatives before committing to action. By lowering the cost of experimentation and accelerating feedback, AI allows teams to test assumptions, compare options, and iteratively refine hypotheses without relying exclusively on real-world trial-and-error.
From the perspective of continuous improvement, this capability compresses the cycle between hypothesis, test, insight, and iteration. Instead of waiting for outcomes to materialise after implementation, organisations can explore potential consequences ex ante,

anticipating trade-offs, sensitivities, and failure modes. This complements After-Project Reviews and Reflection Loops by strengthening pre-project exploration: organisations become better at defining what should be tested, what constitutes success, and which signals merit attention. More broadly, fast feedback supports a learning orientation grounded in iterative adjustment rather than one-shot optimisation, consistent with established accounts of organisational learning as a balance between exploration and exploitation. Within AD1, the key contribution of AI lies not in guaranteeing superior decisions, but in reducing friction in experimentation and enabling learning through repeated cycles of conjecture and refinement.

Taken together, AD1 describes a mechanism through which AI reinforces organisational learning by stabilising continuous improvement as a recurring, evidence-based, and iterative process. Errors and deviations become more visible and diagnosable, supporting disciplined reflection and more robust post-mortems. Learning is routinised through AI-enabled monitoring and reflection triggers, embedding improvement within everyday work. Experimentation accelerates through simulation and fast feedback, enabling organisations to test and refine alternatives with greater speed and lower cost. Through the mediation of practices, these elements combine into a continuous improvement engine in which learning emerges from repeated cycles of monitoring, reflection, experimentation, and institutionalisation.

7.4. AD2–AI-augmented Sensing and Anticipatory Learning

AD2 captures the organisational learning capability through which AI strengthens sensing and enables anticipatory learning, reshaping how organisations detect emerging signals, interpret deviations, and act early enough to prevent escalation. Within the practice-mediated logic of the Grounded Theory Model, this capability becomes organisationally meaningful not simply through the presence of predictive technologies, but through their integration into recurring learning practices. In particular, Real-Time Performance Monitoring Meetings and Error-Driven Reflection and Learning constitute the primary sites where AI-generated signals are collectively interpreted, prioritised, and translated into preventive adaptations.

At a conceptual level, AD2 reflects a shift in the temporal structure of organisational learning. Rather than being predominantly triggered after events–through incidents, breakdowns, or visible performance failures–learning increasingly occurs before outcomes fully materialise. This does not suggest that prediction automatically constitutes learning. Instead, it highlights a reorientation of learning toward earlier stages in the causal chain, where emerging patterns and weak signals can be surfaced, discussed, and acted upon before they crystallise into failure. In this sense, learning under AD2 remains deeply organisational: it emerges when signals are transformed into shared understanding and coordinated action through established routines.

A central aspect of this capability concerns AI-enabled anomaly detection and predictive maintenance. Across cases, organisations deploy machine learning systems within perception and monitoring infrastructures to detect subtle deviations, identify hidden anomalies, and generate real-time alerts. The key shift lies in organisational attention and perception. AI expands the organisation's sensing capacity by registering patterns that would remain difficult to detect through manual monitoring alone, particularly when signals are distributed across large volumes of operational data or arise from complex interactions among variables. By doing so, AI functions as an attentional amplifier, converting diffuse data streams into structured cues–alerts, anomalies, and early warnings–that can be surfaced for human interpretation.

This expansion of sensing capacity reshapes how learning unfolds within Real-Time Performance Monitoring Meetings. Monitoring routines move beyond reliance on lagging indicators and retrospective explanations, becoming increasingly forward-looking. Teams use AI-generated alerts to prioritise emerging issues, interpret deviations as early warnings, and decide whether and how to intervene before performance degradation becomes entrenched. Consequently, learning conversations shift from questions of "what happened" toward "what might happen if this trend continues" and "what should be done now to prevent escalation." Importantly, AI does not replace organisational judgement in this process. Signals are not self-explanatory; they require contextualisation, domain expertise, and cross-functional coordination to determine whether an anomaly reflects noise, a meaningful pattern, or a systemic vulnerability. The contribution of AI therefore lies not in automated learning, but in reducing the friction of early detection and creating more frequent and timely opportunities for learning-oriented dialogue.

AD2 also reshapes Error-Driven Reflection and Learning by shifting error learning upstream. Earlier detection enables organisations to learn not only from realised failures, but also from near-misses, weak signals, and early deviations that reveal latent vulnerabilities. Reflection becomes increasingly prevention-oriented: teams examine why anomalies emerged, how they were detected, and which assumptions, thresholds, or processes require adjustment to avoid recurrence. Rather than replacing traditional error learning, AI-enabled sensing changes its timing and scope, extending learning beyond post hoc correction toward anticipatory inquiry. This shift is particularly consequential in contexts where delayed learning is costly and where early detection itself constitutes a critical learning mechanism that enhances organisational resilience.

Closely connected to this sensing expansion is a broader move from reactive toward anticipatory learning. The empirical concepts associated with AD2 highlight how AI accelerates the event-to-response cycle, supporting an organisational aspiration to act earlier in the face of emerging risks and quality issues. At its core, this orientation foregrounds learning tempo and timing as central determinants of adaptability. When learning is predominantly retrospective, it is constrained by delayed feedback and repeated cycles of avoidable rework. By contrast, AI shortens the time required to recognise emerging issues, align organisational attention, and initiate coordinated responses. Learning speed increases not because decisions are rushed, but because recognition and mobilisation occur earlier.

From a learning-theoretical perspective, this anticipatory orientation can be understood as partially counteracting forms of learning myopia, where organisations focus narrowly on immediate performance pressures at the expense of broader scanning and exploration. By rendering weak signals more salient and operationally actionable, AI widens the organisation's perceptual field. Yet anticipatory learning remains fundamentally organisational: signals must be interpreted, integrated into routines, and supported by shared norms that legitimise acting on early warnings. Learning, in this sense, continues to depend on the conversion of information into changed organisational action and, over time, into institutionalised routines.

Within Real-Time Performance Monitoring Meetings, anticipatory learning becomes visible as monitoring practices evolve from status reporting toward prevention-oriented coordination. Meetings function as structured arenas where predictive cues are translated into prioritisation and action, enabling teams to decide which alerts warrant attention, what additional information is required, and which preventive adjustments should be trialled. These practices operate not only as control mechanisms, but as learning mechanisms, allowing organisations to repeatedly test the meaningfulness of early signals, evaluate the effectiveness of interventions, and recalibrate thresholds and decision rules. Error-Driven Reflection and Learning provides the complementary mechanism through which anticipatory insights are consolidated. As organisations act on early warnings and near-misses, reflective routines codify what has been learned, updating response playbooks, refining quality controls, and stabilising new interpretations of risk and deviation.

Taken together, AD2 captures a single underlying mechanism through which AI augments organisational learning by reshaping both the timing and the tempo of learning.

AI-enabled sensing expands the organisation's capacity to surface weak signals earlier, while anticipatory learning converts these signals into faster, prevention-oriented organisational adaptation. Through the mediation of practices, this sensing-and-anticipation dynamic strengthens how organisations coordinate attention, interpret emerging patterns, and institutionalise preventive learning. Rather than displacing human-centred learning, AD2 shifts learning earlier in the causal chain and accelerates its cycle, reducing the distance between emerging signals and learning-driven action.

7.5. AD3–AI Sensemaking and Decision-Making

In the grounded theory model, AD3 is concerned with what happens when signals and information must be turned into shared meaning and, ultimately, into action. It refers to the capability through which AI strengthens organisational learning by supporting sensemaking–collective interpretation and the construction of shared understanding–and decision-making–the selection of actions under uncertainty.

Viewed conceptually, AD3 reflects a movement away from sensemaking and decisions constrained by bounded attention, fragmented information, and locally held interpretations. In its place, the data suggests a mode of AI-supported interpretation in which information can be filtered, synthesised, and, at time, deliberately challenged. AI can structure inputs, reduce noise, and offer alternative framings, yet learning materialises only when organisational actors translate AI-mediated insights into revised interpretations, choices, and updated routines.

A recurring pattern in the empirical material is the portrayal of AI as a pre-decision intelligence filter and decision support mechanism. AI is described as screening large quantities of contextual information, surfacing what appears relevant, and helping compile the evidence needed to frame the decision space. The organisational learning implication is not that AI makes decisions, but that it can improve the quality of attention: teams can focus on more informative cues, compare alternatives more systematically, and make assumptions explicit before committing to action. This dynamic connects especially to What-if Scenario Analysis and Exploration Sessions, where AI-enabled compilation and filtering enrich how options are constructed and evaluated. Scenario work becomes less dependent on intuition alone and more grounded in structured comparison, sensitivity thinking, and explicit trade-offs–while still requiring human interpretation and intent to determine which criteria matter and why.

The same sensemaking-and-choice capability becomes particularly salient where decisions carry risk, regulatory exposure, or high-stakes quality implications. In these contexts, AI-augmented decision-making is portrayed as strengthening strategic intelligence, not by replacing organisational judgement but by expanding the analytical surface through which risk is reasoned about. Scenario exploration functions here as a vehicle for disciplined risk thinking: AI can generate candidate options, stress-test assumptions, and surface potential consequences that might otherwise be overlooked. Yet the learning contribution depends on how outputs are used. When accountability is high and the cost of error is substantial, AI-enabled decision support tends to intensify requirements for validation, documentation, and governance rather than merely accelerating action. This reinforces a key point in AD3: AI may widen the decision space, but it simultaneously raises the need for explicit and disciplined sensemaking–defining what counts as acceptable risk, what evidence is sufficient, and how uncertainty should be managed.

Alongside these pre-decision mechanisms, AD3 also concerns how AI reshapes reflection itself as a collective learning process. The data suggests that AI can shift learning conversations away from opinion-based or anecdotal accounts toward more evidence-grounded reflection that informs both internal improvement and external adaptation. This becomes most visible in After-Project Reviews and Reflection Loops, where AI-supported reconstruction of events and outcomes can help teams compare expectations with observed results, identify contributing factors, and structure "lessons learned" in ways that are more transferable. The learning gain is therefore not simply an increase in data availability, but an improvement in collective interpretation: a shared account of what happened, why it mattered, and what should change.

Beyond compilation and reconstruction, the empirical concepts also portray AI as a reflection companion and cognitive challenger. In this role, AI is described as prompting alternative interpretations, surfacing blind spots, and helping teams refine ideas. The "companion" framing is analytically useful because it clarifies a distinctive mechanism within AD3: AI can function as an interactive interlocutor that encourages inquiry and counterfactual thinking, thereby strengthening the cognitive quality of reflection. Within after-project reviews, such challenging can deepen learning by making it harder to settle for convenient explanations, pushing teams to test causal narratives against evidence, and exploring "what else could explain this outcome." In scenario exploration, the same mechanism can broaden the set of alternatives considered and reduce premature closure.

Running through these mechanisms is an explicit boundary condition: the continued centrality of human judgment, context, and strategic intent as guardrails. The data emphasises that AI augments decision processes but cannot substitute for accountability, value-laden trade-offs, or strategic intent. This is not merely normative; it follows structurally from the nature of organisational decision-making. Decisions embed priorities, ethics, and context-specific goals that cannot be derived from data alone, and they entail responsibility for consequences. AD3 therefore foregrounds the development of critical capacity to engage with AI models: the organisational ability to question outputs, understand limitations, and decide how much weight AI-generated insights should carry in different contexts. These guardrails matter across both linked practices. In scenario sessions, they shape whether AI outputs are treated as hypotheses to test or as answers to adopt. In after-project reviews, they determine whether reflection remains inquiry-oriented or collapses into post hoc rationalisation and confirmation.

Overall, these themes form an AI-augmented sensemaking-and-decision engine. AI filters and compiles inputs to improve attention and framing before choices are made; it strengthens evidence-based learning conversations that translate outcomes into shared understanding; it can operate as a cognitive challenger that expands perspectives and prompts disciplined inquiry; and it enhances decision-making under risk by supporting structured evaluation of alternatives. Across all mechanisms, human judgment and strategic intent remain essential guardrails that preserve accountability and contextual relevance.

7.6. AD4–AI-enabled Organisational Memory and Shared Knowledge

Organisational learning often fails not because organisations lack experience, but because experience does not reliably travel: it remains locked in individuals, scattered across artefacts, or forgotten between projects and teams. AD4 addresses this problem by describing the capability through which AI strengthens organisational learning via organisational memory and shared knowledge, making insights more retrievable, reusable, and distributable across time and organisational units.

AD4 reflects a shift from "knowledge as static repositories" and fragmented artefacts toward AI-enabled memory as an active capability. In many organisations, knowledge is dispersed across documents, informal communications, and locally held expertise, which makes learning difficult to retrieve and reuse when new problems arise. AD4 highlights how AI changes this dynamic by enabling richer retrieval, synthesis, and recombination across distributed sources, and by supporting expertise location and translation of knowledge into forms that others can apply. Crucially, organisational memory becomes learning-relevant not because information is stored, but because stored experience can be activated–used to reduce reinvention, support continuity, and improve problem solving in present decisions.

However, the data suggests that this form of "active memory" rarely results from deploying AI on top of a messy knowledge landscape. Instead, Tacit Knowledge Externalization and Reuse depends on a foundational layer of structuring and centralisation that makes knowledge findable, intelligible, and maintainable over time. Organisations recognise that documentation must be structured and consolidated if it is to become reusable, and that fragmentation across teams reduces the probability that learning from one context can be located and applied in another. This foundational layer also includes exploration of AI-enabled communication capture, reflecting the fact that much valuable organisational knowledge is embedded in conversations rather than formal documents. From an organisational learning perspective, these moves matter because they stabilise learning outcomes into accessible artefacts, increasing the likelihood that insights are reused rather than forgotten or reinvented.

