The 3rd ASEAN School of Business Network International Conference 2026

www.aseansbn.org August 6-7, 2026 Pathum Thani, Thailand

Analyzing the Interaction between Learning, Artificial Intelligence, and Capabilities: A Study of the Sources of Organizational Dynamism

Anjar Priyono[1]*

[1]Universitas Islam Indonesia, Indonesia

*Corresponding Author: anjar.priyono@uii.ac.id

ABSTRACT

This study examines how the adoption of artificial intelligence (AI) reshapes learning processes in small and medium-sized enterprises (SMEs) and its implications for the evolution of path dependence and dynamic capabilities. Using a qualitative multiple case study design, the research draws on data from AI-adopting SMEs in Yogyakarta, collected through semi-structured interviews, observations, and organizational documents. The analysis combines within-case analysis and cross-case comparison to identify underlying mechanisms and recurring patterns. The findings reveal that AI plays a dual and paradoxical role in organizational evolution. On one hand, AI enhances efficiency, data-driven decision-making, and sensing capabilities, thereby reinforcing existing learning patterns and self-reinforcing mechanisms. On the other hand, AI acts as an exogenous technological shock that can disrupt established trajectories, expand interpretive capacity, and enable path-breaking processes. However, this transformation is not uniformly beneficial. While AI strengthens analytical capabilities, it may also deepen cognitive rigidity and reinforce new forms of path dependence if not critically managed. These findings suggest that AI should not be viewed solely as a tool for operational efficiency, but as a mechanism for cognitive and strategic transformation. This study contributes by conceptualizing AI as both a path-reinforcing and path-breaking force, integrating insights from path dependence and dynamic capabilities literature.

Keywords: Artificial Intelligence; path dependence; dynamic capabilities; organizational learning, SMEs; technological shock.

DOI: https://doi.org/10.64458/asbnic.v3.153

INTRODUCTION

The contemporary business environment is increasingly characterized by a high-velocity context, requiring organizations to continuously implement both incremental and, at times, radical changes. This condition places organizations in a state of fluidity, where long-term stability is difficult to sustain and the capacity for ongoing evolution becomes critical. In this context, dynamic capabilities are understood as patterns of collective activities that enable organizations to renew their resource base and maintain alignment with a volatile environment (Eisenhardt and Martin, 2000).

However, dynamic capabilities—being pattern-based, idiosyncratic, and context-dependent—are highly susceptible to path dependence arising from self-reinforcing mechanisms (Keller *et al.*, 2025). Organizational managers tend to replicate past successes, and such repetition generates persistence, which in turn leads to path dependence. As emphasized by Sydow, Schreyögg and Koch (2020), path dependence reflects a condition in which organizations struggle to enact change due to their tendency to reproduce previously successful practices. Past success reinforces specific routines, interpretive frameworks, and resource configurations, thereby constraining the organization's ability to pursue strategic renewal in the future (Danneels, Verona and Provera, 2018).

This paradox becomes particularly salient when organizations face discontinuous environmental change. Under conditions of gradual change, idiosyncrasies developed through path-dependent capabilities may facilitate adaptation. However, in the face of radical change, these same capabilities may evolve into core rigidities that hinder strategic reorientation (Leonard-Barton, 1992). Failure to adapt to new strategic orientations may result in a loss of competitive relevance. Thus, dynamic capabilities embody an internal paradox: mechanisms that initially support adaptation may eventually lead to lock-in when excessively reinforced (Keller *et al.*, 2025).

Cognitive path dependence refers to the persistence of dominant mental models, interpretive frameworks, and expectation structures that constrain strategic action even when environmental conditions have changed. When managers continue to rely on heuristics grounded in past success, organizations become increasingly constrained in their ability to transform toward the envisioned ideal state. In other words, SMEs may appear structurally flexible while remaining cognitively rigid. In such situations, change requires not only the recombination of resources but also the unlearning of deeply embedded cognitive patterns.

The emergence of AI introduces conditions that can be characterized as an unfamiliar state (Schilke and Helfat, 2025). AI is not merely a technological innovation; rather, it represents a mechanism with the potential to fundamentally reshape organizational learning patterns and decision-making logics. SMEs' willingness to adopt AI can thus be interpreted as a move away from entrenched path-dependent trajectories. Conversely, failure to internalize such technological disruptions may reduce an organization's evolutionary fitness in rapidly changing environments.

Although the literature on AI adoption and dynamic capabilities is rapidly expanding, there remains limited understanding of how AI interacts with path dependence in the SME context (Kanbach *et al.*, 2024). Does AI reinforce existing trajectories by accelerating established learning loops? Or does it mitigate cognitive rigidity by enhancing information-processing capacity and broadening managerial interpretive frames? Given that dynamic capabilities are highly susceptible to self-reinforcing mechanisms, managerial interventions—particularly those of an ad hoc nature—may serve as critical entry points for opening alternative pathways beyond path dependence (Keller *et al.*, 2025).

The urgency of this research lies in the need to understand whether the presence of AI reshapes SME learning patterns in ways that enable organizations to break free from path dependence, or instead reinforces it. Considering that SME learning processes are highly dependent on key individuals, this context offers important insights into how technological shocks influence the evolution of path-dependent capabilities. This tension is particularly salient in the context of small and medium-sized enterprises (SMEs). SMEs are often associated with agility due to their relatively simple organizational structures. However, a critical question arises: why do many seemingly agile SMEs fail to adapt to major environmental changes?

Compared to large firms, SMEs typically face resource constraints, exhibit a high dependence on managers or founders as primary decision-makers, and tend to have lower levels of technological absorption. Learning processes within SMEs are often centralized and highly personalized. While rigidity in large firms frequently emerges from coordination effects and structural complementarities, rigidity in SMEs is more likely to originate at the cognitive level.

How AI influences path dependence in the context of SMEs remains underexplored. The dynamic capabilities literature has not yet explicitly clarified whether AI adoption reinforces self-reinforcing mechanisms or instead intervenes in them in ways that enable strategic reorientation. Given that dynamic capabilities themselves are susceptible to repeated reinforcement (Keller *et al*., 2025), managerial actions—including ad hoc interventions—may play a critical role in opening alternative pathways beyond entrenched path dependence. Accordingly, this study seeks to address the following research question: *How does AI adoption shape learning patterns in SMEs, and what are its implications for the evolution of path dependence—does AI reinforce existing trajectories or enable strategic reorientation?*

LITERATURE REVIEW

Path Dependence

The literature suggests that *"path dependence is an attractive notion since it accounts for how certain organizational features persist over time"* (Vergne & Durand, 2011). Path dependence is understood as a stochastic process triggered by contingent events and subsequently reinforced by self-reinforcing mechanisms, such that initially random trajectories become increasingly dominant and difficult to alter (Vergne and Durand, 2011). In this sense, path dependence may originate from serendipity, but it only becomes truly path-dependent when continuously reinforced by internal organizational mechanisms.

Furthermore, as noted by Vergne and Durand (2011), *"...path dependence leads to lock-in... a situation with a very low potential for endogenous change."* Path dependence can become a property of capabilities when capability paths, initially triggered by contingent events, undergo sustained self-reinforcement. This implies that organizations should not be viewed as following a single trajectory, but rather as a bundle of evolving capabilities, each of which may become path-dependent over time (Vergne and Durand, 2011).

Sydow, Schreyögg and Koch, (2009) identify four self-reinforcing mechanisms that may lead organizations into lock-in: coordination effects, complementarity effects, learning effects, and adaptive expectation effects. Coordination effects arise when actors adhere to the same rules, making deviation increasingly costly. Complementarity effects occur when organizational elements mutually reinforce one another, generating both efficiency and rigidity. Learning effects emerge through the repeated enactment of practices that produce increasing returns. Adaptive expectation effects arise when actors make decisions based on the expectation that others will continue to follow the same established patterns.