Once knowledge is stabilised into a more coherent substrate, AD4 becomes visible in how organisational memory is retrieved and mobilised in practice. The empirical concepts point to organisations piloting chatbots that synthesise fragmented knowledge artefacts, using AI to mine historical project data, and supporting expertise location. Taken together, these signals indicate a shift from retrieval as "searching documents" toward retrieval as synthesis and reconstruction across distributed traces of knowledge. In traditional systems, mobilisation of organisational memory often depends on knowing where information is stored, having the right keywords, or relying on personal networks to identify who knows what. AI-assisted retrieval changes this by aggregating dispersed artefacts–documents, project histories, and other records–into a more coherent response, while also reducing dependence on informal connections through expertise location. In the context of Tacit Knowledge Externalization and Reuse, this matters because reuse becomes practically feasible when prior learning can be located and reconstructed without requiring social proximity or exceptional personal memory.
At the same time, AD4 implies a necessary caution that remains consistent with a sociotechnical view of learning. AI can facilitate retrieval and synthesis, but organisational validation and contextual interpretation remain essential. Organisational memory is rarely "plug-and-play": knowledge developed for one setting often requires adaptation, and AI-mediated synthesis must be assessed for relevance, completeness, and appropriateness. In this respect, AD4 resonates with the broader view that knowledge becomes valuable when it is integrated into action through organisational processes rather than treated as neutral content.

A further aspect of Tacit Knowledge Externalization and Reuse concerns who can access knowledge and how widely learning can spread. The data suggests that organisations see AI as a way to reduce dependency on tacit knowledge holders, improve communication clarity, and make knowledge more accessible and democratised. This responds to a persistent organisational learning vulnerability: expertise is often concentrated in a few individuals, creating a "single point of failure" when critical know-how is inaccessible, difficult to articulate, or unevenly distributed. AI can support externalisation by assisting articulation–, thereby lowering barriers to sharing. As generative systems become embedded in everyday workflows, natural language interaction with organisational content also enables non-experts to ask questions and receive structured answers, widening participation in reuse. Yet the same democratisation introduces new learning demands: as access expands, organisations must ensure that knowledge is interpreted correctly and that users understand the limits, context, and validity of AI-mediated responses. AD4 therefore implies not only broader access, but also the need for shared norms and practices around responsible reuse.

These dynamics also speak directly to the paradox that motivates AD4: data-rich but under-interpreted environments. Organisations may accumulate abundant operational data and many artefacts, yet still struggle with overload, underuse, and difficulty retrieving and applying past knowledge in the moment of need. This paradox is well recognised in knowledge management and organisational learning: data accumulation does not automatically translate into learning, especially when information is fragmented, poorly indexed, or disconnected from decision and work routines. AD4 frames AI-enabled memory not as an expansion of data, but as an improvement in retrievability, relevance, and application. AI can reduce retrieval friction by enabling more flexible queries, linking related artefacts, and synthesising information into actionable formats. Yet even here, the organisational nature of memory remains central: improved retrieval does not generate learning unless teams build routines for consulting, validating, and applying knowledge rather than defaulting to reinvention.

Finally, AD4 captures an evolution from static knowledge to dynamic insight generation. The empirical concepts indicate a shift from documentation-as-endpoint to knowledge-as-process, where knowledge is continuously reprocessed and reinterpreted and organisational value shifts from static documentation toward ongoing interpretation and problem solving. This clarifies that AI-enabled memory does not only store and retrieve artefacts; it can recombine retained knowledge into new, context-sensitive insights. Under this view, organisational memory becomes less like an archive and more like a generative substrate for problem solving: instead of reusing documents as fixed templates, organisations increasingly reuse interpretations, such as dynamic summaries, reconstructed lessons, and tailored guidance adapted to new conditions. This supports continuity by making prior experience easier to reactivate and tailor, extending reuse beyond "what we wrote last time" toward reapplying "what we learned" in a form fit for the present problem. At the same time, it reinforces the need for interpretive discipline: dynamically generated insights may vary with prompts, sources, and context, requiring practices for checking reliability and aligning outputs with organisational standards and intent.

Taken together, AD4 describes an AI-enabled organisational memory engine centred on Tacit Knowledge Externalization and Reuse. Structuring and centralising knowledge provides the substrate that makes experience reusable; AI-assisted retrieval and synthesis reconstruct learning across distributed artefacts and support expertise location; generative support can surface tacit knowledge and broaden access, reducing dependence on individual holders; and these mechanisms respond to the paradox of data abundance and under-interpretation by improving retrievability and usability. The shift toward dynamic insight generation further reframes memory as an active recombination process that supports problem solving, while preserving the need for validation and interpretive discipline.

7.7. AD5–Embedded algorithmic learning systems and organisational learning agents

AD5 articulates the lower-layer dynamic of the grounded model, where AI systems are not primarily positioned as instruments that enhance human-centred organisational learning routines, but as embedded systems that can enact learning routines themselves. This marks a clear shift in agency. Whereas the upper layer (AD1–AD4) explains how AI reshapes organisational learning practices that remain fundamentally human-led, AD5 describes a mode of learning that is AI-led: the system performs core learning activities in an operational, ongoing sense, while human involvement is comparatively thin and oriented to initiating, constraining, and validating what the system does. Analytically, this distinction is central because it supports the model's two-layer architecture without collapsing it into a single generalised loop: the layers connect through organisational learning practices as an organisational interface, yet they remain conceptually distinct in terms of who performs the learning routines and where learning agency is located.

Within this lower layer, "organisational learning agency" is attributed to the system's capacity to run recurrent learning cycles that would traditionally be enacted through human reflection and collective sensemaking. Embedded AI can detect regularities, update representations, generate alternatives, and iteratively refine outputs across time, often at a tempo and scale that exceed what human attention and processing capacity can sustain.

At the same time, AD5 does not redefine organisational learning as a purely technical phenomenon. Instead, it captures algorithmic learning as a new locus of learning work inside organisations: embedded because it is situated within organisational contexts, tasks, and feedback channels, yet distinct because the system performs the learning routines as part of its ongoing functioning rather than merely furnishing inputs for human learning routines.

One expression of this learning agency lies in AI-based pattern discovery and dynamic knowledge representation. The data suggests that embedded systems are increasingly expected to detect weak signals, emergent patterns, and subtle trends that remain difficult to identify through manual monitoring or conventional analytics. Crucially, the system does more than flag anomalies. As patterns are detected, it continuously reconfigures how information is represented and prioritised, updating its internal mappings of what counts as relevant, unusual, or predictive and linking signals across sources that might otherwise remain disconnected. This creates a form of algorithmic noticing that is persistent rather than episodic: instead of waiting for human-driven inquiry to begin, the system can surface novel regularities as they form, shifting the organisation's visibility of its operations, risks, and opportunities over time. Representational dynamism is therefore central to why this layer is conceptualised as learning agency: outputs are not static reports, but evolving pattern-based interpretations that change through exposure to new data and performance feedback.

A related strand concerns AI-enabled innovation, exploration, and solution generation. Here, the data indicates that generative AI is increasingly integrated into creative and analytical functions, where it can expand the search space of ideas and contribute candidate solutions. In the logic of AD5, the distinctive element is that exploration is not limited to supporting a human brainstorming exercise. The system itself can generate, recombine, and refine options at scale, producing alternative framings, prototypes, or strategic pathways with limited human prompting beyond initial objectives and constraints. This capability can shift the organisation's learning frontier by enabling rapid production of possibilities that can be screened, iterated, or tested. Its learning contribution lies in how generative outputs evolve through repeated interaction with organisational constraints and evaluation criteria: over time, the system can become more attuned to what constitutes a viable or valuable option within the organisation's context, thereby changing the relevance and quality of what it generates. Exploration, in this sense, becomes embedded as a recurring system activity rather than an occasional human-led workshop.

The mechanism that most clearly differentiates the lower layer is the continuous improvement of AI systems through feedback loops. The data suggests that organisations increasingly experience embedded AI systems as entities that can be incrementally refined, calibrated, and improved through repeated use, performance assessment, and feedback on successes and failures. In AD5, this is not peripheral maintenance but the core way algorithmic learning agency becomes visible. Through ongoing feedback channels, the system can adjust outputs, refine sensitivity to patterns, update recommendation logic, or improve the quality of generated alternatives. At the same time, organisational understanding of how to interact with the system evolves iteratively: users learn how to structure requests, interpret outputs, and recognise failure modes, which in turn reshapes the feedback the system receives and the ways it is deployed. The grounded model locates the principal recursive dynamic precisely here, in the relationship between the AI system and organisational learning practices as the organisational interface. Practices provide recurring moments in which outputs are evaluated and decisions are made to adopt, reject, refine, or redeploy the system; the system then incorporates these signals, directly or indirectly, into subsequent outputs. The result is an ongoing adaptation process rather than a one-off implementation.

Consistent with this logic, the human role in AD5 is intentionally narrow and is treated analytically as an enabling interface rather than the centre of learning activity. Humans may initiate tasks, specify objectives, set constraints, and validate whether outputs are acceptable for organisational use. They may also decide whether to escalate, pause, or redirect system activity when outputs deviate from expectations. However, these interventions do not constitute the primary learning routine in the lower layer; they function as orchestration and gatekeeping actions that determine which system outputs are admitted into organisational work and which are rejected. This thin human role is essential for preserving the conceptual separation between layers: AD5 is not another account of how AI improves human learning conversations, but an explanation of how algorithmic systems can perform learning work in an ongoing way, with humans primarily acting as selectors, boundary setters, and validators of system outputs.

At the same time, AD5 is delineated by salient limits and risks that define the boundary conditions of algorithmic learning agency. The data suggests that AI could sometimes reinforce rather than challenge existing cognitive biases, particularly when outputs reflect prevailing patterns in historical data or dominant frames in organisational discourse. In such cases, algorithmic learning may stabilise what the organisation already believes, producing apparent coherence rather than genuine challenge. Trust in AI-generated outputs therefore emerges as a critical tension: outputs can appear plausible and authoritative even when they are incomplete, misaligned with context, or sensitive to hidden assumptions, creating the risk of misplaced reliance. Additional limitations stem from opacity and the difficulty of tracing how outputs were produced, which can complicate error diagnosis and reduce confidence in the appropriateness of system learning. These risks help explain why experimentation with AI agents is often initially bounded to well-structured routine tasks, where evaluation criteria are clearer and the consequences of error are more controllable. Within AD5, these constraints are treated as intrinsic features of algorithmic learning in organisational settings: they shape the conditions under which learning agency can be deployed, scaled, and relied upon, rather than disappearing simply because human validation exists.

Taken together, AD5 can be understood as an embedded algorithmic learning system that performs three interrelated forms of learning work: discovering patterns and updating representations dynamically; expanding exploration by generating and refining alternatives; and improving iteratively through feedback-driven adjustment across repeated cycles of use. These dynamics matter organisationally because they relocate part of the learning process from human-centred routines to system-level operations, introducing a distinct form of learning agency within organisational life. The model therefore treats AD5 as conceptually independent from the upper layer, while remaining connected to it through the organisational interface of learning practices that structure how outputs enter work and how feedback is produced.
Overall, the effect of AD5 is to introduce an AI-led mode of organisational learning in which embedded systems can notice, generate, and adapt continuously, with human involvement narrowed to orchestration and validation rather than primary learning performance. This sets up AD6, which clarifies how the broader socio-technical context–culture, governance, readiness, and legitimacy conditions–encloses and conditions both human-led AI-enabled learning in the upper layer and AI-led embedded learning agency in the lower layer, shaping whether these dynamics can be sustained and institutionalised within organisations.

7.8. AD6–Culture and governance for AI-enabled organisational learning

AD6 captures the socio-technical environment that encloses the entire architecture and conditions whether AI-enabled learning is feasible, beneficial, and sustainable over time. Rather than sitting within a single layer or operating as an additional capability alongside AD1–AD4, AD6 functions as an overarching boundary: it surrounds both layers (AD1–AD5) and the organisational learning practices that connect them, shaping how AI-enabled learning is legitimised, governed, and maintained as an organisationally acceptable way of working.

In this sense, AD6 is not a generator of learning episodes in its own right. Its influence is indirect but decisive: it shapes the conditions under which learning practices are enacted and under which embedded algorithmic learning can be trusted, improved, and aligned. On one side, it modulates whether upper-layer capabilities translate into consistent organisational learning behaviours. On the other, it conditions the integrity of the recursive dynamic located in the AD5-practices relationship by influencing how feedback is produced, how evaluation discipline is sustained, and how accountability and risk boundaries are established. AD6 therefore clarifies why AI-enabled learning outcomes are not determined by tools alone, but by the organisational setting that determines how tools are used, contested, refined, and institutionalised.

When an organisation introduces AI in a pervasive way, it often increases the visibility of what is happening: more signals, more alerts, more recommendations arrive, and therefore problems can emerge earlier, patterns become clearer and decisions can also be evaluated with more evidence. However, this transparency does not automatically lead to more learning: it depends greatly on the climate in which people work. If the culture is improvement-oriented, then seeing errors and anomalies more clearly helps: teams can treat them as opportunities to understand, correct, and refine their work, speaking openly instead of trying to "appear perfect". For this to happen, however, people must feel truly empowered, socially and institutionally, to say "I don't know", to report problems and to try solutions without fear of being blamed. This is where the concept of "guilt-free time and space to learn" comes in: learning requires protected time to reflect and experiment, and the fact that this attention is protected communicates that learning is not a waste of time, but part of the job. If this space does not exist, there is a risk that AI will be used in a superficial or defensive way: you end up "pretending to learn", or constantly putting out fires, because you lack the time and energy to interpret outputs, test hypotheses and transform insights into stable changes.

The central idea is that experimenting with AI only truly becomes "organisational learning" if the organisation legitimises it, but at the same time sets boundaries and rules. The data shows that many companies do not adopt AI in a completely free manner: they put it through structured experiments and a sort of "internal vetting". This is because there is a balance to be struck: exploring new solutions accelerates learning, but governance is needed to make it sustainable and safe. To experiment responsibly, shared criteria are needed on what is an acceptable risk, what is appropriate use of AI, and what kind of evidence is considered credible. In practice, this means that freedom and control are not opposites: freedom to try only works if control is built in a way that helps learning, rather than blocking everything. If governance is absent or unclear, two extreme things can happen: either adoption becomes disorderly–everyone uses AI in their own way, with inconsistent practices and fragile trust–or the organisation becomes too cautious and stops experimenting. The balance point is when experimentation is seen as legitimate, but also as something that needs to be evaluated, documented and, if necessary, limited.

In this context, leadership does not appear as a mere "side factor", but as a real mechanism that makes learning stable over time. The data shows that leadership support serves to clearly communicate that experimenting with AI is valuable, to protect time and resources for iterative work, and to prevent these activities from being overwhelmed by short-term operational urgencies. Furthermore, leadership is necessary to transform bottom-up innovation into a shared capability of the organisation. Often, the best ideas and practical skills emerge from local experimentation, but without support from above, they risk remaining isolated, dependent on a few people–and therefore fragile if those people change roles or leave–and disconnected from business priorities. Conversely, if adoption is driven from the top but there is no real involvement from the bottom, everything may appear to be "formally" implemented but in reality remain superficial. AD6 therefore describes this combination: bottom-up experimentation that generates learning, and top-down support that allows that learning to last, spread and become a stable part of the organisation.

Finally, the data also highlights the issue of "readiness", which is not only technical but also socio-technical. Even if AI tools exist, their impact on learning depends on whether processes and workflows are redesigned so that AI outputs can actually be interpreted and used in daily routines. If AI remains "outside" the moments of decision-making and reflection, it can produce information without producing learning, because signals and recommendations do not enter the decision-making and reflection cycles. Redesigning workflows, therefore, is not just implementation: it is an action that enables learning, because it establishes who looks at the outputs, when they are discussed, what kind of questions are asked and how they are transformed into updated routines. Readiness is also supported by social structures that help to create shared expertise and interpretations: internal communities or "ambassador" roles disseminate practical know-how, reduce overly personal and inconsistent uses, and create common norms for interpreting and validating AI outputs. These communities reinforce learning because they build a collective reference point on "how we use AI here", which is particularly important when AI enters practices that influence performance, decisions and changes in routines.

Seen through the model architecture, these cultural and institutional conditions shape the enactment of upper-layer capabilities and the reliability of the lower-layer learning-agent dynamic simultaneously. For AD1–AD4, the boundary conditions determine whether AI-enabled continuous improvement, sensing, decision support, and organisational memory are embedded in recurring learning practices rather than activated only by exceptional events or individual initiative. For AD5, the same conditions determine whether the recursive AD5-practices loop becomes virtuous or fragile. Embedded algorithmic systems improve through feedback, but feedback is not automatic: it requires an environment where people are willing to surface failures, where evaluation is treated as a learning activity rather than a threat, and where agreed processes translate evaluation into update decisions. Trust, in this framing, is not merely a psychological attitude but an institutional accomplishment. It is built through shared standards, disciplined validation behaviours, and clear accountability for how outputs are used. Where these conditions are weak, the loop can degrade–either because outputs are accepted without scrutiny, depriving the organisation of learning and correction, or because outputs are distrusted categorically, starving the system of adoption and feedback.

Overall, AD6 functions as the integrated conditioning infrastructure of the grounded model. It captures how learning orientation, protected space for reflection and experimentation, leadership legitimacy, governance structures for vetting AI use, and socio-technical readiness for workflow integration jointly determine whether AI-enabled learning is sustained, scalable, and institutionally legitimate. The same conditions can also operate as constraints when misaligned–through defensiveness under increased visibility, risk aversion that blocks experimentation, unclear accountability that erodes trust, or insufficient readiness that prevents learning from becoming embedded in practice. AD6 thus explains why AI-enabled organisational learning is not a matter of deploying technologies, but of shaping the socio-technical context that allows those technologies to produce durable learning outcomes.

7.9. Integrated interpretation and answer to SRQ1

7.9.1. Integrated interpretation of the model

Taken as a whole, the model describes an evolution of organisational learning in which AI does not merely "support" specific activities, but restructures the conditions and ways in which organisations learn on an ongoing basis. In the upper layer (AD1–AD4), learning remains fundamentally human-led: learning routines are performed by individuals and teams through recurring organisational practices, but the presence of AI profoundly changes the pace, quality and continuity of these routines. The aggregate effect that emerges from the findings is a shift from episodic learning cycles, which are often reactive and dependent on fragmented interpretations, towards more continuous, evidence-based and scalable cycles. In this sense, AD1–AD4 do not describe an autonomous "loop" between capability and technology, but a set of AI-reshaped capabilities that materialise in the way practices are actually carried out.

The lower layer (AD5) introduces a qualitative change in the distribution of agency, which is the main theoretical reason for the two-level structure. Here, learning takes on an AI-led character: it is no longer just AI that enhances a human routine, but embedded algorithmic systems that autonomously perform learning routines such as pattern discovery, generative exploration and iterative improvement through feedback. The organisation does not "learn" because it replaces human interpretation with an automatic response, but because part of the learning work is delegated to systems that discover regularities, update representations and produce alternatives on an ongoing basis. The connection with the rest of the model does not occur through a generic bidirectional exchange between the two layers, but through the logic of practices as operational units on which algorithmic agency is grafted. In this lower layer, in fact, embedded systems do not merely support human practices, but autonomously perform organisational learning routines which, in the overall model, constitute the recurring infrastructure of learning. It is precisely the repeated execution of these practices that feeds an internal learning loop of the agent: through successive iterations, the AI refines pattern recognition, updates its representations and improves the quality of the outputs generated, making learning progressively more effective and continuous. In this sense, the connection with the model is given by the fact that organisational learning practices do not serve here as a mere channel of use, but become the recursive substrate through which the AI learning agent learns and improves over time.

AD6, which does not belong to a single level but acts as a socio-technical boundary, intervenes to make this architecture stable and sustainable: learning culture, sponsorship, governance and readiness define whether and how the capabilities of the upper layer actually become routine, and whether and how the learning agency of AI in the lower layer can be legitimised, governed and maintained over time.

7.9.2. Answering SRQ1: theoretical shift and grounded answer

To respond concisely but theoretically explicitly to SRQ1, it is useful to make visible the conceptual shift with respect to the Organisational Learning Capabilities framework proposed by Chiva et al. (2007). Table 7.1 compares the classic OLC logic and the Grounded Theory Model along three interpretative axes—what, how, who—which allow us to immediately clarify the proposed extension: not only an enhancement of human capabilities, but also the emergence of an embedded algorithmic learning agency, both made operational through practices and conditioned by an enabling socio-technical context.

Lens	**Chiva et al. (2007): OLC**	**GTM (Upper layer: AD1–AD4)**	**GTM (Lower layer: AD5)**
What	Organisational learning capabilities as enabling conditions for organisational learning (human-centred).	AI-shaped organisational learning capabilities that reshape how learning practices are enacted.	Embedded algorithmic learning systems as organisational learning agents performing learning routines autonomously.
How	Learning occurs primarily through social and behavioural mechanisms. It depends on human attention and interpretation, tends to be more episodic and frequently retrospective, and is triggered by events, problems or moments of reflection, that translates into slower and intermittent cycles.	AI changes the dynamics of learning, making it more continuous, timely and evidence-based: it accelerates feedback loops, improves the timing with which signals and deviations emerge, enables faster and more informed interpretations, and supports a shift from predominantly reactive learning to more proactive/anticipatory forms.	AI continuously processes data, identifies patterns and produces outputs that evolve through feedback-driven updating; organisational interaction serves primarily to provide steering signals and to decide whether or not to adopt the outputs, rather than to directly execute the learning routine.
Who	Primarily humans and teams; learning agency is organisationally distributed but human-driven.	Humans remain the primary performers of learning routines; AI augments and reshapes practice execution (human-led, AI-enabled).	AI performs core learning routines; humans act mainly as orchestrators/validators (AI-led, human-governed) via the practice interface.

Table 7.1: From Chiva et al. (2007) OLC to the GTM: What–How–Who shifts

In response to SRQ1—*how does AI reshape organisational learning practices within organisations, both by augmenting existing organisational learning capabilities and by acting as an organisational learning agent?*—the Grounded Theory Model shows that AI restructures organisational learning through a practice-mediated logic that operates on two distinct but complementary registers.
With regard to the first component of SRQ1–"by augmenting existing organisational learning capabilities"–the findings indicate that AI increases and reshapes organisational learning capabilities in a human-led manner (upper layer: AD1–AD4), transforming the execution of organisational learning practices: it makes learning cycles more continuous, timely and evidence-based, accelerates feedback loops, anticipates the emergence of signals and deviations, and strengthens sensemaking, decision learning and knowledge reuse in the workflow.
Moreover, regarding the second component of SRQ1–"by acting as an organisational learning agent"–the findings show that AI can act as an organisational learning agent (lower layer: AD5) by autonomously performing routine learning tasks through system-led cycles of continuous data processing and feedback-driven updating: the system detects patterns and weak signals, updates dynamic representations, generates and explores alternatives, and iteratively refines its outputs based on performance and usage feedback, while the organisation acts primarily as a "thin" interface for orchestration and validation—defining objectives and constraints, and deciding whether, how, and under what conditions these outputs enter organisational processes and practices.
In both cases, AD6 acts as a socio-technical boundary that conditions the legitimacy, sustainability, and direction of AI-enabled learning, determining whether these dynamics become institutionalised as stable routines or remain episodic initiatives. In summary, AI reshapes organisational learning practices both by enhancing and reconfiguring human-led learning through AI-shaped capabilities, and by introducing an embedded algorithmic learning agency that performs learning routines with operational autonomy, with practices as a connective mechanism and AD6 as a cross-cutting condition of stabilisation.

In conclusion, SRQ1 finds its answer in the Grounded Theory Model, showing how AI transforms organisational learning both by enhancing the execution of human-led practices (upper layer) and by introducing embedded systems that perform learning routines in operational autonomy (lower layer), with practices as a mediation interface and AD6 as an enabling and binding framework. Chapter 8 takes up this architecture to extend the analysis from the transformation of practices and capabilities to its organisational outcomes, discussing how the combination of AI-enabled organisational learning and human organisational learning contributes to value creation.

8 | Linking Human-Driven and AI-Driven organisational Learning to Value Creation

8.1. Introduction and bridge from Chapter 7

This chapter answers the second sub-research question (SRQ2): *How does the combination of AI-driven organisational learning and human-driven organisational learning contribute to value creation?*

While Chapter 7 clarified how AI transforms organisational learning practices and how it can also act as a learning agent, the aim of Chapter 8 is to take a further interpretative step: to explain why and how the coexistence of different forms of learning–one guided by humans and enhanced by AI, the other guided by AI and governed by humans–can generate value for the organisation. In this perspective, the chapter builds directly on the grounded model, but shifts the focus from the descriptive level of learning dynamics to the explanatory level of their outcomes: from the transformation of processes to the emergence of plausible paths of value creation.

The results of Chapter 7 led to a two-layer model which, in addition to organising the Aggregate Dimensions, highlights a fundamental distinction between two learning modes. The first is human-driven and AI-enabled learning, in which AI reinforces and reconfigures the way people carry out learning routines. The second is AI-driven and human-governed learning, in which embedded algorithmic systems perform learning routines autonomously while human intervention focuses primarily on orchestration, validation and definition of constraints. In other words, in the upper layer, AI helps humans learn, while in the lower layer, humans help AI learn responsibly. While conceptually distinct, these two ways of learning are connected through a practice-mediated logic: organisational learning practices represent the organisational interface where learning takes shape, is oriented and becomes relevant for action.

Based on this architecture, Chapter 8 is structured as follows. First, it compares the two learning modes, focusing on operational characteristics, functionality, advantages and limitations, and summarising this comparison in a table. Secondly, it derives a logic of complementarity: it shows how the strengths of one mode of learning compensate for the limitations of the other, enabling more robust organisational learning than either mode considered in isolation. Thirdly, it articulates value creation pathways: mechanisms through which the combination of human-driven and AI-driven learning can translate into value creation. Finally, it guides the answer to SRQ2 through the findings of the second model.

8.2. Characterising the two learning modes

The two learning modes derive directly from the two-layer architecture of the grounded model. In the upper layer, learning remains human-driven: learning practices are performed by individuals and teams, while AI acts as a support that strengthens the evidence base, speed and scalability of routines. In the lower layer, however, learning becomes AI-driven: embedded algorithmic systems autonomously perform learning routines and produce dynamic outputs that evolve over time; human intervention is mainly in the form of governance, orchestration and validation, i.e. it guides, constrains and decides whether and how these outputs enter organisational processes. This distinction does not imply that organisations operate exclusively in one of the two ways; on the contrary, the analysis suggests that the coexistence of the two modes is plausible and, above all, theoretically relevant.

Table 8.1 summarises the main features of the two learning modes, with particular attention to operational functionality, advantages and limitations.