Over time, these repeated processes become embedded within the organization and form routines. However, not all processes are path dependent; path dependence occurs only when self-reinforcing mechanisms narrow the range of available alternatives. Learning plays a central role in this process, as noted by Vergne and Durand (2011), who argue that *"increasing returns to education or learning can also nurture path dependence."* Learning loops reinforce prior practices, generating increasing returns that make it progressively more difficult for organizations to deviate from established trajectories. Moreover, *"increasing managerial cognitive focus ... created negative externalities that decreased the attractiveness of alternative paths"* (Vergne & Durand, 2011). Thus, the sequence of phenomena can be conceptualized as follows: learning → routines → increasing returns → self-reinforcement → lock-in.

Core capabilities may become dominant in organizational development processes through historical trajectories that embed specific competencies within structures of legitimacy, power distribution, and resource allocation (Danneels, Verona, & Provera, 2018). However, in the face of discontinuous environmental change, capabilities that once served as sources of competitive advantage may evolve into rigidities. While core capabilities are essential, they may also become detrimental, as *"core rigidities are the flip side of core capabilities"* (Leonard-Barton, 1992). Deep and highly specialized

knowledge may support exploitation, yet it can simultaneously hinder exploration and strategic renewal.

Under such conditions, path-dependent capabilities may become dysfunctional, as they tend to replicate past practices that may no longer be relevant (Danneels, 2011). Cognitive lock-in occurs when outdated mental models continue to guide decision-making despite changes in the external environment (Heubeck, 2023). Nevertheless, paths are not entirely rigid. The concept of path plasticity suggests that there remains some degree of flexibility for innovation within existing trajectories (Strambach & Halkier, 2013). However, path breaking—defined as an organization's deliberate departure from its current strategic trajectory—requires the dismantling or interruption of the self-reinforcing mechanisms that sustain such developmental paths (Sydow, Schreyögg and Koch, 2020; Keller *et al*., 2025).

Dynamic capabilities and the evolutionary trajectories of capability configurations

Dynamic capabilities are developed through deliberate learning, which consists of *experience accumulation, knowledge articulation, and knowledge codification* (Zollo and Winter, 2002). These capabilities emerge from the *"coevolution of tacit experience accumulation processes with explicit knowledge articulation and codification activities,"* resulting in patterns of collective activity that are relatively stable yet adaptive.

However, dynamic capabilities are not a generic capacity to facilitate change; rather, they are organizational processes that are specific, idiosyncratic, and context-dependent (Helfat et al., 2007; Teece, 2007; Keller et al., 2025). Given that knowledge has time-based relevance, capabilities must be continuously renewed to remain effective in addressing environmental change. The causality of learning in dynamic capabilities is inherently ambiguous. As the relationship between actions and performance becomes increasingly unclear, managers require higher-order learning to evaluate and reconfigure existing capabilities (Zollo and Winter, 2002). In the context of discontinuous environmental change, even dynamic capabilities may become dysfunctional if organizations fail to engage in effective asset orchestration and renewal (Teece, 2012).

Within this framework, organizational evolution requires more than operational adaptation; it also demands cognitive capabilities and structural approaches (Danneels, 2011). This view is consistent with prior literature suggesting that *"the capability for evaluating and prescribing changes to the configuration of assets … rests on the shoulders of top management"* (Teece, 2012). This implies that while elements of dynamic capabilities are embedded within the organization, organizational transformation is ultimately initiated by managerial action (Teece, 2014).

The role of managers is particularly pronounced in SMEs. As noted by Teece, 92012), *"there is also a critical role for the entrepreneurial manager in both transforming the enterprise and shaping the ecosystem through sui generis strategic acts…"* Managers not only reconfigure internal resources (seizing), but also influence routines at the ecosystem level. Accordingly, overcoming path dependence requires endogenous intervention, whereby actors at higher organizational levels actively disrupt entrenched self-reinforcing mechanisms.

Furthermore, prior research suggests that technological transitions can be understood as path-dependent processes, in which mechanisms that once reinforced capabilities may be repurposed to enable change (Danneels, Verona, & Provera, 2018). Thus, dynamic capabilities provide a useful lens for understanding how organizations can undertake evolutionary path reconfiguration. However, the literature has yet to explicitly explain how emerging technologies—particularly AI—mediate this process.

AI for Overcoming Path Dependence

Artificial Intelligence (AI) can function as an exogenous technological shock that disrupts existing self-reinforcing mechanisms and opens up the possibility for the emergence of new developmental trajectories in SMEs. This technological shock is reflected in shifts in the cost structures of production and coordination, as well as in the acceleration of learning curves through data accumulation and machine

learning (Vergne and Durand, 2010). Within a path dependence framework, the emergence of AI can be understood as a contingent event that prompts organizations to explore alternative trajectories.

Path breaking is unlikely to occur through internal actors alone, as organizations tend to become entrenched in deeply rooted self-reinforcing mechanisms (Schreyögg & Kliesch-Eberl, 2007). Therefore, external stimuli are often required to trigger strategic drift, and AI represents a particularly promising candidate in this regard (Lambert *et al*., 2022). The adoption of AI can thus be positioned as a mechanism that enables organizations to break from existing path dependence by enhancing their analytical and cognitive capacities.

AI enables SMEs to better respond to external demands by strengthening their sensing and learning capabilities. Managerial sensing capabilities can be augmented through AI, thereby expanding the scope of interpretation and decision-making. In this context, AI-driven dynamic managerial capabilities may act as a key driver in overcoming path dependence, particularly when routine-based solutions are no longer sufficient. Although managerial cognition remains the primary foundation of dynamic managerial capabilities (Kryeziu *et al*., 2024), relying solely on individual cognitive capacity may be insufficient to generate strategic breakthroughs.

However, the risk of becoming trapped in a new form of path dependence also emerges. AI not only has the potential to disrupt existing paths but may also create new and potentially stronger self-reinforcing mechanisms that are even more difficult to escape. Managerial ambivalence toward AI reflects the tension between its transformative potential and the risks of disruption. If the technological shock is not effectively internalized, the gap between market demands and organizational trajectories may further widen.

Although prior literature emphasizes that strategic drift cannot be generated solely through organizational routines, there remains limited understanding of how managers, through the use of AI, can enact sui generis strategic acts (Teece, 2012) that enable such drift. Therefore, an integration of the literatures on path dependence, dynamic capabilities, and AI is needed to better understand how organizations can overcome lock-in in an evolutionary manner within the context of technological transformation.

Methodology

Metode: Multiple case study design

A multiple case study approach is considered more robust than a single case study, as it enables the use of replication logic (Yin, 2018). This approach treats each case as a distinct theoretical experiment, which is then systematically compared to identify both consistent patterns and meaningful variations across contexts (Gehman et al., 2018; Volmar and Eisenhardt, 2020). By comparing multiple cases, researchers can enhance the robustness and internal validity of their findings through cross-case pattern matching, without relying on statistical sampling logic (Eisenhardt, 2021).

Case Selection Technique: Theoretical Sampling

Case selection in this study follows a theoretical sampling approach rather than random sampling as commonly employed in quantitative research (Eisenhardt, 2021). This strategy involves selecting cases based on their theoretical relevance to the research question. Specifically, case selection may incorporate designs such as polar types, matched pairs, racing designs, and common process designs (Eisenhardt and Ott, 2017; Volmar and Eisenhardt, 2020). Such strategies enable researchers to deliberately choose relevant, extreme, or contrasting cases, thereby enriching theoretical insights and facilitating concept development. In a multiple case study design, each case is treated as an independent unit of analysis prior to conducting cross-case comparisons. This approach enhances the external validity of findings by identifying patterns that hold across different cases (Eisenhardt, 1989; Yin, 2014). The recommended number of cases for a multiple case study ranges from four to ten cases, which is considered sufficient for

theory building through replication logic and cross-case comparison (Eisenhardt, 2021). The subjects of this study consist of small and medium-sized enterprises (SMEs) in Yogyakarta that have adopted AI in their business processes.