Dimension	Human-driven learning (AI-enabled) *(Upper layer: humans execute the learning practices)*	AI-driven learning (Human-governed) *(Lower layer: AI executes learning routines autonomously)*
Characteristic	Learning situated in organisational routines, based on interpretation, reflection and collective decisions; AI supports with evidence and summaries, but judgement remains human	Continuous and system-led learning, in which AI performs learning routines autonomously; humans define constraints, objectives and validation criteria.
Functionality (what it actually does)	People interpret signals and insights (including AI-generated ones), integrate context and tacit knowledge, and translate shared understanding into decisions and organisational changes.	AI identifies patterns, connects heterogeneous data, generates and updates solutions and recommendations through iterative learning-by-updating processes.
Benefits	High capacity to manage ambiguity and complex contexts; greater legitimacy and adoption of outputs thanks to interpretative and collective processes.	Speed, scalability and continuity of learning; greater exploratory capacity and reduced latency in updating insights.
Limitations	Constrained by time, attention and human bias; risk of slowness, discontinuity and difficulty in translating insights into action.	Risk of opacity, drift and misalignment; difficulty in incorporating intent and context without explicit governance mechanisms.
Disadvantages (typical trade-offs)	Trade-off between depth and scale: rich learning but less rapid and difficult to disseminate.	Trade-off between scale and controllability: rapid learning but more difficult to make transparent and governable.

Table 8.1: Human-driven Learning and AI-driven learning comparison.

The comparative analysis highlights some contrasts that become central to the subsequent argument on complementarity. First, there is a tension between speed/scale and contextual judgement/strategic intent: AI-driven learning allows for continuous and scalable processing, while human-driven learning remains more capable of attributing meaning, managing trade-offs and producing decisions consistent with strategic intent. Secondly, there is a difference in the temporality and form of learning: the AI-driven mode tends to operate through continuous updating of outputs, while the human-driven mode is more often achieved through cycles of sensemaking and institutionalisation which, although they can be accelerated, remain linked to collective interactions and deliberations. Finally, the risks are different in nature: on the one hand, overload and fragmentation when human interpretative capacity cannot keep pace with the growth of signals; on the other, bias, opacity and misalignment when algorithmic outputs are used beyond the boundaries of validation and control.

Precisely because the two learning modes have non-overlapping strengths and different vulnerabilities, the table suggests that value creation does not derive so much from the exclusive choice of one approach as from the organisation's ability to orchestrate the two modes of learning in a coherent manner. From this perspective, the differences highlighted are not simply alternatives: on the one hand, they make a logic of complementarity plausible, in which the scalability and continuity of AI-driven learning can compensate for the limitations of human speed and cognitive capacity, while contextual judgement, strategic intent and the ability to institutionalise change can mitigate the risks and fragility of algorithmic learning; on the other hand, they also indicate that some forms of value can emerge in a mode-specific way, i.e. from the effective functioning of one of the two learning modes even in the absence of full integration.

8.3. Complementarity logic between Human-driven and AI-driven OL

In the context of this thesis, complementarity is not understood as a simple balance between "strengths" and "weaknesses", nor as a compromise between two alternatives. Rather, it describes a division of learning work and a consequent integration of contributions that are structurally different. AI-driven organisational learning excels at producing high-scale, high-speed learning outputs through autonomous pattern detection, alternative generation, cross-source linking, and iterative output updating. Human-driven organisational learning, on the other hand, excels in the functions that make organisational learning socially and strategically meaningful: contextual interpretation, strategic intent, judgement and accountability, as well as the ability to institutionalise the consequences of learning in practices, decisions and rules. In this sense, value creation does not derive from the mere "sum" of the two contributions, but from how the organisation orchestrates their interaction through practices and decisions that act as an interface between the production of outputs and their transformation into organisational change.

The theoretical contribution we intend to make here is to show why this combination makes the learning system as a whole more robust, more sustainable and capable of generating value over time. In particular, the integration between autonomous outputs produced by AI and human processes of interpretation and institutionalisation makes it possible to reduce the fragilities typical of each mode when adopted exclusively, transforming differentiated vulnerabilities into a more resilient configuration.

Table 8.2 summarises the four complementary pairings that emerged from the analysis. These pairings represent recurring configurations in which the two learning modes play distinct but interdependent roles: AI-driven learning tends to "open" the learning space, producing signals, alternatives or synthesised knowledge; human-driven learning tends to "close" the cycle, giving meaning, priority, responsibility and organisational stability to the outputs produced.

Complementarity	**AI-driven learning: contribution**	**Human-driven learning contribution**	**Tension that the pairing resolves**
Exploration at scale and solution generation ↔ strategic selection & institutionalisation	Generates multiple alternatives, scenarios and options; expands the search and quickly proposes candidate solutions.	Select based on strategic intent, trade-offs and priorities; convert options into implemented initiatives.	Avoid 'idea overload' and scattered experimentation; transform variety into realised innovation
Pre-decision intelligence ↔ contextual judgement & accountability	Filter noise, synthesise signals and insights, compile multi-source evidence; prepare the decision space	Interprets in the local context, weighs implications and constraints; decides and takes accountability; translates into actions and rules. Translates into actions and rules.	Avoid decisions that are "data-rich but context-poor"; limit over-trust and out-of-context applications.
Continuous anomaly detection ↔ prioritisation & operational translation	Detects anomalies, weak patterns and deviations; pre- triage and preliminary analysis of signals	Defines what is 'relevant', prioritises interventions, decides on corrective actions and process updates	Reduces alert fatigue and noise; converts signals into operational improvements without overload
Knowledge surfacing & synthesis ↔ contextual reuse in execution	Recovers and reassembles fragmented knowledge; makes know-how accessible and supports expertise location	Apply knowledge to the specific case with contextual adaptation; incorporate reuse into training and routine	Reduces 'reinvention', dependence on experts and loss of context; avoids mechanical or out-of-context reuse.

Table 8.2: Complementarity between human-driven and AI-driven organisational learning

The first pairing clarifies the complementarity between exploration at scale and strategic selection and institutionalisation. The findings suggest that AI-driven learning can rapidly produce a wide variety of alternatives, scenarios and candidate solutions, expanding the exploratory space and making the generation of options more accessible. However, when exploration expands without an organising principle, the risk is not only inefficiency but also the dispersion of learning: many alternatives remain “possible” without becoming “feasible” and, above all, without transforming into coherent trajectories. This is where human-driven learning comes in, acting as a mechanism to close the cycle: it selects based on strategic intent and trade-offs, assigns ownership and converts options into implemented initiatives. Complementarity thus resolves a tension typical of AI-driven exploration: abundance of variety can become overload and dispersive experimentation if it is not accompanied by the human ability to orient, decide and institutionalise. AI “opens up” the field of possibilities; humans make some of those possibilities viable and stabilised within the organisational structure.

The second pairing concerns the relationship between pre-decision intelligence and contextual judgement and accountability. The analysis indicates that AI-driven learning can operate as a filtering and synthesis device: it reduces information noise, aggregates multi-source evidence and prepares the decision space by making it clearer which elements deserve attention. This contribution is particularly relevant in contexts characterised by information complexity and speed of change, where the risk is not so much the lack of data as the inability to transform it into usable insights. However, synthesis is not equivalent to decision-making. Without contextual judgement and responsibility, pre-decision intelligence can produce a paradox: “data-rich but context-poor” decisions, where the output appears convincing but is not aligned with local constraints, organisational values or strategic intent. The human contribution therefore becomes indispensable, not as simple “interpretation”, but as an act of accountability: weighing implications and constraints, taking responsibility, translating output into actions and rules. In this complementarity, AI “opens” the field by making the decision informed and rapid; humans “close” the cycle by making the decision legitimate, contextualised and institutionalisable, reducing the risks of over-trust and out-of-context applications.

The third pairing highlights the complementarity between continuous anomaly detection and prioritisation and operational translation. The model indicates that AI-driven learning is particularly effective in detecting anomalies, weak patterns and deviations and, where possible, in providing a pre-triage that sorts or synthesises the signals that emerge. This type of output is essential for anticipating problems and making visible dynamics that would otherwise remain distributed and difficult to observe. However, even in this case, the output does not coincide with organisational learning in the full sense: continuous detection can generate alert fatigue, i.e. an overload of reports that reduces attention and produces defensive reactions or selective ignorance routines. Human-driven learning intervenes as a capacity for prioritisation and operational translation: it defines what is relevant–thresholds and criteria–decides which signals require intervention, and converts information into corrective actions and process updates. In this complementary relationship, AI "opens" the cycle by making the problem visible; humans "close" the cycle by establishing priorities and operational consequences, transforming signals into improvements without overload.

The fourth pairing focuses on the relationship between knowledge surfacing and synthesis and contextual reuse in execution. The findings suggest that AI-driven learning can recover and recompose fragmented knowledge–lessons learned, artefacts, distributed documentation–making know-how accessible and also supporting the localisation of expertise. This contribution reduces a recurring friction in organisations: knowledge exists but is scattered, difficult to find and often not reused, fuelling reinvention and dependence on individual experts. However, the availability of knowledge does not guarantee its effective use. The risk, in the absence of human expertise, is mechanical or out-of-context reuse: applying "similar" solutions to problems that are only apparently equivalent, or reproducing procedures without understanding local constraints and implications. Human-driven learning plays a critical role here in contextual adaptation and incorporation into routines: it applies knowledge to the specific case, translating it into training and operational practices. In this complementarity, AI "opens" access and reduces retrieval friction; humans "close" the cycle by transforming retrieved knowledge into effective execution and local institutionalisation, while reducing dependency and loss of context.

Taken together, the four complementarities do not represent four separate cases, but four manifestations of the same underlying principle: AI-driven learning expands noticing, processing and generating capabilities, while human-driven learning ensures meaning, priority, responsibility and stabilisation of learning outcomes. This principle explains why combining the two learning modes produces a more robust system than choosing one of the two exclusively. A predominantly AI-driven approach risks producing large-scale output without adequate contextualisation, with vulnerabilities related to overload, over-trust or improper applications. A predominantly human-driven approach, on the other hand, risks keeping learning anchored to slower times, limited cognitive abilities and fragmented knowledge processes. The proposed complementarity does not eliminate these limitations, but recombines them in a configuration in which each mode structurally compensates for the fragilities of the other.

8.4. Conceptualising Value Creation in Organisational Contexts

In the management literature, the concept of value creation is widely recognised as a dynamic process through which organisations transform resources, competences, and relationships into superior organisational outcomes and sustainable competitive advantage over time. In particular, recent studies show that value creation is not limited to economic performance, but also includes the ability to innovate business models, increase operational efficiency, and generate collective value through relationships and continuous learning among organisational actors (Arena et al., 2022). Moreover, an organisation's ability to create value is connected to its capability to respond to environmental and technological change by continually evolving its practices and strategies (Costa Climent & Haftor, 2021). Finally, the literature highlights value creation as a multidimensional construct linking innovation, marketing, and competitive advantage, and as a central element of organisational strategies aimed at sustaining growth and performance in the long run (Risitano, 2025).

Building on these perspectives, this thesis adopts a process-oriented understanding of value creation that is internal to organisational functioning. In other words, value creation is defined as the set of organisationally meaningful improvements that emerge when resources, competences, and knowledge are recombined and stabilised into more effective ways of operating–improvements that sustain performance and resilience over time through innovation, efficiency, and learning-enabled renewal (Costa Climent & Haftor, 2021; Arena et al., 2022; Risitano, 2025). This stance is deliberately broader than a purely financial interpretation and is consistent with contributions that describe value creation as a multidimensional construct, encompassing both the organisation's capacity to generate and implement change and its ability to reduce frictions, inefficiencies, and coordination costs in execution (Costa Climent & Haftor, 2021; Arena et al., 2022).

To make this multidimensional construct analytically tractable in the context of organisational learning, the remainder of this section focuses on a set of value outcome categories that the literature recurrently associates with organisational renewal and improved performance: (i) innovation acceleration and reduced time-to-market, understood as the ability to shorten the cycle from exploration to implementable solutions; (ii) increased decision speed and decision quality, as information and expertise are translated into more timely and accountable choices; (iii) reduced operational waste and recurring errors, enabled by more reliable execution and lower variability, rework, and inefficiencies; and (iv) reduced time and cost of exploiting existing knowledge, through the ability to surface, synthesise, and reuse prior learning rather than repeatedly “reinventing” it (Costa Climent & Haftor, 2021; Arena et al., 2022; Risitano, 2025). These categories represent established ways in which organisations translate adaptation and learning into durable benefits, and they provide the conceptual bridge between the complementarities discussed in the previous section and the integrative framework introduced next.

8.5. Value creation pathways and answer to SQR2

In this section, the objective is not to ‘demonstrate’ a performance effect in quantitative terms, but to articulate plausible and grounded mechanisms through which learning work–whether human-driven or AI-driven–can generate organisationally tangible results. The conceptual shift is therefore from a comparison of capabilities and vulnerabilities to an explanatory chain: from learning output to value creation.