Data Collection and Analysis Techniques

The next stage involves data collection using multiple sources in a triangulated manner. Data may be obtained through semi-structured interviews, direct or non-participant observations, and organizational archival documents. The use of multiple data sources enables researchers to gain a more comprehensive understanding of the phenomenon while reducing potential bias. A case study protocol is employed to ensure consistency in the data collection process across cases. This strategy not only enriches the dataset but also enhances the reliability and credibility of the findings (Ridder, Hoon and Mccandless Baluch, 2014).

Data analysis in case study research follows an iterative and inductive process. The analytical procedure involves within-case analysis to develop an in-depth understanding of each case, followed by cross-case comparison to identify consistent patterns and build replication logic. This process is complemented by constant comparison between empirical data and emerging theoretical constructs (Eisenhardt, 1989; Eisenhardt and Graebner, 2007).

Findings and Analaysis

Empirical Findings: The case companies

Deepublish

Deepublish is an Indonesian publishing company operating in academic publishing, printing, and book distribution, headquartered in Sleman, Yogyakarta. Established to address the gap between knowledge production and accessibility, the company initially focused on transforming lecturers' intellectual outputs into structured publications. Over time, Deepublish has evolved beyond a traditional publisher into a knowledge intermediary that facilitates the circulation and utilization of knowledge within a broader ecosystem. This intermediary role positions the firm as a relevant case for examining how learning processes emerge and are coordinated at the meso level, particularly within networks that connect multiple organizational actors.

From an operational perspective, Deepublish adopts an independent (self-) publishing model that emphasizes flexibility and responsiveness to authors' needs, while maintaining a structured internal organization encompassing functions such as author acquisition, manuscript processing, production, and distribution. This configuration enables the firm to integrate technological tools and data-driven processes into its operations, creating conditions where organizational learning and emerging artificial intelligence (AI)-enabled practices can interact with routine activities. In this context, the firm's internal processes and digital infrastructure provide a micro-foundation through which capabilities are continuously adapted and reconfigured, reflecting early manifestations of dynamic capabilities in practice.

Beyond its internal structure, Deepublish actively develops and orchestrates a network of partnerships involving authors, production partners, distributors, and reseller networks. This networked configuration represents a meso-level system in which learning, coordination, and capability development occur through interactions among multiple actors rather than within a single firm. Through its role in facilitating collaboration, knowledge exchange, and resource integration, Deepublish contributes to shaping the conditions under which dynamic capabilities emerge across the network. As such, the company provides a relevant empirical setting to explore how the interplay between learning processes, AI-related practices, and inter-organizational relationships generates sources of dynamism at the meso level.

Alito Sportwear

Alito Sportswear is a local apparel manufacturing business based in Yogyakarta, operating primarily in the production of customized sportswear, particularly jerseys for football and futsal communities. The company initially emerged as a small-scale production unit responding to the growing demand for personalized sports apparel, leveraging digital technologies and online platforms to directly engage with customers. This direct-to-consumer orientation reflects a shift from traditional intermediary-based distribution toward digitally enabled interactions, positioning Alito Sportswear as a relevant empirical setting for examining how learning and capability development unfold within digitally mediated business environments.

The firm's business model is characterized by continuous product and process innovation, particularly through the expansion of its product offerings beyond jerseys to include complementary products such as customized sports socks. This diversification strategy is driven by insights derived from customer interactions, indicating a learning process embedded within daily operations. The integration of digital tools for marketing, ordering, and customer communication further enables the firm to capture and process market signals in real time, creating conditions in which data-driven decision-making and AI-related practices can potentially enhance responsiveness and operational efficiency. In this sense, Alito Sportswear's routines illustrate how learning mechanisms are translated into adaptive capabilities at the firm level.

Beyond its internal operations, Alito Sportswear operates within a broader ecosystem involving suppliers, customers, and distribution channels, forming a networked structure in which value is co-created. The firm's interactions with customers—particularly through customization requests and bundled product offerings—highlight how knowledge flows across organizational boundaries, contributing to capability development not only within the firm but also across the network. This configuration represents a meso-level context in which learning, technological adoption, and inter-organizational interactions collectively shape the emergence of dynamic capabilities. Accordingly, Alito Sportswear provides a complementary case to explore how sources of dynamism arise through the interplay between learning processes, AI-enabled practices, and network relationships.

Meso-Level Learning in the Age of AI

Our findings reveal that the adoption of AI fundamentally reshapes learning processes at the meso level by simultaneously enabling and constraining both adaptive and creative learning.

Adaptive Learning: From Collective Sensemaking to AI-Supported Optimization

On the one hand, AI significantly enhances adaptive learning by enabling teams to process large volumes of data rapidly and make more structured, data-driven decisions. Participants consistently highlighted how AI improves efficiency and speed in their daily work:

"We were able to take that workflow and reduce it by 4x in terms of end-to-end time… which of course is a massive productivity gain" (Staff, Allito).

This increased efficiency is also reflected in everyday operational activities. Several participants emphasized how AI contributes to the standardization and optimization of work processes:

"How do I take a whole workflow… and actually rethink that end to end… that's where the magic starts to happen" (Staff, Allito).

In addition, AI enhances teams' ability to respond to change and improves problem-solving processes. Taken together, these findings suggest that AI strengthens key dimensions of adaptive learning, particularly in terms of efficiency, speed, optimization, and pattern recognition, which were previously more dependent on individual cognitive capacity and team interactions.

However, these efficiency gains also come with unintended consequences. Several participants reported an increasing tendency to accept AI outputs without critical reflection. Decision-making becomes "more driven by the system than by the team," accompanied by reduced discussion and limited questioning of underlying assumptions. Over time, this leads to cognitive rigidity, where teams "no longer explore alternatives as much as before". Thus, adaptive learning shifts from a socially embedded process of collective sensemaking toward a system-driven process of optimization, where increased efficiency may come at the expense of critical engagement.

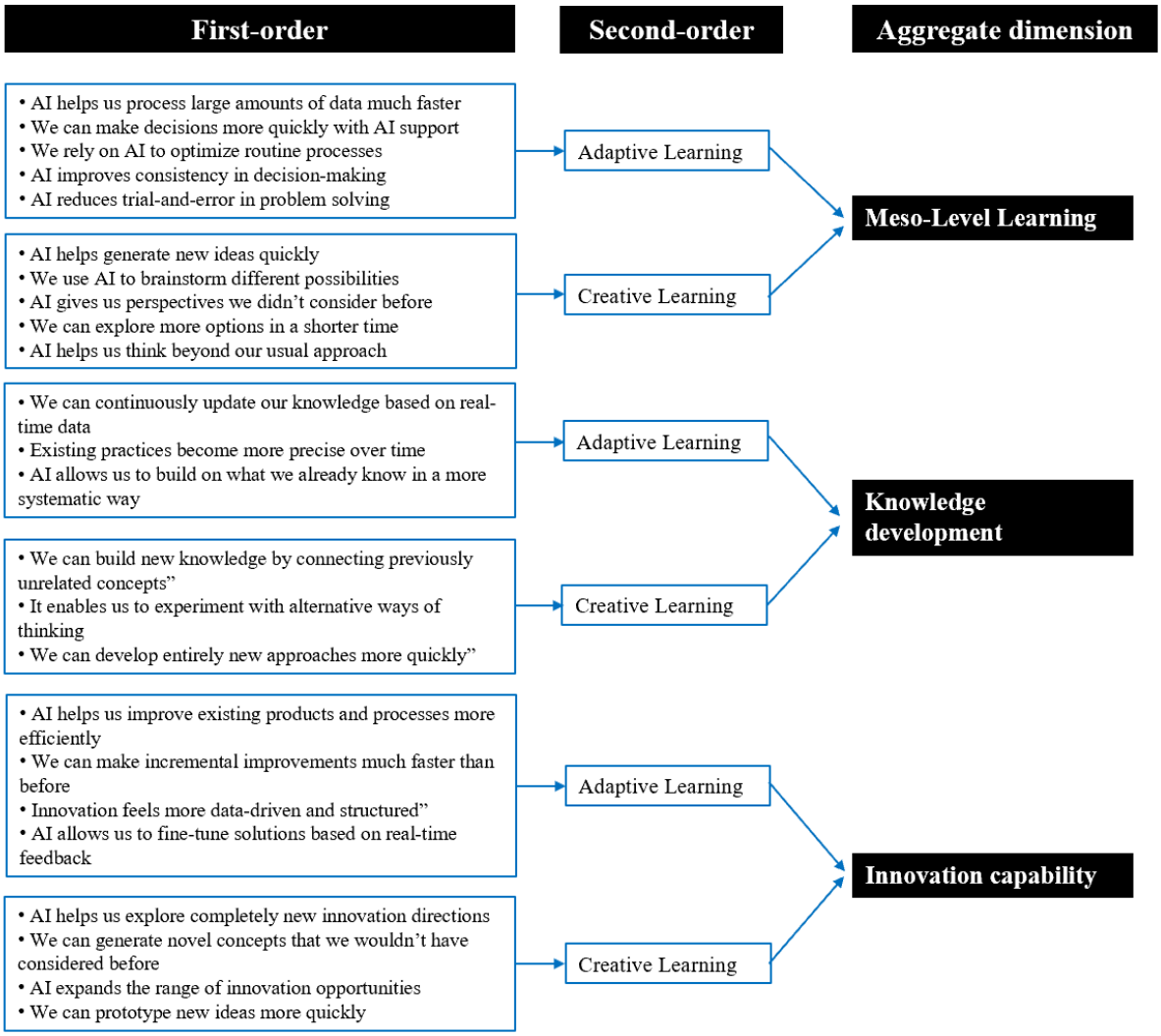


Figure 1. Data Structure
Source: Authors' Own Work

Creative Learning: Expanding Ideation While Constraining Originality

AI reshapes creative learning in fundamentally paradoxical ways, simultaneously expanding the breadth of ideation while constraining the depth and originality of knowledge creation processes within teams.

On the one hand, participants consistently described how AI significantly enhances the generative capacity of teams by enabling rapid and wide-ranging idea production. AI allows individuals and teams to move beyond their habitual cognitive patterns and explore a broader space of possibilities:

"that requires a set of individuals who can do that type of problem solving… leaders who can pick areas that are really ripe." (Manager, Wicapu)

This expansion is particularly evident in the early stages of creative processes, where AI functions as a catalyst for divergent thinking. Rather than starting from a blank slate, teams are now able to engage with a wide array of pre-generated inputs, which accelerates ideation and reduces cognitive barriers to exploration. As one participant noted, AI enables teams to "think beyond our usual approach" and "consider options we might not have come up with on our own."

Moreover, AI facilitates the recombination of knowledge across domains, enabling novel connections that would otherwise require extensive expertise or time to develop. Participants highlighted how AI supports cross-boundary thinking:

"We can experiment with multiple concepts in a short time." (Manager, Wicapu).

In this sense, AI extends the cognitive reach of teams, allowing them to operate across a broader knowledge landscape. It also supports rapid experimentation, enabling teams to test multiple ideas simultaneously and iterate quickly:

"[you need to] connect it with your proprietary knowledge… about your products and services" (Manager, Wicapu).

Taken together, these findings suggest that AI enhances creative learning by amplifying generativity, variation, and exploratory search, thereby lowering the cost of ideation and expanding the space of potential solutions. However, this apparent expansion of creativity is accompanied by subtle but significant constraints. Despite the increase in idea generation, participants frequently expressed concerns about the originality and distinctiveness of AI-supported outputs. Many observed that ideas generated through AI tend to converge toward similar patterns:

"You're using a system you don't fully trust… AI outputs often lead us toward safe, quite similar" (Staff, Allito)

Rather than fostering truly novel thinking, AI appears to guide users toward statistically probable or widely represented ideas, which may limit divergence at a deeper level. As a result, while the quantity of ideas increases, their qualitative distinctiveness may decrease. In addition, the presence of AI alters the nature of individual cognitive engagement in creative processes. Several participants noted a shift from active sensemaking to passive acceptance:

"The LLM doesn't catch enough of the issues… consistently it's missing certain things" (Staff, Allito)

This shift reduces the need for sustained reflection and cognitive struggle—processes that are often essential for deep creativity. Instead of engaging in iterative questioning and reinterpretation, individuals may prematurely converge on AI-generated outputs. The impact is also visible at the team level. Creative learning, which traditionally relies on dialogue, disagreement, and the synthesis of diverse perspectives, becomes less interactive. The reduction in dialogical interaction weakens the social processes through which ideas are challenged, refined, and transformed. Over time, this leads to a perceived decline in the uniqueness of creative outputs:

"[with the use of AI] it's often easier… to identify something rather than produce the right thing" (Staff, Allito)

Taken together, these findings reveal a fundamental tension in AI-supported creative learning. While AI enhances the breadth of ideation by increasing the volume and diversity of initial ideas, it simultaneously constrains the depth of creativity by reducing cognitive engagement, limiting divergence at later stages, and weakening dialogical processes. This results in a form of "expanded but shallow creativity," where teams generate more ideas than ever before, but struggle to develop ideas that are truly original, deeply elaborated, and meaningfully differentiated.

AI and the Transformation of Knowledge Development

Beyond reshaping learning processes, AI adoption also fundamentally reconfigures how knowledge is developed within teams. Our findings indicate that AI transforms knowledge development through two distinct but interrelated pathways: the reinforcement of existing knowledge through adaptive mechanisms, and the expansion of knowledge through creative recombination. However, both pathways are characterized by inherent tensions that shape the depth, direction, and trajectory of knowledge evolution.

Adaptive Pathways: Reinforcing and Stabilizing Existing Knowledge

On the one hand, AI significantly enhances the development of existing knowledge by enabling continuous refinement and improvement based on real-time data. Participants consistently described how AI allows them to build upon what is already known in a more structured and systematic manner:

"we can see if it was effective… then we push that up in the algorithm… similar profile will then be pushed similar content" (Staff, Allito)

This refinement process reduces uncertainty and increases the reliability of knowledge applications. Rather than relying on fragmented or experience-based adjustments, teams are now able to iteratively improve their knowledge base through data-driven feedback loops. As one participant explained, AI enables them to "improve what we already know without starting from scratch," suggesting a shift toward cumulative and path-dependent knowledge development. In addition, AI supports the consolidation and standardization of knowledge across teams and projects. Through these mechanisms, knowledge development becomes more stable, scalable, and transferable. Teams are able to codify best practices more effectively and ensure consistency in how knowledge is applied across contexts.

However, this increasing stability is accompanied by emerging rigidity. Several participants noted that AI tends to reinforce existing knowledge structures rather than challenge them. Because AI systems rely heavily on historical data, they often privilege proven solutions over novel alternatives. As a result, teams may become increasingly anchored in established ways of thinking. This dynamic leads to a form of path dependency, where knowledge development follows incremental trajectories rather than transformative shifts. Participants frequently described their work as becoming more optimization-oriented. Moreover, the reliance on data-driven refinement can reduce the motivation to revisit underlying assumptions: Taken together, these findings suggest that AI strengthens the *stabilization and exploitation of knowledge*, but at the cost of reducing epistemic flexibility. Knowledge becomes more precise and reliable, yet less open to fundamental reconfiguration.

Creative Pathways: Expanding Recombination While Diluting Depth

In parallel, AI also transforms knowledge development through creative pathways by enabling the recombination of ideas across domains. Participants emphasized that AI expands the scope of knowledge by facilitating connections between previously unrelated concepts:

"you'll be able to do so much more of that with the assistance of agents" (Staff, Allito)

This recombinatory capability allows teams to move beyond domain-specific constraints and engage in more exploratory forms of knowledge development. AI acts as a bridge across knowledge domains, enabling individuals to access and integrate diverse perspectives. Through these processes, knowledge development becomes more dynamic and generative. Teams are able to explore multiple trajectories simultaneously, increasing the likelihood of discovering novel configurations of knowledge.