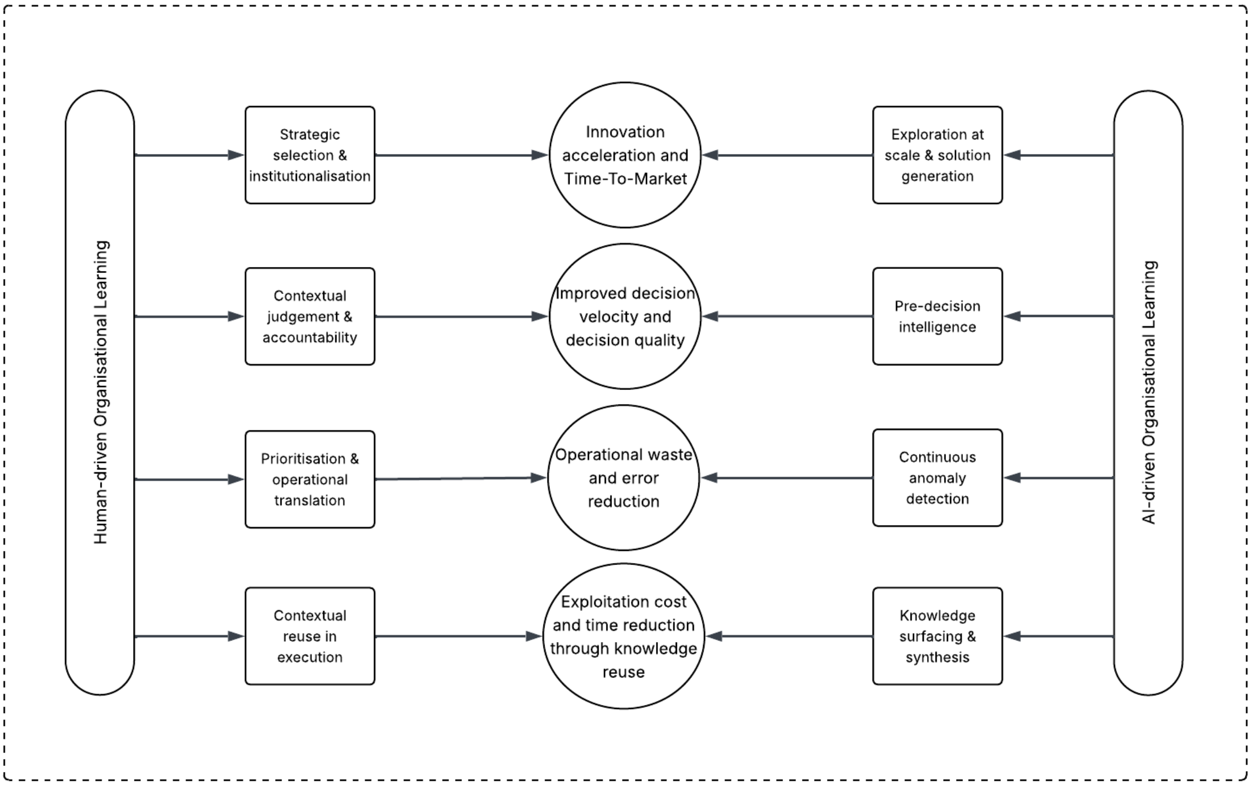


Figure 8.1: From Hybrid Learning to Value Creation

The "From Hybrid Learning to Value Creation" model articulates value creation as the result of the interaction between two modes of organisational learning that coexist and integrate: Human-driven organisational learning, in which learning routines are performed by human actors with AI support, and AI-driven organisational learning, in which embedded algorithmic systems autonomously perform learning operations–e.g., pattern detection, generation of alternatives, and iterative updating of outputs–while the organisation governs their use. The connection between the two learning modes occurs through four complementary pairs that describe how their respective strengths combine in learning work: exploration at scale and generation of solutions by AI, balanced by strategic selection and human institutionalisation; pre-decision intelligence produced by AI, complemented by human contextual judgement and accountability; continuous detection of anomalies and signals by AI, converted into prioritisation and operational translation by human actors; and knowledge surfacing and algorithmic synthesis, made effective through contextualised reuse in execution and incorporation into routines and training. In this framework, the four complementarities constitute the central "bridge" of the model: it is through these couplings that learning outputs are transformed into organisational action and, consequently, into the four value creation pathways discussed in the following sections.

8.5.1. Innovation acceleration and time to market

The first value creation concerns accelerating innovation and reducing time-to-market. In tangible terms, this means compressing the time between generating a solution option and transforming it into an implemented initiative: not just "more ideas", but greater speed in converging towards a viable direction, prototyping and making the choice executable through ownership, resources and standardisation. The model suggests that this value creation emerges when the variety generated by AI-driven learning does not remain an exercise in exploration for its own sake, but becomes structured input that feeds into decision-making and experimental practices managed by human actors.

AI's contribution to the creation of this value lies in its ability to rapidly expand the space of options and continuously produce exploratory inputs that the organisation can use as a working basis. This includes generating alternatives, proposing scenarios and configurations, and the ability to support a broader exploration than is realistic for a team with limited cognitive and time resources. The key function is not to "innovate on behalf of the organisation", but to make innovation quicker to trigger, because the organisation does not start from a blank sheet every time and can compare multiple directions more quickly.

The human contribution to this value creation is what makes the acceleration truly organisational and not just computational. The role of human actors is to transform options into implemented innovation: selecting based on priorities and trade-offs, deciding in line with strategic intent, assigning ownership and resources, and above all making the solution institutionalisable (i.e. integrable into processes, products or services, with clear responsibilities and standards). This step is at the heart of value, because acceleration only becomes concrete when the organisation converts exploratory output into choices and implementations, preventing variety from remaining a sterile exploration.

Complementarity produces value because it allows breadth and speed in the development of options to be combined with convergence and implementability in choices. AI reduces the time needed to generate and compare alternatives, while humans reduce the time needed for decision-making convergence and organisational implementation, preventing dispersion and endless cycles of experimentation. The result is acceleration that does not come from “doing more”, but from making the entire journey from idea to implementation more efficient and manageable.

8.5.2. Improved decision velocity and decision quality

"Improved decision velocity and decision quality" indicates a simultaneous improvement in two dimensions that often come into conflict: on the one hand, the ability to make decisions more quickly, and on the other, the ability to make better decisions, i.e. with less likelihood of systematic errors, continuous revisions and rework. The value created is tangible because it translates into more stable operational and strategic decisions, fewer fluctuations, and greater consistency between available evidence and action taken. It is not a question of “more data”, but of faster decisions without compromising robustness and appropriateness to the context.

AI’s contribution to creating this value mainly concerns the preparation of a clearer and more manageable decision space: filtering noise, synthesising evidence, aggregating signals and insights from different sources, and presenting what is relevant to a choice in an understandable way. In this way, AI reduces the cognitive cost of decision-making: it decreases the time needed to reconstruct the information picture and allows decision-makers to start from a more structured basis.

The human contribution is what ensures that the decision is contextualised and responsible. Human actors interpret content in the local context, evaluate implications not directly inferable from data, and assume accountability. In practice, humans are decisive in the transition from “available evidence” to “appropriate choice”: they translate insights into actions and rules, coordinate change between units and functions, and establish how the decision will be implemented and monitored. Without this step, even well-synthesised evidence remains an input without consequences.

Complementarity generates value because it reduces decision-making time without slipping into fragile or out-of-context decisions. AI accelerates the availability and readability of evidence, while humans ensure that decisions maintain strategic consistency, compatibility with constraints, and organisational legitimacy. In this way, speed and quality are not treated as alternatives: the former derives from the reduction of information friction, the latter from contextualisation and responsibility in transforming evidence into action.

8.5.3. Operational waste and error reduction

"Operational waste and error reduction" refers to value creation linked to the organisation's ability to reduce waste (rework, scrap, downtime, recurring inefficiencies) and prevent repeated errors, not through a purely reactive 'repair' approach, but through a learning process that transforms deviations and anomalies into reusable knowledge. The value is tangible because it manifests itself in the stabilisation of operational performance and the reduction of unwanted variability; however, this only occurs in a manner consistent with organisational learning when the signals are interpreted, discussed and translated into persistent changes in routines, decision-making thresholds and execution methods, preventing the organisation from "putting out the fire" without understanding why it started.

The contribution of AI in this pathway is not simply to "signal a problem", but to make more frequent and earlier learning triggers available: detecting anomalies, weak patterns and deviations that would otherwise remain invisible, and providing an initial organisation of evidence useful for questioning what is going wrong. In this way, AI shifts the focus from the single event to the idea that the error is an interpretable signal, potentially attributable to recurring causes or operating conditions that generate variability. The point, therefore, is not the "fix" itself, but the enabling of a cycle in which the organisation can formulate plausible hypotheses, compare them with evidence, and recognise repeated patterns that warrant an update of operating rules.

Human input is what makes these triggers learning tools rather than mere alerts. Human actors perform the work of operational sensemaking: they reconstruct the sequence that led to the deviation, distinguish noise from meaningful signals, and, above all, engage in cause-oriented reflection and the selection of effective countermeasures. This includes the ability to decide which anomalies to investigate, which questions to ask of the data, which alternatives to test, and how to assess whether an intervention is truly corrective or only temporary. In other words, humans do not "perform a correction", but interpret the anomaly as an opportunity to learn which conditions generate waste and error, and which process changes reduce the likelihood of recurrence.

Complementarity produces value because it coherently links noticing and learning closure. AI increases sensitivity and timeliness in detection; humans convert these signals into stabilised learning, translating evidence into process updates and decisions that prevent the same inefficiencies from recurring. In this way, the reduction of waste and errors does not result from an indiscriminate increase in controls or interventions, but from a learning cycle in which deviation becomes material for reflection, choice and institutionalisation of countermeasures, making the operation progressively more reliable and less costly.

8.5.4. Exploitation cost and time reduction through knowledge reuse

This value creation is linked to efficiency in the execution of existing processes: reducing the time and costs associated with having to continually rebuild solutions, procedures, know-how and decisions that have already been tried and tested in the past. The value created is tangible because it translates into shorter ramp-up times, less duplication between teams, fewer errors linked to loss of organisational memory, and greater continuity in execution. Here, 'knowledge reuse' does not mean mechanically reusing documents, but effectively reusing experiences and lessons learned by incorporating them into operational work.

The contribution of AI in this pathway is to make knowledge findable, recomposable and accessible: retrieving fragmented information, synthesising artefacts and lessons learned, supporting expertise location and reducing dependence on individual holders of tacit knowledge. In essence, AI reduces the friction of accessing knowledge: it lowers the cost of "searching" for and "rebuilding" what the organisation already knows, making it more likely that past experience will actually be reused. This contribution becomes particularly relevant in contexts where knowledge is dispersed and where information overload makes it difficult to distinguish what is useful.

Human input is what makes reuse contextual and operational. Human actors apply knowledge to the specific case, adapt it to local constraints and conditions, and, above all, incorporate it into tools and routines that stabilise learning: operating procedures, standards, training, onboarding, and execution practices. Without this step, accessible knowledge remains potential. It is humans who transform knowledge into repeatable organisational behaviour, reducing the risk of out-of-context or superficial reuse and ensuring that learning does not remain confined to a repository but becomes part of operations.

Complementarity creates value because it combines accessibility and synthesis with contextual application and institutionalisation. AI makes knowledge available when needed; humans make it effective in the real world and translate it into routine. The result is a reduction in costs and time in the management and execution of existing processes, achieved not through cuts or simplifications, but through a better ability to reuse what the organisation has already learned, avoiding reinvention and repetition of errors.

8.5.5. Integrated answer to SRQ2

Overall, the four value creation pathways respond to SRQ2 by clarifying how the combination of human-driven and AI-driven organisational learning can generate value in a mechanistic and grounded way. AI contributes by producing continuous and scalable learning outputs–alternatives, synthesised evidence, signals and recomposed knowledge–while humans transform these outputs into value through contextualisation, responsible choice and institutional stabilisation in decisions, interventions and routines. In this sense, value creation emerges when learning does not remain an information flow, but is converted into coherent and repeatable organisational action.

9 | Conclusions, Limitations and Future Directions

9.1. Research gap and thesis scope

This thesis stems from a clear gap: while the literature has already discussed organisational learning extensively as a social and routine process, and has also begun to explore the adoption of AI in organisations, there is still a lack of a sufficiently integrated and "mechanistic" explanation of how the impact of AI actually transforms organisational learning and, above all, how this transformation can translate into value creation. In other words, it is not enough to say that AI "supports" learning or "improves" decisions and processes: it is necessary to clarify what dynamics it enables, where the agency of learning lies, and how the learning outputs produced or enhanced by AI are converted into stable organisational action and thus into tangible results.

The contribution of this work lies precisely in this space: building a grounded model that explains the impact of AI on organisational learning and, starting from this, articulating the mechanisms through which this impact can generate value creation. Consistent with this objective, the structure of the research questions guides the entire thesis.

The first sub-research question (SRQ1) aims to understand how AI reshapes organisational learning practices within organisations.

The second sub-research question (SRQ2) shifts the analysis from the transformation of learning to value creation: the objective is not to assume that value creation automatically results from the presence of multiple learning modalities, but to show how the impact of AI on learning–as emerged from the grounded model–can be translated into explanatory pathways that link learning and value in a plausible and data-consistent manner.

The main research question (MRQ) brings this logic together in a broader synthesis, extending the reasoning towards the potential development of competitive advantage: not as a quantitatively demonstrated outcome, but as a theoretical and managerial implication that derives from a set of value creation mechanisms made more robust and sustainable over time.

In terms of scope, the thesis adopts a qualitative and interpretative approach, based on a multiple-case design and a Grounded Theory approach aimed at constructing explanations at the process and mechanism level. This results in a precise methodological choice: the objective is not to causally measure performance or competitive advantages, but rather to explain how AI transforms organisational learning and how this transformation can be converted into value through logical chains anchored to the findings.

9.2. Key findings and answers to the research questions

This study answered the main research question by clarifying how Artificial Intelligence generates value creation through its impact on Organisational Learning. The starting point is a change of perspective: in the contemporary context, the organisational problem is no longer a scarcity of knowledge, data or know-how, as many organisations already have abundant sources of information and numerous knowledge artefacts. The critical issue lies rather in transforming this abundance into value: without organisational practices that make knowledge interpretable, shareable, reusable and translatable into action, the availability of data does not automatically translate into improvement, innovation or efficiency. In this regard, the thesis chose not to investigate AI as a generic factor supporting knowledge management, but to place the analysis at the point where knowledge becomes organisationally relevant, i.e. in OLPs and collective routines in which signals, evidence and interpretations are negotiated, stabilised and incorporated into repeatable changes.

The answer to SRQ1 took shape through the Grounded Theory Model developed from the cases: the analysis shows that AI reshapes learning practices along two distinct registers. In the first register, defined as Human-driven organisational learning (AI-support), AI enhances and reorients the way humans perform OLPs: it accelerates improvement cycles, makes the identification of deviations and signals more timely, broadens the information base for sensemaking and decision-making, and transforms organisational memory into a more accessible and reusable resource. In this register, learning remains guided by people and teams: it is the practices of reflection, discussion, decision-making and institutionalisation that determine whether AI outputs become change. In the second register, defined as AI-driven organisational learning (human-governed), the possibility emerges that embedded AI systems can autonomously perform operational learning routines, such as pattern discovery, alternative generation and iterative output updating. Here, the difference is not in the presence of human-AI interaction, which remains, but in the centre of gravity of agency: AI performs the routine, while human intervention focuses on orchestration, validation and constraints. In both cases, the model highlights that the impact of AI becomes relevant when it enters into practice: the thesis does not describe AI as a substitute for the social dimension of learning, but as a force that changes its pace, scope, timing, and quality of evidence, redefining what is possible within OLPs.

The response to SRQ2 shifted the focus from "how" AI reshapes practices to "how" this impact generates value. The thesis shows that value creation emerges when organisations combine AI-driven and human-driven contributions in a coherent manner: AI produces scalable and continuous outputs, and humans transform them into value through contextualisation, responsible choice and stabilisation in decisions, interventions and routines. On this basis, the model in Chapter 8 articulated four value creation pathways, understood as grounded and plausible causal chains that link learning to tangible outcomes: Innovation acceleration and time to market, Improved decision velocity and decision quality, Operational waste and error reduction, and Exploitation cost and time reduction through knowledge reuse. In summary, the research suggests that AI creates value not because it generically increases the availability of information, but because it affects the conditions and ways in which the organisation learns: it accelerates and expands learning inputs, while OLPs determine whether these inputs are translated into concrete and replicable results.

Overall, the thesis responds to the MRQ by showing that AI enables value creation precisely because it transforms the way the organisation learns, acting on Organisational Learning Practices as a central operational lever. It is therefore not Organisational Learning "in the abstract" that explains value creation, but Organisational Learning made qualitatively different by AI: practices that become more continuous, timely and scalable thanks to signals, synthesised evidence, alternatives and recomposed knowledge produced by AI, and which are then converted into change through the human contribution of contextualisation, responsible choice and institutionalisation. In this sense, value creation emerges when Human–AI collaboration is not limited to adding information, but reshapes and enhances learning practices, accelerating the transformation of insights into decisions, interventions and stable routines.

9.3. Theoretical contributions

On a theoretical level, this thesis helps to clarify how Artificial Intelligence can enhance organisational learning and, through this enhancement, enable value creation. The starting point is the conceptual extension of Organisational Learning Capabilities in the context of

AI, going beyond the formulation of Chiva et al. (2007). The results suggest that, in the AI era, it is not enough to treat capabilities as relatively stable enabling conditions that favour experimentation, dialogue and participation: AI substantially changes their operational content and, above all, the way in which they translate into practices. From this perspective, the theoretical novelty does not consist in simply adding "more information" to decision-making and learning processes, but in making explicit the shifts that AI introduces on three intertwined levels: what becomes concretely possible to do within learning practices, how these practices are performed and accelerated by AI-enabled mechanisms, and how the distribution of agency between human actors and systems changes. In other words, the thesis proposes a way of rethinking OLCs as capabilities that, in the AI context, become more continuous, scalable and integrated into organisational processes, but only to the extent that they are absorbed and stabilised in collective routines.

This extension leads to a further conceptual contribution, which concerns the agency of AI. The thesis clarifies that part of the impact of AI on organisational learning is not limited to providing information support to human actors, but includes the possibility that embedded systems can autonomously perform routines that are "learning-like" in nature: discovering patterns and weak signals, linking heterogeneous sources, generating alternatives, and iteratively updating outputs. The contribution lies in clearly distinguishing between AI that enhances practices performed by humans and AI that directly performs learning routines, requiring the organisation to play a different and more focused role. In this framework, human intervention is not interpreted as co-execution of practices, but as a function of orchestration, validation, and definition of constraints, necessary to channel algorithmic agency within criteria of legitimacy and responsibility. This conceptualisation allows us to move beyond purely instrumental readings of AI and describe a new theoretical equilibrium in which organisational learning incorporates, alongside social practices, a component of embedded algorithmic learning.

Finally, the thesis contributes to linking AI-enhanced organisational learning to value creation through a mechanistic rather than reductionist logic. Instead of treating value creation as a quantitative outcome or as an automatic consequence of technological adoption, the work proposes pathways based on grounded causal chains: AI produces more continuous and scalable learning outputs, but these outputs only generate value when they are transformed into organisational change through practices and routines that stabilise their outcomes. It is in this conversion that the theoretical contribution of the thesis with respect to MRQ lies: AI enhances learning not only by expanding the capacity to produce knowledge and signals, but also by making it more likely that such content will be incorporated into organisational practices and thus become operational and strategic levers for value creation.

9.4. Limitations

Like any qualitative study based on a multi-case design, this research has limitations that must be clearly stated, distinguishing between what the work can support with conceptual robustness and what, on the other hand, requires interpretative caution. Methodologically, the choice of a grounded approach and a logic of comparison between cases aims to produce analytical and mechanistic generalisations, not statistical generalisability. It follows that the proposed model does not claim to "measure" how much AI improves organisational learning or how much value is created, but rather to explain how the impact of AI translates into transformations in practices and, through these, into plausible pathways for value creation.

In this framework, a first limitation stems from the self-referential nature of the data: interviews may incorporate informant bias, memory selectivity and retrospective rationalisations, especially when participants reconstruct the meaning of technological choices and organisational changes ex post.

A second methodological limitation concerns temporality: the analysis offers a cross-sectional snapshot of processes that are, by their nature, dynamic. AI-enabled organisational learning, as well as the evolution of embedded systems and related feedback mechanisms, tends to manifest itself fully in the long term; as a result, some dynamics of stabilisation, routinisation or iterative correction can only be inferred as emerging logics and not observed longitudinally.

In terms of scope, the thesis deliberately stops at value creation, articulated in terms of mechanistic pathways, without going as far as performance measurement or empirical demonstration of competitive advantage. This choice is consistent with the orientation of the model, but implies that the relationship between the impact of AI on learning practices and economic-competitive results remains outside the scope of direct empirical validation.

A further limitation of transferability concerns sectoral variability and the nature of work: in some contexts, AI may play a marginal or "lateral" role in relation to core processes, making the dynamics described by the model less salient. In particular, the case of Company H highlights that the adoption of AI, at least in the configuration observed, does not permeate core design routines, but focuses on generic uses–for example, queries to GPT-type tools–and on support applications in specific phases such as post-production of renderings. In that same context, professional and creative logic seems to push towards a strong tendency to "start over", even in the presence of rich and reusable archives: the difficulty is not the absence of artefacts, but the nature of the work that encourages variation and uniqueness, with implications for systematic reuse and, therefore, for the applicability of certain standardisation and scalability mechanisms. This does not invalidate the model, but suggests that its explanatory power may be higher in data-intensive, process-oriented or operational contexts than in domains where the output remains highly artisanal and situated. At the same time, the same case shows that digital tools such as BIM (building information modelling) can reduce design errors by identifying "clashes" during the design phase, preventing problems from only emerging on site. This detail reinforces an important clarification: sectoral variability does not imply an absence of algorithmic support, but profound differences in the degree and point in the process at which such support can influence learning practices and operational consequences.

Finally, on a conceptual level, some boundaries of the model remain necessarily provisional. The distinction between human-driven organisational learning (AI-support) and AI-driven organisational learning (human-governed) was constructed as an analytical separation of agency and the location of learning routines; however, this boundary may evolve rapidly with technological change and organisational maturity, blurring the hybrid zones where semi-autonomous systems and human practices co-determine each other. Furthermore, while recognising that governance and culture–the AD6 boundary–affect the legitimacy and sustainability of AI-enabled learning, the model does not fully resolve certain tensions of accountability and attribution of responsibility when algorithmic outputs influence decisions and routines. In this sense, the conceptual limitations do not represent a weakness of the contribution, but clearly delimit the scope of the explanation: the thesis clarifies the mechanisms through which AI reshapes learning practices and enables value creation pathways, while intentionally leaving open–as a direction for future research–the question of how these mechanisms stabilise over time in increasingly autonomous and interdependent socio-technical configurations.

9.5. Future Directions

The limitations discussed naturally open up a research agenda that can consolidate and test the proposed model, while maintaining the MRQ of the thesis as the focus.

First, there is a strong need to introduce a more explicit temporal perspective. Many of the mechanisms described only fully manifest themselves in the medium to long term. Longitudinal studies, based on repeated observations and more granular process reconstructions, would allow for a more precise distinction between episodic adoptions, progressive integrations, and structural transformations, clarifying when value creation pathways become persistent, when they remain fragile, and what conditions determine their continuity or interruption over time.

At the same time, an important extension concerns the empirical reinforcement of value creation pathways through research designs capable of better triangulating observable organisational mechanisms and signals. The thesis proposes grounded causal chains that link the impact of AI on learning practices to four tangible forms of value; future research could translate these chains into process indicators and traceable evidence, without transforming the model into a reductive measurement of performance. Mixed-method approaches, combining interviews, document analysis, routine observation and operational traces, would strengthen the link between practice change and value creation, clarifying not only whether an improvement emerges, but above all how it is produced and through which organisational steps it stabilises in decisions, interventions and repeatable routines.

In parallel, the distinction between human-driven organisational learning (AI-support) and AI-driven organisational learning (human-governed) can be further developed as a dynamic object rather than a static category. The thesis uses this distinction to clarify the distribution of agency and the architecture of mechanisms, but it is plausible that organisations will evolve towards hybrid configurations in which the autonomy of embedded systems gradually increases and, at the same time, the ways in which humans orchestrate, validate and constrain these systems change. Studying the trajectories by which activities and responsibilities shift over time between the two registers–and how this affects the continuity of value pathways–would allow us to understand not only the coexistence of learning modes, but also the conditions that govern their reconfiguration and operational stability.

Finally, without turning this thesis into a normative work on governance, future research could explore in a more targeted way how culture and governance make the mechanisms described sustainable and legitimate, especially when AI is more deeply integrated into practices and processes. In particular, it becomes relevant to understand how validation criteria, decision-making responsibilities, control routines and learning practices are transformed when algorithmic outputs become more continuous and central, and how such organisational choices affect the ability to convert evidence, signals and knowledge into effective and repeatable changes. Taken together, these directions converge towards a common goal: to move from a grounded explanation of mechanisms to a more comprehensive understanding of their dynamics over time, their transferability between contexts, and their ability to reliably support value creation, avoiding both techno-deterministic readings and interpretations that reduce AI to mere information technology, when in fact its contribution has emerged as that of a catalyst that profoundly reshapes the way in which organisational learning practices can generate value.

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A | Appendix A

A.1. Coding - Gioia Methodology

ID interview	Role	First Order Concept	Second Order Themes	Aggregate Dimension
I_01	Managing Director	Exploring AI for communication capture	Structuring and centralizing knowledge for human–AI reuse	AI-enabled organisational memory and shared knowledge
I_01	Managing Director	Using AI for design tasks	AI-enabled innovation, exploration and solution generation	Embedded algorithmic learning systems as OL agents
I_01	Managing Director	Bringing in external AI expertise	Governance, compliance and readiness conditions for AI-enabled learning	Culture and governance for AI-enabled organisational learning
I_01	Managing Director	ERP as process backbone	Structuring and centralizing knowledge for human–AI reuse	AI-enabled organisational memory and shared knowledge
I_01	Managing Director	Monitoring performance with live metrics	Data-driven reflection and learning conversations	AI sensemaking and decision-making
I_01	Managing Director	Emphasizing continuous improvement	Culture of continuous improvement and psychological safety	Culture and governance for AI-enabled organisational learning
I_01	Managing Director	Using real-time alert systems	AI-enabled predictive maintenance and anomaly detection	AI-augmented sensing and anticipatory learning
I_01	Managing Director	Collecting data to diagnose operational problems	Data-driven error learning and root-cause reflection	AI-enabled continuous improvement and experimentation
I_01	Managing Director	Training for addressing recurring issues and improve technical literacy	Data-driven error learning and root-cause reflection	AI-enabled continuous improvement and experimentation
I_01	Managing Director	Allocating time for tech exploration	Learning-oriented culture and leadership sponsoring AI experimentation	Culture and governance for AI-enabled organisational learning
I_01	Managing Director	Using visual learning aids via QR codes	AI-enabled surfacing of tacit knowledge and democratization of organisational knowledge	AI-enabled organisational memory and shared knowledge
I_01	Managing Director	Supporting bottom-up innovation	Culture of continuous improvement and psychological safety	Culture and governance for AI-enabled organisational learning
I_01	Managing Director	Using AI to accelerate proposal development	AI as reflection companion and cognitive challenger	AI sensemaking and decision-making
I_01	Managing Director	Using AI to model workflow optimization	AI-supported fast-feedback simulation and experimentation	AI-enabled continuous improvement and experimentation