However, this expansion of recombination is not without limitations. Despite the increase in the breadth of knowledge exploration, participants frequently expressed concerns about the depth and

coherence of the knowledge being developed. Many noted that while ideas are generated quickly, they are not always meaningfully integrated:

"the LLM doesn't catch enough of the issues… consistently it's missing certain things" (Staff, Allito)

The speed of recombination often outpaces the processes required for deep understanding and synthesis. As a result, knowledge development can become superficial. Participants also highlighted a tendency to move rapidly between ideas without fully elaborating or validating them. This creates a form of epistemic fragmentation, where knowledge exists as loosely connected ideas rather than coherent, well-developed constructs. In such cases, the abundance of ideas does not necessarily translate into robust knowledge.

Taken together, these findings reveal a fundamental trade-off in AI-enabled knowledge development. While AI expands the breadth of knowledge recombination, it may simultaneously reduce the depth of knowledge integration. This results in a pattern of "broad but shallow knowledge development," where the organization is able to generate and connect a wide range of ideas, but struggles to develop them into deeply grounded and internally consistent knowledge structures.

Across both adaptive and creative pathways, AI introduces a structural shift in knowledge development: knowledge becomes simultaneously more refined and more expansive, yet also more path-dependent and more superficial. This dual transformation suggests that AI does not simply enhance knowledge development, but fundamentally reshapes its underlying dynamics—shifting the balance between *stability and flexibility, depth and breadth, and refinement and exploration*.

AI and the Transformation of Knowledge Development

The transformations in learning processes and knowledge development described above ultimately culminate in a fundamental reconfiguration of innovation capability. Our findings suggest that AI does not simply enhance innovation performance, but reshapes the underlying mechanisms through which innovation is generated, developed, and implemented. In particular, AI introduces two distinct yet interrelated pathways: the strengthening of incremental innovation through adaptive learning, and the simultaneous expansion—yet fragilization—of radical innovation through creative learning.

Adaptive Pathways: Accelerating and Structuring Incremental Innovation

On the one hand, AI significantly strengthens innovation capability by enhancing the efficiency, precision, and scalability of incremental improvements. Participants consistently described how AI enables them to refine existing products, processes, and solutions in a more systematic and data-driven manner:

"we can see if it was effective… then we push that up in the algorithm… similar profile will then be pushed similar content" (Staff, Allito).

Through these mechanisms, innovation becomes more continuous and iterative. Rather than relying on sporadic breakthroughs, teams are able to introduce a steady stream of small but meaningful improvements. This aligns with a more exploitation-oriented mode of innovation, where existing knowledge is leveraged and optimized. Participants also emphasized the increased predictability and consistency of innovation processes.

This shift toward structured innovation reflects the growing role of AI in reducing uncertainty and standardizing decision-making processes. By identifying patterns and generating recommendations, AI enables teams to focus on optimizing known solutions rather than exploring uncertain alternatives. As one participant noted, AI helps them "identify small but impactful changes," suggesting a refinement-oriented approach to innovation.

However, this increased efficiency is accompanied by a narrowing of innovation scope. Several participants expressed concerns that innovation efforts are increasingly focused on incremental improvements rather than transformative change. This shift reflects a growing bias toward low-risk, high-certainty innovation pathways. As AI provides data-driven validation for existing solutions, teams may become less willing to pursue uncertain or unconventional ideas:

"we do need to kind of make sure we have the right risk controls in place" (Staff, Allito)

Over time, this dynamic leads to a form of exploitation trap, where organizations become highly efficient at improving existing offerings but less capable of generating fundamentally new ones. As one participant reflected, "it becomes harder to justify radical changes," indicating that the very mechanisms that enhance efficiency may simultaneously constrain transformative innovation.

Creative Pathways: Expanding Possibilities While Undermining Breakthrough Innovation

In parallel, AI also opens up new possibilities for radical innovation by expanding the range of ideas and enabling rapid experimentation. Participants described how AI allows them to explore entirely new directions and challenge existing assumptions:

"if this is truly going to radically transform everything about our business..." (Staf, Wicapu)

This expansion is particularly evident in early-stage innovation processes, where AI lowers the barriers to ideation and prototyping. Teams are able to generate, test, and iterate on multiple concepts simultaneously, thereby increasing the breadth of exploration. Through these mechanisms, AI enhances the generative capacity of organizations, enabling them to engage with a wider range of innovation opportunities. However, despite this expansion, participants frequently noted that AI-enabled innovation does not necessarily translate into truly radical or distinctive outcomes. Many observed that ideas generated with AI tend to converge toward similar patterns.

Rather than producing breakthrough innovations, AI-supported processes often lead to variations of existing ideas. This reflects a deeper limitation in how AI operates—by drawing on existing data distributions, it may privilege familiarity over novelty. In addition, the speed of AI-enabled ideation appears to undermine the depth of innovation development. Participants highlighted a tendency to move rapidly between ideas without fully committing to or elaborating them:

"they're going to be able to supercharge the speed at which they can do innovation" (Staf, Wicapu)

This dynamic results in a form of superficial innovation, where the abundance of ideas does not translate into meaningful or transformative outcomes. As one participant noted, "AI-driven innovation can feel superficial," reflecting a gap between ideation and realization. Taken together, these findings reveal a fundamental tension in AI-enabled innovation capability. While AI expands the *breadth of innovation opportunities* and accelerates experimentation, it may simultaneously reduce the *depth, distinctiveness, and transformative potential of innovation outcomes.* This leads to a pattern of *"efficient but constrained innovation,"* where organizations become highly capable of generating and implementing incremental improvements, yet struggle to sustain the conditions necessary for breakthrough innovation. In this sense, AI does not uniformly enhance innovation capability, but reconfigures it toward efficiency, scalability, and predictability—often at the expense of novelty, risk-taking, and deep transformation.

Discussions

Reconfiguring Meso-Level Learning in the Age of AI

Our findings contribute to the literature on organizational learning by demonstrating how AI fundamentally reshapes learning processes at the meso level. Traditionally, organizational learning has been conceptualized as a socially embedded process involving interaction, shared sensemaking, and

mutual adaptation among organizational members (Argote, 2012; Salvato and Vassolo, 2018). In this view, learning emerges through ongoing dialogue, collective interpretation, and the alignment of actions within teams. However, our findings suggest that AI introduces a significant shift in how these processes unfold, transforming learning from a primarily social and interaction-driven activity into a socio-technical process mediated by data and algorithms.

First, our findings show that AI significantly enhances adaptive learning by enabling faster information processing, pattern recognition, and decision-making. This aligns with prior research emphasizing the role of digital technologies in improving organizational responsiveness and information-processing capacity (Galbraith, 1974; Faraj, Pachidi and Sayegh, 2018). By reducing uncertainty and enabling real-time analysis, AI allows teams to respond more efficiently to environmental changes, reinforcing the adaptive function of learning. In this sense, AI strengthens what can be understood as the information-processing dimension of organizational learning, making adaptation more rapid, structured, and scalable.

However, this increased efficiency also alters the social dynamics of learning. While traditional accounts emphasize the importance of interaction, dialogue, and shared interpretation (Salvato and Rerup, 2018), our findings indicate that AI reduces the need for collective sensemaking by providing ready-made interpretations and recommendations. As teams increasingly rely on AI-generated outputs, opportunities for discussion, disagreement, and mutual adjustment may decline. This shift suggests a movement from ***collective sensemaking toward system-supported sensegiving***, where the locus of interpretation partially shifts from human actors to technological systems. Such a transition may limit the diversity of perspectives and reduce the depth of learning, echoing concerns about the diminishing role of human cognition in algorithmically mediated environments (Faraj, Pachidi and Sayegh, 2018; Raisch and Krakowski, 2021).

Second, our findings reveal that AI reshapes creative learning in paradoxical ways. On the one hand, AI expands the scope of ideation by enabling access to diverse knowledge sources and facilitating rapid generation of alternatives. This supports the exploratory dimension of learning, which is critical for innovation and adaptation in dynamic environments (March, 1991). By lowering the cognitive and temporal costs of idea generation, AI enables teams to engage in broader exploratory search and recombination.