I_01	Managing Director	Tracking and learning from errors and data	Data-driven error learning and root-cause reflection	AI-enabled continuous improvement and experimentation
I_01	Managing Director	Using root cause analysis to reflect on mistakes	Data-driven error learning and root-cause reflection	AI-enabled continuous improvement and experimentation
I_01	Managing Director	Systematically using feedback for learning	Data-driven error learning and root-cause reflection	AI-enabled continuous improvement and experimentation
I_01	Managing Director	Openness to AI-enhanced decision-making	AI-augmented decision-making and risk management	AI sensemaking and decision-making
I_01	Managing Director	Acknowledging risks of AI in regulated domains	Governance, compliance and readiness conditions for AI-enabled learning	Culture and governance for AI-enabled organisational learning
I_01	Managing Director	Receptive to AI as a diagnostic partner	AI as reflection companion and cognitive challenger	AI sensemaking and decision-making
I_01	Managing Director	Data quality tied to human inputs	Governance, compliance and readiness conditions for AI-enabled learning	Culture and governance for AI-enabled organisational learning
I_01	Managing Director	Using AI for decision support experiment	AI-augmented decision-making and risk management	AI sensemaking and decision-making
I_02	Head of Operations	using dashboard as daily learning trigger	Embedding AI in monitoring, reflections and learning routines	AI-enabled continuous improvement and experimentation
I_02	Head of Operations	Detecting hidden anomalies through AI to gain predictive visibility	AI-enabled predictive maintenance and anomaly detection	AI-augmented sensing and anticipatory learning
I_02	Head of Operations	heavy reliance on codified procedures	Structuring and centralizing knowledge for human–AI reuse	AI-enabled organisational memory and shared knowledge
I_02	Head of Operations	Building trust in AI-generated outputs	Limits and risks of AI as learning agent	Embedded algorithmic learning systems as OL agents
I_02	Head of Operations	data insights rely on operator expertise	Human judgment, context and strategic intent as guardrails	AI sensemaking and decision-making
I_02	Head of Operations	Institutionalizing AI performance reviews	Continuous improvement of AI systems through feedback loops	Embedded algorithmic learning systems as OL agents
I_02	Head of Operations	Solving issues through cross-site peer exchange	AI-enabled surfacing of tacit knowledge and democratization of organisational knowledge	AI-enabled organisational memory and shared knowledge

I_02	Head of Operations	Developing translator roles between data and operations	AI-enabled surfacing of tacit knowledge and democratization of organisational knowledge	AI-enabled organisational memory and shared knowledge
I_02	Head of Operations	Integrating AI into decision-making processes	AI-augmented decision-making and risk management	AI sensemaking and decision-making
I_02	Head of Operations	AI used for exploitation of ideas	AI as reflection companion and cognitive challenger	AI sensemaking and decision-making
I_02	Head of Operations	turning local improvements into standard routines	Data-driven error learning and root-cause reflection	AI-enabled continuous improvement and experimentation
I_02	Head of Operations	Redesigning workflows to fit AI integration	Governance, compliance and readiness conditions for AI-enabled learning	Culture and governance for AI-enabled organisational learning
I_02	Head of Operations	Building reflection time into routines	Data-driven reflection and learning conversations	AI sensemaking and decision-making
I_02	Head of Operations	AI generating novel product ideas	AI-enabled innovation, exploration and solution generation	Embedded algorithmic learning systems as OL agents
I_02	Head of Operations	AI Stimulating curiosity and data-driven inquiry	AI as reflection companion and cognitive challenger	AI sensemaking and decision-making
I_02	Head of Operations	Evolving expectations toward actionable insights	Evolution of static knowledge to dynamic insight generation	AI-enabled organisational memory and shared knowledge
I_02	Head of Operations	Learning from model's successes and failures	Continuous improvement of AI systems through feedback loops	Embedded algorithmic learning systems as OL agents
I_02	Head of Operations	Developing critical capacity to engage with AI models	Human judgment, context and strategic intent as guardrails	AI sensemaking and decision-making
I_02	Head of Operations	Non-blaming dialogue enables learning	Culture of continuous improvement and psychological safety	Culture and governance for AI-enabled organisational learning
I_03	Managing Director	Searchable documentation for current projects	Structuring and centralizing knowledge for human–AI reuse	AI-enabled organisational memory and shared knowledge
I_03	Managing Director	Using AI to structure historical knowledge	AI-assisted organisational memory and retrieval	AI-enabled organisational memory and shared knowledge
I_03	Managing Director	Perceived AI strength in contextual data filtering	AI as pre-decision intelligence filter and decision support	AI sensemaking and decision-making

I_03	Managing Director	Using AI to front-load requirements	AI as pre-decision intelligence filter and decision support	AI sensemaking and decision-making
I_03	Managing Director	Human-AI collaboration in project setup	AI-augmented decision-making and risk management	AI sensemaking and decision-making
I_03	Managing Director	Iterative AI use based on evolving understanding	Continuous improvement of AI systems through feedback loops	Embedded algorithmic learning systems as OL agents
I_03	Managing Director	AI-enhanced communication clarity	AI-enabled surfacing of tacit knowledge and democratization of organisational knowledge	AI-enabled organisational memory and shared knowledge
I_03	Managing Director	Intention to use AI for real-time fault detection	AI-enabled predictive maintenance and anomaly detection	AI-augmented sensing and anticipatory learning
I_03	Managing Director	Layered data architecture for more effective Knowledge storage	Structuring and centralizing knowledge for human–AI reuse	AI-enabled organisational memory and shared knowledge
I_03	Managing Director	Fragmented knowledge tools across workflows	Data-rich but under-interpreted environments	AI-enabled organisational memory and shared knowledge
I_03	Managing Director	Prioritising problem-solving processes over static knowledge	Evolution of static knowledge to dynamic insight generation	AI-enabled organisational memory and shared knowledge
I_03	Managing Director	Shift from knowledge scarcity to process capability	Evolution of static knowledge to dynamic insight generation	AI-enabled organisational memory and shared knowledge
I_03	Managing Director	Real-time learning embedded in project execution	Data-driven reflection and learning conversations	AI sensemaking and decision-making
I_03	Managing Director	Learning from conflict reinforces organizational values	Culture of continuous improvement and psychological safety	Culture and governance for AI-enabled organisational learning
I_03	Managing Director	Informal and formal mechanisms for knowledge sharing	AI-enabled surfacing of tacit knowledge and democratization of organisational knowledge	AI-enabled organisational memory and shared knowledge
I_03	Managing Director	External coaching to support AI-based business learning	Governance, compliance and readiness conditions for AI-enabled learning	Culture and governance for AI-enabled organisational learning
I_03	Managing Director	Emphasis on insight extraction over raw data scale	Evolution of static knowledge to dynamic insight generation	AI-enabled organisational memory and shared knowledge

I_03	Managing Director	AI seen as strategic differentiator	AI-enabled innovation, exploration and solution generation	Embedded algorithmic learning systems as OL agents
I_03	Managing Director	Organizational culture seen as primary enabler of learning	Culture of continuous improvement and psychological safety	Culture and governance for AI-enabled organisational learning
I_03	Managing Director	AI can't substitute for strategic intent or judgment	Human judgment, context and strategic intent as guardrails	AI sensemaking and decision-making
I_03	Managing Director	Purpose-led AI adoption seen as essential	Human judgment, context and strategic intent as guardrails	AI sensemaking and decision-making
I_04	Head of Innovation	Strategic push to structure and surface knowledge	Structuring and centralizing knowledge for human–AI reuse	AI-enabled organisational memory and shared knowledge
I_04	Head of Innovation	Formalizing project learning reporting	Structuring and centralizing knowledge for human–AI reuse	AI-enabled organisational memory and shared knowledge
I_04	Head of Innovation	Daily cross-site data reviews and meetings to adjust operations	Embedding AI in monitoring, reflections and learning routines	AI-enabled continuous improvement and experimentation
I_04	Head of Innovation	Centralizing knowledge across teams to reduce fragmentation	Structuring and centralizing knowledge for human–AI reuse	AI-enabled organisational memory and shared knowledge
I_04	Head of Innovation	Capturing tacit knowledge from informal interactions	AI-enabled surfacing of tacit knowledge and democratization of organisational knowledge	AI-enabled organisational memory and shared knowledge
I_04	Head of Innovation	Using AI to mine historical project data	AI-assisted organisational memory and retrieval	AI-enabled organisational memory and shared knowledge
I_04	Head of Innovation	AI used to identify recurring issues	AI-based pattern discovery and dynamic knowledge representation	Embedded algorithmic learning systems as OL agents
I_04	Head of Innovation	Surfacing tacit know-how through metric challenges	Data-driven reflection and learning conversations	AI sensemaking and decision-making
I_04	Head of Innovation	Using GenAI for meeting summarization and follow-ups	Embedding AI in monitoring, reflections and learning routines	AI-enabled continuous improvement and experimentation
I_04	Head of Innovation	Needing guilt-free time and space to learn	Culture of continuous improvement and psychological safety	Culture and governance for AI-enabled organisational learning
I_04	Head of Innovation	Framing AI as a reflection companion	AI as reflection companion and cognitive challenger	AI sensemaking and decision-making

I_04	Head of Innovation	Exploring AI for knowledge transfer and onboarding	AI-enabled surfacing of tacit knowledge and democratization of organisational knowledge	AI-enabled organisational memory and shared knowledge
I_04	Head of Innovation	Expert knowledge trapped at individual level	AI-enabled surfacing of tacit knowledge and democratization of organisational knowledge	AI-enabled organisational memory and shared knowledge
I_04	Head of Innovation	Integrating lessons learned data with AI tools	AI-assisted organisational memory and retrieval	AI-enabled organisational memory and shared knowledge
I_04	Head of Innovation	Recognizing contextual dependency in learning transfer	Human judgment, context and strategic intent as guardrails	AI sensemaking and decision-making
I_04	Head of Innovation	Aspiration to use AI for matching current problems with past solutions	AI-assisted organisational memory and retrieval	AI-enabled organisational memory and shared knowledge
I_04	Head of Innovation	AI for scenario simulation and decision support	AI-supported fast-feedback simulation and experimentation	AI-enabled continuous improvement and experimentation
I_04	Head of Innovation	Exploring AI to mine insights from images and data	AI-based pattern discovery and dynamic knowledge representation	Embedded algorithmic learning systems as OL agents
I_04	Head of Innovation	AI adoption hindered by compliance concerns	Governance, compliance and readiness conditions for AI-enabled learning	Culture and governance for AI-enabled organisational learning
I_04	Head of Innovation	Leadership endorsement enables AI experimentation	Learning-oriented culture and leadership sponsoring AI experimentation	Culture and governance for AI-enabled organisational learning
I_04	Head of Innovation	Use of social platforms for informal learning	AI-enabled surfacing of tacit knowledge and democratization of organisational knowledge	AI-enabled organisational memory and shared knowledge
I_04	Head of Innovation	Learning focuses on process issues, not just technical flaws	Evolution of static knowledge to dynamic insight generation	AI-enabled organisational memory and shared knowledge
I_04	Head of Innovation	Difficulty measuring AI's impact on learning	Governance, compliance and readiness conditions for AI-enabled learning	Culture and governance for AI-enabled organisational learning
I_04	Head of Innovation	AI used to trigger post-project reflection	Embedding AI in monitoring, reflections and learning routines	AI-enabled continuous improvement and experimentation
I_04	Head of Innovation	AI-supported cognitive reframing during redesign	AI as reflection companion and cognitive challenger	AI sensemaking and decision-making

I_05	Quality manager	Business problems as triggers for knowledge creation	Data-driven error learning and root-cause reflection	AI-enabled continuous improvement and experimentation
I_05	Quality manager	Decentralized knowledge generation based on performance metrics	Data-driven reflection and learning conversations	AI sensemaking and decision-making
I_05	Quality manager	Structured documentation as basis for knowledge retention	Structuring and centralizing knowledge for human–AI reuse	AI-enabled organisational memory and shared knowledge
I_05	Quality manager	Using structured AD root-cause method to create reusable learning	Data-driven error learning and root-cause reflection	AI-enabled continuous improvement and experimentation
I_05	Quality manager	Lessons from problems reused for future projects	Data-driven error learning and root-cause reflection	AI-enabled continuous improvement and experimentation
I_05	Quality manager	Process improvement driven by prior failure and learning	Data-driven error learning and root-cause reflection	AI-enabled continuous improvement and experimentation
I_05	Quality manager	Turning past pin-press failures into sensor-based real-time diagnostics	AI-enabled predictive maintenance and anomaly detection	AI-augmented sensing and anticipatory learning
I_05	Quality manager	Wanting AI to recall relevant past problems and solutions	AI-assisted organisational memory and retrieval	AI-enabled organisational memory and shared knowledge
I_05	Quality manager	Perceived potential of AI in large-scale data analysis	AI-based pattern discovery and dynamic knowledge representation	Embedded algorithmic learning systems as OL agents
I_05	Quality manager	Underuse of existing operational data	Data-rich but under-interpreted environments	AI-enabled organisational memory and shared knowledge
I_05	Quality manager	Dashboards showing data but not guiding action, creating need for AI advice	Data-rich but under-interpreted environments	AI-enabled organisational memory and shared knowledge
I_05	Quality manager	Linking dashboards, traceability and AD method to correct processes and standards	Data-driven error learning and root-cause reflection	AI-enabled continuous improvement and experimentation
I_05	Quality manager	Desire for AI-enabled real-time insight generation	From reactive to anticipatory learning via AI	AI-augmented sensing and anticipatory learning
I_05	Quality manager	Organizational memory encoded in systems over people	Structuring and centralizing knowledge for human–AI reuse	AI-enabled organisational memory and shared knowledge

I_05	Quality manager	Difficulty retrieving and applying past knowledge	Data-rich but under-interpreted environments	AI-enabled organisational memory and shared knowledge
I_05	Quality manager	AI envisioned as retrieval aid for experiential knowledge	AI-assisted organisational memory and retrieval	AI-enabled organisational memory and shared knowledge
I_05	Quality manager	Data-driven discussion embedded in team routines	Data-driven reflection and learning conversations	AI sensemaking and decision-making
I_05	Quality manager	AI expected to detect subtle trends and cross-source links	AI-based pattern discovery and dynamic knowledge representation	Embedded algorithmic learning systems as OL agents
I_05	Quality manager	Aspirational shift from reactive to anticipatory learning via AI	From reactive to anticipatory learning via AI	AI-augmented sensing and anticipatory learning
I_06	CEO	Knowledge sources include people, data, research, clients, and accumulated project experience	AI-enabled surfacing of tacit knowledge and democratization of organisational knowledge	AI-enabled organisational memory and shared knowledge
I_06	CEO	Organizational knowledge is perishable and context-sensitive	Evolution of static knowledge to dynamic insight generation	AI-enabled organisational memory and shared knowledge
I_06	CEO	Setting up war rooms with live KPIs for new projects	AI-supported fast-feedback simulation and experimentation	AI-enabled continuous improvement and experimentation
I_06	CEO	Formalized documentation is supported by AI tools for onboarding and process access	AI-assisted organisational memory and retrieval	AI-enabled organisational memory and shared knowledge
I_06	CEO	Lack of codified causal learning limits knowledge transfer	Data-rich but under-interpreted environments	AI-enabled organisational memory and shared knowledge
I_06	CEO	Chatbots are being piloted to synthesize fragmented knowledge artifacts	AI-assisted organisational memory and retrieval	AI-enabled organisational memory and shared knowledge
I_06	CEO	Experiential knowledge remains tacit and difficult to scale	AI-enabled surfacing of tacit knowledge and democratization of organisational knowledge	AI-enabled organisational memory and shared knowledge
I_06	CEO	Experimentation is essential to learn in rapidly evolving digital environments	AI-supported fast-feedback simulation and experimentation	AI-enabled continuous improvement and experimentation