On the other hand, our findings indicate that this expansion of ideation may not translate into deeper creative learning. Instead, the increased reliance on AI may reduce individual cognitive effort and limit the extent to which ideas are critically examined, debated, and refined. This results in a form of learning that is broader but less dialogical and less reflective. In contrast to traditional views that emphasize the importance of interaction and constructive conflict in learning processes (Argote, 2012; Salvato and Rerup, 2018), AI-mediated learning appears to reduce the intensity of these social mechanisms. Consequently, creative learning becomes characterized by a tension between increased generativity and reduced originality.

Taken together, these findings suggest that AI introduces a fundamental shift in the nature of meso-level learning. Specifically, learning processes evolve from being primarily ***socially embedded and interaction-driven*** toward becoming ***socio-technical and system-mediated***. While this transformation enhances efficiency and expands the scope of learning, it also risks weakening the social and cognitive foundations that enable deep, reflective, and creative learning. This shift has important implications for organizational learning theory. It suggests that existing models, which emphasize human interaction and experiential learning, may need to be extended to account for the role of AI as an active participant in learning processes. Rather than simply supporting human learning, AI increasingly shapes what is learned, how it is interpreted, and how decisions are made. In this sense, learning becomes distributed across human and technological actors, raising important questions about agency, cognition, and the future of collective learning in organizations.

Reinterpreting Knowledge Creation and Dynamic Capabilities in the Age of AI

Our findings offer important implications for both the theory of organizational knowledge creation (Nonaka, Hirose and Takeda, 2016) and the dynamic capabilities framework (Teece, 2007). Specifically, they suggest that AI adoption not only reconfigures the mechanisms through which knowledge is created, but also reshapes the microfoundations of dynamic capabilities by altering how organizations sense, seize, and transform opportunities.

From a Nonaka perspective, knowledge creation is traditionally understood as a dynamic, dialectical process emerging from the interaction between tacit and explicit knowledge through the socialization, externalization, combination and internalization (SECI) cycle (Nonaka, 1994; Nonaka and Takeuchi, 2007). However, our findings indicate that this process is increasingly mediated by AI systems, which introduce a data-driven and algorithmic layer into organizational epistemic processes. Rather than relying primarily on social interaction and experiential knowledge exchange, teams increasingly engage with AI-generated outputs, shifting the locus of knowledge development toward data processing and system-supported interpretation. This observation resonates with recent arguments that digital technologies reshape the nature of knowledge work and epistemic processes in organizations (Faraj, Pachidi and Sayegh, 2018; Leonardi, 2020).

This transformation has direct implications for the microfoundations of dynamic capabilities. In Teece's framework, dynamic capabilities are rooted in organizational processes that enable firms to sense opportunities, seize them through decision-making, and transform their resource base accordingly (Teece, 2007, 2018). These processes are deeply dependent on learning, knowledge integration, and managerial cognition (Felin, Foss and Ployhart, 2015). Our findings suggest that AI fundamentally reshapes these underlying mechanisms.

First, AI significantly enhances the sensing capability by enabling rapid data processing, pattern recognition, and environmental scanning. As reflected in adaptive learning processes, teams are able to identify trends and signals more quickly and accurately than before. This aligns with Teece's notion of sensing as an information-intensive activity (Teece, 2007). However, while AI strengthens the analytical dimension of sensing, it may simultaneously narrow interpretive diversity. The reduced reliance on dialogue and experiential knowledge may limit the organization's ability to generate alternative interpretations of environmental signals, echoing concerns about algorithmic narrowing and reduced cognitive diversity (Faraj, Pachidi and Sayegh, 2018) (Raisch and Krakowski, 2021).

Second, AI transforms the seizing capability by making decision-making processes more structured, data-driven, and efficient. Organizations are better able to evaluate options and implement solutions with greater speed and consistency. This is reflected in the strengthening of adaptive learning and incremental innovation. However, this efficiency comes with a trade-off. As decision-making becomes increasingly reliant on AI-generated recommendations, the space for managerial judgment and strategic discretion may shrink. This may result in a bias toward safer, more predictable choices, thereby constraining the organization's ability to pursue novel or high-risk opportunities (Verganti, Vendraminelli and Iansiti, 2020; Raisch and Krakowski, 2021).

Third, and most critically, AI affects the transforming capability, which is central to long-term innovation and organizational renewal. Transforming requires the recombination of knowledge, the reconfiguration of resources, and the creation of new organizational pathways (Teece, 2007). While AI enhances recombination by enabling connections across diverse knowledge domains, our findings suggest that this process often lacks depth and integration. The weakening of socialization and externalization processes—core elements in Nonaka's model—reduces the organization's capacity to develop deeply embedded and transformative knowledge (Nonaka, 1994; Nonaka and Takeuchi, 2007). As a result, transformation becomes more incremental and less radical.

Taken together, these shifts indicate a growing imbalance in the configuration of dynamic capabilities. AI strengthens sensing and seizing—particularly in their analytical and efficiency-oriented dimensions—but may weaken transforming by undermining the social and cognitive processes required

for deep knowledge creation. This imbalance is closely linked to the broader shift observed in our findings, where adaptive learning becomes dominant while creative learning becomes more fragile. This pattern is consistent with prior research highlighting tensions between exploration and exploitation in technologically mediated environments (March, 1991; Levinthal and March, 1993).

Importantly, this transformation also reframes the relationship between knowledge creation and dynamic capabilities. In Nonaka's theory, knowledge creation is the foundation of organizational adaptability and innovation (Nonaka, 1994). In Teece's framework, dynamic capabilities depend on the organization's ability to generate, integrate, and apply knowledge (Teece, 2007, 2018). Our findings suggest that AI introduces a decoupling risk: while organizations become more efficient in processing and applying existing knowledge, their ability to generate new, deeply grounded knowledge may decline. This echoes recent discussions on the tension between automation and human creativity in AI-enabled organizations (Jarrahi, 2018; Raisch and Krakowski, 2021).

This leads to a critical theoretical insight: AI does not simply enhance dynamic capabilities, but reconfigures their underlying epistemic foundations. Specifically, AI shifts dynamic capabilities from being socially embedded and experience-driven toward being socio-technical and data-driven. While this enhances scalability and efficiency, it may reduce the richness, diversity, and depth of knowledge required for radical innovation. In this sense, AI creates a structural tension within dynamic capabilities, where gains in efficiency and responsiveness may come at the expense of deep transformation and breakthrough innovation.

Reconfiguring Innovation Capability in the Age of AI

Our findings provide important insights into how AI reshapes innovation capability, extending existing theories of innovation and dynamic capabilities. Traditionally, innovation capability has been understood as the organization's ability to generate, develop, and implement novel ideas, often grounded in a balance between exploration and exploitation (March, 1991; O'Reilly III and Tushman, 2013). However, our findings suggest that AI fundamentally alters this balance by disproportionately strengthening exploitation-oriented processes while simultaneously constraining the conditions necessary for exploration.

First, our findings show that AI significantly enhances incremental innovation by increasing efficiency, precision, and scalability. This aligns with prior research highlighting the role of digital technologies in enabling continuous improvement and data-driven innovation processes (Nambisan *et al.*, 2017; Verhoef *et al.*, 2021). Through AI-enabled pattern recognition and real-time feedback, organizations are able to refine existing products and processes more systematically, reinforcing what March (1991) conceptualizes as exploitation. In this sense, AI acts as an accelerator of incremental innovation, enabling organizations to optimize known solutions and scale improvements more effectively.

However, this strengthening of incremental innovation comes with an important trade-off. As organizations increasingly rely on AI-generated insights, decision-making becomes more structured and risk-averse, leading to a preference for predictable and validated solutions. This dynamic resonates with recent work suggesting that algorithmic decision-making may bias organizations toward efficiency and reliability at the expense of novelty (Raisch and Krakowski, 2021). Consequently, innovation becomes more oriented toward optimization rather than transformation, limiting the pursuit of high-risk, high-reward opportunities.

Second, while AI expands the scope of ideation and enables broader exploration, our findings indicate that this does not necessarily translate into radical innovation. Although AI allows organizations to generate a wider range of ideas and explore new combinations, these ideas often lack depth, distinctiveness, and long-term development. This observation challenges the assumption that increased idea generation automatically leads to breakthrough innovation. Instead, it suggests that the relationship

between ideation and innovation is mediated by processes of evaluation, integration, and commitment—processes that appear to be weakened in AI-supported environments.

This paradox can be understood through the lens of exploration. While AI enhances the ***breadth*** of exploration by increasing variation and recombination, it may simultaneously reduce the ***depth*** of exploration by limiting sustained engagement with ideas. As a result, organizations may experience what can be described as "shallow exploration," where many ideas are generated but few are developed into transformative innovations. This finding extends prior work on exploration by highlighting how digital technologies can alter not only the extent but also the quality of exploratory processes (O'Reilly III and Tushman, 2013; Nambisan *et al*., 2017).

Third, our findings suggest that AI introduces a structural shift in innovation capability by creating an imbalance between incremental and radical innovation. While incremental innovation becomes more efficient and scalable, radical innovation becomes more fragile and difficult to sustain. This imbalance reflects a broader tension between efficiency and novelty, which has long been recognized in the innovation literature but is now intensified by AI. In particular, the dominance of data-driven decision-making may crowd out the uncertainty, experimentation, and cognitive diversity required for breakthrough innovation (March, 1991; Raisch and Birkinshaw, 2008).

Importantly, this shift has implications for the dynamic capabilities framework. Innovation capability is closely tied to the organization's ability to transform its resource base and create new value (Teece, 2007). However, as our findings suggest, AI may weaken this transforming capability by reinforcing existing knowledge structures and limiting deep recombination. While AI enhances sensing and seizing through improved data processing and decision efficiency, it does not necessarily support the deeper organizational changes required for radical innovation. This creates a capability imbalance, where organizations become highly effective at adapting within existing trajectories but less capable of redefining them.

Taken together, these findings lead to a key theoretical insight: AI does not uniformly enhance innovation capability, but reconfigures its underlying mechanisms in ways that favor efficiency, scalability, and predictability over novelty and transformation. In doing so, AI shifts innovation toward what we conceptualize as *"efficient but constrained innovation,"* where organizations excel at incremental improvement but struggle to sustain breakthrough innovation. This insight contributes to the literature by reframing AI not merely as a tool for enhancing innovation outcomes, but as a structural force that reshapes the balance between exploration and exploitation, and ultimately the nature of innovation capability itself.

Conclusions

This study set out to examine how AI adoption reshapes learning processes, knowledge development, and innovation capability at the meso level. By integrating insights from organizational learning, knowledge creation, and dynamic capabilities, our findings reveal that AI does not simply enhance organizational effectiveness, but fundamentally reconfigures the underlying mechanisms through which organizations learn, develop knowledge, and innovate.

Our findings highlight a consistent and overarching pattern: AI simultaneously enables efficiency, speed, and scalability, while constraining reflection, originality, and depth. At the level of learning, AI shifts processes from socially embedded sensemaking toward system-mediated optimization, strengthening adaptive learning while rendering creative learning more fragile. At the level of knowledge development, AI expands both refinement and recombination, yet introduces risks of path dependency and superficial integration. At the level of innovation capability, these shifts culminate in a structural imbalance, where incremental innovation is amplified while radical innovation becomes increasingly difficult to sustain.

Taken together, these findings contribute to theory in several important ways. First, we extend Nonaka's theory of knowledge creation by showing that AI reconfigures the SECI process, amplifying

combination while weakening the social and experiential mechanisms underlying knowledge creation. Second, we contribute to the dynamic capabilities literature by demonstrating how AI reshapes its microfoundations, strengthening sensing and seizing capabilities while potentially constraining transforming capability. Third, we introduce the notion of an AI-induced imbalance in organizational learning and innovation, where adaptive processes dominate at the expense of creative processes, leading to what we conceptualize as efficient but constrained innovation.

Beyond theoretical contributions, this study also offers important managerial implications. While AI can significantly enhance efficiency and decision-making, organizations must be cautious not to over-rely on AI at the expense of human interaction, dialogue, and critical reflection. Sustaining innovation capability in the age of AI requires actively preserving spaces for creative learning, encouraging debate and diverse perspectives, and ensuring that knowledge development remains both deep and integrative. In other words, the challenge is not simply to adopt AI, but to balance AI-driven optimization with human-centered processes of meaning-making and knowledge creation.

This study is not without limitations. As a qualitative investigation at the meso level, our findings are context-dependent and may not fully capture variations across industries, organizational structures, or levels of analysis. Future research could extend this work by examining how these dynamics unfold across different contexts, by quantitatively testing the relationships identified in this study, or by exploring how organizations can effectively balance adaptive and creative learning in AI-enabled environments. In conclusion, this study suggests that AI represents not only a technological shift but an epistemic transformation. By reshaping how organizations learn, develop knowledge, and innovate, AI challenges existing theoretical assumptions and calls for a rethinking of the foundations of organizational capability in the digital age.

Theoretical Contributions

This study makes several contributions to the literature on knowledge creation, dynamic capabilities, and AI in organizations. *First*, this study extends Nonaka's theory of knowledge creation by demonstrating that AI fundamentally reconfigures the socialization, externalization, combination and internalization (SECI) process. Specifically, we show that AI amplifies knowledge combination while attenuating socialization, externalization, and the depth of internalization, thereby shifting knowledge creation from a socially embedded, dialectical process toward a socio-technical, data-driven process.

Second, this study contributes to the dynamic capabilities literature by uncovering how AI reshapes its microfoundations. We show that AI strengthens sensing and seizing capabilities through enhanced data processing and decision efficiency, but may weaken transforming capabilities by undermining the social and cognitive mechanisms required for deep knowledge development and organizational renewal. *Third*, this study introduces the concept of an *AI-induced imbalance in learning and innovation*, where adaptive learning becomes dominant while creative learning becomes more fragile. This imbalance leads to a structural shift in innovation capability, favoring incremental innovation over radical innovation.

Fourth, this study contributes to the emerging literature on AI in organizations by moving beyond performance-oriented perspectives and theorizing AI as an epistemic force that reshapes how knowledge is generated, interpreted, and applied. In doing so, we highlight a central paradox: while AI enhances efficiency, scalability, and responsiveness, it simultaneously risks reducing cognitive diversity, depth of knowledge, and the conditions necessary for breakthrough innovation.

Acknowledgement

The researcher extends sincere gratitude to the Center for Development of Management Studies, Department of Management, Faculty of Business and Economics, Universitas Islam Indonesia, for providing research funding and institutional support.

References

Argote, L. (2012) *Organizational learning: Creating, retaining and transferring knowledge*. Springer Science & Business Media.

Danneels, E. (2011) 'Trying to become a different type of company: Dynamic capability at Smith Corona', *Strategic management journal*, 32(1), pp. 1–31.

Danneels, E., Verona, G. and Provera, B. (2018) 'Overcoming the inertia of organizational competence: Olivetti's transition from mechanical to electronic technology', *Industrial and Corporate Change*, 27(3), pp. 595–618.

Eisenhardt, K.M. (1989) 'Building theories from case study research', *The Academy of Management Review*, 14(4), pp. 532–550. Available at: https://doi.org/10.5465/amr.1989.4308385.

Eisenhardt, K.M. (2021) 'What is the Eisenhardt Method, really?', *Strategic Organization*, 19(1), pp. 147–160.

Eisenhardt, K.M. and Graebner, M.E. (2007) 'Theory building from cases: Opportunities and challenges', *Academy of Management Journal*, 50(1), pp. 25–32.

Eisenhardt, K.M. and Martin, J.A. (2000) 'Dynamic capabilities: What are they?', *Strategic Management Journal*, pp. 1105-1121. Available at: https://doi.org/https://www.jstor.org/stable/3094429.