I_06	CEO	Fast-feedback mechanisms are necessary to enable adaptive learning	AI-supported fast-feedback simulation and experimentation	AI-enabled continuous improvement and experimentation
I_06	CEO	Experimenting with platform formats to discover what works	AI-enabled innovation, exploration and solution generation	Embedded algorithmic learning systems as OL agents
I_06	CEO	Performance data is used to validate organizational learning outcomes	Data-driven reflection and learning conversations	AI sensemaking and decision-making
I_06	CEO	Agile-inspired team configurations are used to foster adaptive learning	AI-enabled innovation, exploration and solution generation	Embedded algorithmic learning systems as OL agents
I_06	CEO	Data-driven reflection guides both internal and external improvements	Data-driven reflection and learning conversations	AI sensemaking and decision-making
I_06	CEO	AI adoption is governed through structured experimentation and internal vetting	Governance, compliance and readiness conditions for AI-enabled learning	Culture and governance for AI-enabled organisational learning
I_06	CEO	AI-enabled decision support enhances strategic intelligence	AI-augmented decision-making and risk management	AI sensemaking and decision-making
I_06	CEO	Generative AI is integrated into core creative functions	AI-enabled innovation, exploration and solution generation	Embedded algorithmic learning systems as OL agents
I_06	CEO	Organizational learning is shifting from plan-act to act-sense-respond models	Evolution of static knowledge to dynamic insight generation	AI-enabled organisational memory and shared knowledge
I_06	CEO	AI is envisioned as a real-time learning facilitator in dynamic environments	AI as reflection companion and cognitive challenger	AI sensemaking and decision-making
I_06	CEO	Agile change practices are being enhanced with AI to support continuous learning	Embedding AI in monitoring, reflections and learning routines	AI-enabled continuous improvement and experimentation
I_07	IT Director	Using genAI chatbots to support insurance agents	AI-enabled surfacing of tacit knowledge and democratization of organisational knowledge	AI-enabled organisational memory and shared knowledge
I_07	IT Director	Using genAI to design and execute software tests	AI-supported fast-feedback simulation and experimentation	AI-enabled continuous improvement and experimentation

I_07	IT Director	AI-enabled domain-specific knowledge transfer	AI-assisted organisational memory and retrieval	AI-enabled organisational memory and shared knowledge
I_07	IT Director	AI used to reduce dependency on tacit knowledge holders	AI-enabled surfacing of tacit knowledge and democratization of organisational knowledge	AI-enabled organisational memory and shared knowledge
I_07	IT Director	Documentation is core to pre-AI knowledge management	Structuring and centralizing knowledge for human–AI reuse	AI-enabled organisational memory and shared knowledge
I_07	IT Director	Gen-AI makes knowledge more accessible and democratized	AI-enabled surfacing of tacit knowledge and democratization of organisational knowledge	AI-enabled organisational memory and shared knowledge
I_07	IT Director	Peer-led knowledge sharing through ambassador and community roles	Learning-oriented culture and leadership sponsoring AI experimentation	Culture and governance for AI-enabled organisational learning
I_07	IT Director	Cross-functional sharing and reflection through regular meetings	Data-driven reflection and learning conversations	AI sensemaking and decision-making
I_07	IT Director	Scaling AI use across the organization is a strategic goal	Governance, compliance and readiness conditions for AI-enabled learning	Culture and governance for AI-enabled organisational learning
I_07	IT Director	Continuous improvement of AI systems through user feedback loops	Continuous improvement of AI systems through feedback loops	Embedded algorithmic learning systems as OL agents
I_07	IT Director	AI seen as support for decision-making	AI as pre-decision intelligence filter and decision support	AI sensemaking and decision-making
I_07	IT Director	Experimenting with AI agents for well-structured routine tasks	Limits and risks of AI as learning agent	Embedded algorithmic learning systems as OL agents
I_07	IT Director	Gen-AI used to augment or substitute less experienced human roles	Limits and risks of AI as learning agent	Embedded algorithmic learning systems as OL agents
I_07	IT Director	Using genAI to aggregate dispersed data for management decisions	AI as pre-decision intelligence filter and decision support	AI sensemaking and decision-making
I_07	IT Director	Top-down and systemic learning through internal communications	Learning-oriented culture and leadership sponsoring AI experimentation	Culture and governance for AI-enabled organisational learning

I_07	IT Director	AI as a pre-decision intelligence filter and compiler	AI as pre-decision intelligence filter and decision support	AI sensemaking and decision-making
I_07	IT Director	Social structures support AI learning and cultural integration	Governance, compliance and readiness conditions for AI-enabled learning	Culture and governance for AI-enabled organisational learning
I_07	IT Director	Barriers to AI adoption include scale and individual readiness	Governance, compliance and readiness conditions for AI-enabled learning	Culture and governance for AI-enabled organisational learning
I_07	IT Director	AI being piloted in regulated, high-stakes decision contexts	AI-augmented decision-making and risk management	AI sensemaking and decision-making
I_09	BDM	Knowledge originates from diverse human and data sources	AI-enabled surfacing of tacit knowledge and democratization of organisational knowledge	AI-enabled organisational memory and shared knowledge
I_09	BDM	Data-centric culture in knowledge validation for mantainance and reliability decisions	Data-driven reflection and learning conversations	AI sensemaking and decision-making
I_09	BDM	Traditional knowledge sharing limits retention and access	Data-rich but under-interpreted environments	AI-enabled organisational memory and shared knowledge
I_09	BDM	Asynchronous, searchable collaboration enables rapid knowledge sharing	Structuring and centralizing knowledge for human–AI reuse	AI-enabled organisational memory and shared knowledge
I_09	BDM	AI-assisted organizational memory and expertise location	AI-assisted organisational memory and retrieval	AI-enabled organisational memory and shared knowledge
I_09	BDM	Formal post-mortem reflections to institutionalize learning	Data-driven error learning and root-cause reflection	AI-enabled continuous improvement and experimentation
I_09	BDM	Open innovation and external learning as organizational routines	AI-enabled innovation, exploration and solution generation	Embedded algorithmic learning systems as OL agents
I_09	BDM	Shift in organizational attitude toward AI after observed benefits	Governance, compliance and readiness conditions for AI-enabled learning	Culture and governance for AI-enabled organisational learning
I_09	BDM	Machine learning and AI used in both perception systems and early development tasks	AI-enabled predictive maintenance and anomaly detection	AI-augmented sensing and anticipatory learning
I_09	BDM	Using AI to analyse contracts and suggest negotiation options	AI-augmented decision-making and risk management	AI sensemaking and decision-making

I_09	BDM	AI enables expanded strategic exploration and analysis	AI-enabled innovation, exploration and solution generation	Embedded algorithmic learning systems as OL agents
I_09	BDM	Using AI tools to speed robot layout and solution generation	AI-enabled innovation, exploration and solution generation	Embedded algorithmic learning systems as OL agents
I_09	BDM	AI routinely integrated into daily decision-making	AI-augmented decision-making and risk management	AI sensemaking and decision-making
I_09	BDM	AI seen as critical to risk mitigation and quality control	From reactive to anticipatory learning via AI	AI-augmented sensing and anticipatory learning
I_09	BDM	AI used to augment, not replace, human capabilities	Human judgment, context and strategic intent as guardrails	AI sensemaking and decision-making
I_09	BDM	AI improves operational efficiency through predictive maintenance	AI-enabled predictive maintenance and anomaly detection	AI-augmented sensing and anticipatory learning
I_10	CEO	AI-driven predictive maintenance reshapes technical knowledge processes	AI-enabled predictive maintenance and anomaly detection	AI-augmented sensing and anticipatory learning
I_10	CEO	Knowledge becomes dynamic and constantly reprocessed	Evolution of static knowledge to dynamic insight generation	AI-enabled organisational memory and shared knowledge
I_10	CEO	Organizational value shifts from static documentation to dynamic interpretation	Evolution of static knowledge to dynamic insight generation	AI-enabled organisational memory and shared knowledge
I_10	CEO	Data abundance creates information overload challenges	Data-rich but under-interpreted environments	AI-enabled organisational memory and shared knowledge
I_10	CEO	AI used to detect weak signals and emergent patterns	AI-based pattern discovery and dynamic knowledge representation	Embedded algorithmic learning systems as OL agents
I_10	CEO	Importance of decision-integrated data interpretation	AI as pre-decision intelligence filter and decision support	AI sensemaking and decision-making
I_10	CEO	AI accelerates event-to-response cycle in learning	From reactive to anticipatory learning via AI	AI-augmented sensing and anticipatory learning
I_10	CEO	Bottom-up experimentation needs top-down support	Learning-oriented culture and leadership sponsoring AI experimentation	Culture and governance for AI-enabled organisational learning

I_10	CEO	Organizational learning framed as cyclic experimentation	AI-supported fast-feedback simulation and experimentation	AI-enabled continuous improvement and experimentation
I_10	CEO	AI reveals organizational blind spots	AI-based pattern discovery and dynamic knowledge representation	Embedded algorithmic learning systems as OL agents
I_10	CEO	Context-sensitive dashboards as AI-driven learning tools	Embedding AI in monitoring, reflections and learning routines	AI-enabled continuous improvement and experimentation
I_10	CEO	AI enables simulation and exploratory learning	AI-supported fast-feedback simulation and experimentation	AI-enabled continuous improvement and experimentation
I_10	CEO	AI can reinforce rather than challenge cognitive bias	Limits and risks of AI as learning agent	Embedded algorithmic learning systems as OL agents
I_10	CEO	AI-integrated learning encourages epistemic humility	AI as reflection companion and cognitive challenger	AI sensemaking and decision-making
I_10	CEO	AI supports generative thinking and problem framing	AI as reflection companion and cognitive challenger	AI sensemaking and decision-making
I_10	CEO	Cross-functional teams use AI as thinking support, not answer engine	AI as reflection companion and cognitive challenger	AI sensemaking and decision-making

A.2. Question List

Questions list

1. What about you & your company?

1.1 Your role

1.2 Your experience (in years)

1.3 Company's sector

1.4 Company's size (in employee/contractors)

1.5 Main products/services

1.6 Can you walk us through a typical day in the company in your role?

2. Knowledge Management (KM)

2.1 When you think about how knowledge is handled in your company – creating, sharing, storing and using it – which of these aspects do you think are more developed, and why?

2.2 Could you describe a recent situation that shows how people actually use a knowledge management process in practice?

2.3 Even if you don't use a formal framework, how would you describe your own way of managing knowledge here?

2.4 Can you recall a time when something (culture, tool, person) really helped or blocked the flow of knowledge?

3. Organizational Learning (OL)

3.1 When mistakes happen, can you tell me what typically happens next? Does the team just fix the issue, or also reflect on why it happened?

3.2 Could you describe an example where the company tried something entirely new? And another where it just improved an existing process? Which one do you think happens the most?

3.3 Can you recall a specific case where an idea or insight from one individual or team was successfully transformed into an organizational practice or routine? How did the different levels of the organisation get connected during this learning process?

3.4 What conditions make it easier for people here to learn from experience?

4. The development of new capabilities for innovation

4.1 Can you tell us about a specific project or moment when your organization developed a new capability or competence - perhaps through learning from past experiences or using knowledge differently?
(What triggered it? Who was involved? What changed afterwards?)

5. Artificial Intelligence (AI)

5.1 How would you describe the company's overall attitude and culture toward AI? Could you recall any moment that illustrates this attitude (enthusiasm, skepticism, etc.)?

5.2 Could you describe which AI tools or digital platforms (including systems such as ERPs or CRMs) your organization currently uses, what purposes they serve and how these tools are actually integrated into daily operations or across different teams?

5.3 Have you noticed any change in how people learn, share information or make decisions since AI tools were introduced? Did this lead to the development of new capabilities for innovation?

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List of Acronyms

Acronym	Definition
AD	Aggregate Dimension
AI	Artificial Intelligence
AIDUA	AI Device Use Acceptance
CIP	Corporate Innovation Performance
DL	Deep Learning
GTM	Grounded Theory Model
ICT	Information and Communication Technologies
IT	Information Technologies
KA	Knowledge Acquisition
KAPP	Knowledge Application
KC	Knowledge Creation
KCOD	Knowledge Codification
KM	Knowledge Management
KMP	Knowledge Management Process
KMS	Knowledge Management System
KS	Knowledge Storage
KST	Knowledge Sharing/Transfer
LLM	Large Language Model
LR	Literature Review
ML	Machine Learning
MRQ	Main Research Question
NLP	Natural Language Processing
OL	Organisational Learning
OLC	Organisational Learning Capabilities
OLP	Organisational Learning Practice
PEOU	Perceived Ease of Use
PU	Perceived Usefulness

Acronym	Definition
SRQ	Sub-Research Question
TAM	Technology Acceptance Model
TK	Tacit Knowledge
TOE	Technology–Organisation–Environment
VC	Value Creation
XAI	Explainable Artificial Intelligence

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