Eisenhardt, K.M. and Ott, T.E. (2017) 'Rigor in theory building from multiple cases', in *The Routledge Companion to Qualitative Research in Organization Studies*. Routledge, pp. 79–91.

Faraj, S., Pachidi, S. and Sayegh, K. (2018) 'Working and organizing in the age of the learning algorithm', *Information and organization*, 28(1), pp. 62–70.

Felin, T., Foss, N.J. and Ployhart, R.E. (2015) 'The microfoundations movement in strategy and organization theory', *The Academy of Management Annals*, 9(1), pp. 575–632.

Galbraith, J.R. (1974) 'Organization design: An information processing view', *Interfaces*, 4(3), pp. 28–36.

Gehman, J. *et al.* (2018) 'Finding theory–method fit: A comparison of three qualitative approaches to theory building', *Journal of Management Inquiry*, 27(3), pp. 284–300.

Helfat, C.E. *et al.* (2007) *Dynamic capabilities: Understanding strategic change in organizations.* John Wiley & Sons.

Heubeck, T. (2023) 'Looking back to look forward: a systematic review of and research agenda for dynamic managerial capabilities', *Management Review Quarterly*, pp. 1–45.

Jarrahi, M.H. (2018) 'Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making', *Business horizons*, 61(4), pp. 577–586.

Kanbach, D.K. *et al.* (2024) 'The GenAI is out of the bottle: generative artificial intelligence from a business model innovation perspective', *Review of Managerial Science*, 18(4), pp. 1189–1220.

Keller, A. *et al.* (2025) 'Overcoming path-dependent dynamic capabilities', *Strategic Organization*, p. 14761270221125808.

Kryeziu, L. *et al.* (2024) 'Cognitive styles and dynamic managerial capabilities: implications for SMEs in a transition economy', *International Journal of Entrepreneurial Behavior & Research*, 30(1), pp. 200–231. Available at: https://doi.org/10.1108/IJEBR-04-2023-0406.

Lambert, B. *et al.* (2022) 'Individual-centered interventions: Identifying what, how, and why interventions work in organizational contexts', *Academy of Management Annals*, 16(2), pp. 508–546.

Leonard-Barton, D. (1992) 'Core capabilities and core rigidities: A paradox in managing new product development', *Strategic Management Journal*, 13(S1), pp. 111–125. Available at: https://doi.org/10.1002/smj.4250131009.

Leonardi, P.M. (2020) 'COVID-19 and the new technologies of organizing: digital exhaust, digital footprints, and artificial intelligence in the wake of remote work', *Journal of Management Studies*, 58(1), p. 249.

Levinthal, D.A. and March, J.G. (1993) 'The myopia of learning', *Strategic Management Journal*, 14(S2), pp. 95–112.

March, J.G. (1991) 'Exploration and exploitation in organizational learning', *Organization science*, 2(1), pp. 71–87.

Nambisan, S. *et al.* (2017) 'Digital innovation management: Reinventing innovation management research in a digital world', *MIS Quarterly*, 41(1), pp. 223–238. Available at: https://doi.org/10.25300/MISQ/2017/41:1.03.

Nonaka, I. (1994) 'A dynamic theory of organizational knowledge creation', *Organization science*, 5(1), pp. 14–37.

Nonaka, I., Hirose, A. and Takeda, Y. (2016) '"Meso"-foundations of dynamic capabilities: team-level synthesis and distributed leadership as the source of dynamic creativity', *Global Strategy Journal*, 6(3), pp. 168–182.

Nonaka, I. and Takeuchi, H. (2007) 'The knowledge-creating company', *Harvard business review*, 85(7/8), p. 162.

O'Reilly III, C.A. and Tushman, M.L. (2013) 'Organizational ambidexterity: Past, present, and future', *Academy of Management Perspectives*, 27(4), pp. 324–338. Available at: https://doi.org/10.5465/amp.2013.0025.

Raisch, S. and Birkinshaw, J. (2008) 'Organizational ambidexterity: Antecedents, outcomes, and moderators', *Journal of Management*, 34(3), pp. 375–409. Available at: https://doi.org/10.1177/0149206308316058.

Raisch, S. and Krakowski, S. (2021) 'Artificial intelligence and management: The automation–augmentation paradox', *Academy of management review*, 46(1), pp. 192–210.

Ridder, H.G., Hoon, C. and Mccandless Baluch, A. (2014) 'Entering a dialogue: Positioning case study findings towards theory', *British Journal of Management*, 25(2), pp. 373–387.

Ritala, P. *et al.* (2024) 'Developing industrial AI capabilities: An organisational learning perspective', *Technovation*, 138, p. 103120.

Salvato, C. and Rerup, C. (2018) 'Routine regulation: Balancing conflicting goals in organizational routines', *Administrative Science Quarterly*, 63(1), pp. 170–209.

Salvato, C. and Vassolo, R. (2018) 'The sources of dynamism in dynamic capabilities', *Strategic Management Journal*, 39(6), pp. 1728–1752.

Schilke, O. and Helfat, C.E. (2025) 'Unlocking dynamic capabilities: Pathways for empirical research', *Journal of Management Scientific Reports*, 3(2), pp. 71–87.

Sydow, J., Schreyögg, G. and Koch, J. (2009) 'Organizational path dependence: Opening the black box', *Academy of Management Review*, 34(4), pp. 689–709.

Sydow, J., Schreyögg, G. and Koch, J. (2020) 'On the theory of organizational path dependence: Clarifications, replies to objections, and extensions', *Academy of Management Review*, 45(4), pp. 717–734.

Teece, D.J. (2007) 'Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance', *Strategic Management Journal*, 28(13), pp. 1319–1350. Available at: https://doi.org/https://www.jstor.org/stable/20141992.

Teece, D.J. (2012) 'Dynamic capabilities: Routines versus entrepreneurial action', *Journal of Management Studies*, 49(8), pp. 1395–1401.

Teece, D.J. (2014) 'A dynamic capabilities-based entrepreneurial theory of the multinational enterprise', *Journal of International Business Studies*, 45(1), pp. 8–37. Available at: https://doi.org/10.1057/jibs.2013.54.

Teece, D.J. (2018) 'Dynamic capabilities as (workable) management systems theory', *Journal of Management & Organization*, 24(3), pp. 359–368.

Verganti, R., Vendraminelli, L. and Iansiti, M. (2020) 'Innovation and design in the age of artificial intelligence', *Journal of product innovation management*, 37(3), pp. 212–227.

Vergne, J.P. and Durand, R. (2010) 'The missing link between the theory and empirics of path dependence: Conceptual clarification, testability issue, and methodological implications', *Journal of*

Management Studies, 47(4), pp. 736–759. Available at: https://doi.org/https://doi.org/10.1111/j.1467-6486.2009.00913.x.

Vergne, J.P. and Durand, R. (2011) 'The path of most persistence: An evolutionary perspective on path dependence and dynamic capabilities', *Organization Studies*, 32(3), pp. 365–382.

Verhoef, P.C. *et al.* (2021) 'Digital transformation: A multidisciplinary reflection and research agenda', *Journal of business research*, 122, pp. 889–901.

Volmar, E. and Eisenhardt, K.M. (2020) 'Case study research: A state-of-the-art perspective', in R.J. Aldag (ed.) *Oxford Research Encyclopedia of Business and Management*. Oxford University Press. Available at: https://doi.org/10.1093/acrefore/9780190224851.013.206.

Whetten, D.A. (1989) 'What constitutes a theoretical contribution?', *Academy of Management Journal*, 14(4), pp. 490–495.

Yin, R.K. (2018) *Case study research and application*. 6th edn. London, United Kingdom: Sage Publications, Inc.

Zollo, M. and Winter, S.G. (2002) 'Deliberate learning and the evolution of dynamic capabilities', *Organization Science*, 13(3), pp. 339–351. Available at: https://doi.org/10.1287/orsc.13.3.339.2780.