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Learning to Innovate with AI: Organizational Learning Mechanisms in Business Model Experimentation

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Abstrak

Artificial intelligence is increasingly reshaping how organizations create, deliver, and capture value in digitally mediated environments. Despite its rapid diffusion across industries, existing research remains conceptually fragmented in explaining how artificial intelligence interacts with human expertise to transform business model innovation . Prior studies emphasize algorithmic capabilities and automation, while business model research focuses on value creation architectures, leaving the socio-technical mechanisms linking these perspectives underexplored. This article addresses this gap by developing a conceptual framework explaining the emergence of hybrid human–AI business models. Adopting a theory-building approach based on conceptual synthesis across artificial intelligence, business model innovation, and socio-technical systems theory, the study identifies three core mechanisms: cognitive augmentation, task reconfiguration, and adaptive value creation. These mechanisms explain how algorithmic capabilities interact with human expertise to reshape value proposition design, transform value delivery architectures, and enable the continuous adaptation of business models. The framework contributes by integrating fragmented literature and conceptualizing AI-enabled business models as hybrid socio-technical systems, while offering a foundation for future empirical research on human–AI collaboration and strategic transformation in digital economies.

Keywords

artificial intelligence; business model innovation; socio-technical systems; human–AI collaboration; digital transformation; adaptive value creation

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1. Introduction

Artificial intelligence (AI), including generative models, predictive analytics, and autonomous decision systems, is reshaping how organizations search for growth opportunities, design offerings, and reconfigure value creation, delivery, and capture mechanisms. Firms increasingly rely on algorithmic systems to explore strategic alternatives, simulate scenarios, personalize interactions, and redesign organizational processes at unprecedented speed and scale. Under these conditions, business model experimentation becomes strategically central because organizations must continuously test whether AI-enabled opportunities can translate into viable value propositions, governance arrangements, and monetization logics. This development is consequential not only for practice, as it reshapes competitive dynamics and strategic renewal, but also for theory because it challenges established explanations of innovation under conditions of algorithmic augmentation and uncertainty (Holmström & Carroll, 2024; Jorzik et al., 2024).

Existing scholarship addresses this phenomenon from several theoretical perspectives that remain only loosely integrated. Business model research conceptualizes firms as systems of interdependent choices shaping value creation, delivery, and capture. Innovation research highlights experimentation as a mechanism for reducing uncertainty and validating new strategic configurations. Organizational learning theory explains how organizations transform dispersed experiences into shared interpretations, routines, and institutionalized knowledge, particularly through Crossan et al.'s (1999) multilevel learning framework and Argyris and Schön's (1978) distinction between adaptive and generative learning. AI research, in contrast, focuses primarily on how algorithmic systems enhance prediction, search, and decision processes. Although these perspectives offer important insights, they have largely evolved in parallel. As a result, business model experimentation is often examined without an explicit theory of learning, while AI is frequently treated as a technological antecedent rather than as a factor reshaping how organizations generate and institutionalize knowledge (Crossan et al., 1999; Argyris & Schön, 1978; Sjödin et al., 2021).

Research on digital transformation and digital innovation further highlights how digital technologies reshape value creation architectures by enabling modularity, recombination, and rapid experimentation in organizational processes (Yoo et al., 2010; Nambisan et al., 2017). Digital infrastructures allow firms to test alternative configurations of products, services, and business models with reduced technological and organizational constraints. The proliferation of data platforms, analytics infrastructures, and algorithmic systems has consequently intensified experimentation as a core mechanism of innovation in digital environments (Autio et al., 2018; Nambisan et al., 2019). Understanding how organizations interpret and learn from digitally enabled experimentation therefore becomes central for explaining innovation dynamics in contemporary digital economies.

Recent research indicates that AI-driven business model innovation has become a rapidly expanding research domain. A systematic review by Jorzik et al. (2024) shows that the field has grown substantially but remains conceptually fragmented. Empirical studies demonstrate that AI capabilities enable new forms of value creation through feedback loops and co-evolutionary processes, particularly in digital servitization contexts (Sjödin et al., 2021). Emerging work also suggests that generative AI reshapes innovation processes by expanding automation and augmentation strategies available to firms (Holmström & Carroll, 2024; Mariani et al., 2024). At the same time, research on business model dynamics emphasizes experimentation, validation, scaling, and strategic pivots as mechanisms through which business models evolve (Sanasi, 2023; Macca et al., 2025). Collectively, these studies indicate that AI-enabled business model innovation has moved from a peripheral topic toward an emerging field requiring stronger theoretical consolidation.

Despite these advances, several conceptual tensions remain unresolved. Much AI research assumes that improved prediction and richer data automatically enhance innovation outcomes, whereas organizational learning theory emphasizes that information becomes knowledge only through interpretation, integration, and institutionalization. Similarly, research on business model experimentation typically conceptualizes experiments as episodic tests of assumptions, while AI-enabled experimentation generates continuous streams of signals whose strategic meaning remains ambiguous and contested. Although recent studies distinguish between automation and augmentation and between exploratory and exploitative innovation, the literature still lacks a clear explanation of why some AI-supported experiments merely optimize existing business models while others enable more fundamental redefinitions of value creation logics (Holmström & Carroll, 2024; Singh et al., 2024). These tensions suggest that the literature has advanced more rapidly in documenting innovation outcomes than in explaining the mechanisms connecting AI use, experimentation, and organizational transformation.

The central gap is therefore theoretical rather than empirical. Existing studies show that AI can support innovation and that experimentation plays a key role in business model development, yet they do not provide a sufficiently integrated explanation of how AI-mediated experimentation becomes organizational learning capable of validating, scaling, or transforming business models. The missing link lies in explaining the learning mechanisms through which algorithmic outputs become shared interpretations, are retained across organizational levels, and become embedded in new business model logics. Without such explanation, the literature risks overstating the direct technological effects of AI while under-theorizing the organizational processes that determine whether AI-generated variation leads to incremental adaptation or transformative change (Jorzik et al., 2024; Sanasi, 2023; Sjödin et al., 2021).

To address this gap, this study develops a conceptual framework that uses organizational learning theory as an integrating lens for explaining AI-enabled business model experimentation. The central argument is that AI functions not as a direct driver of business model innovation but as a learning enabler shaping how organizations generate variation, interpret experimental feedback, retain validated insights, and institutionalize new value logics. Building on the 4I framework of intuiting, interpreting, integrating, and institutionalizing (Crossan et al., 1999) and the distinction between single-loop and double-loop learning (Argyris & Schön, 1978), the study conceptualizes business model experimentation under AI as a multilevel learning process. Within this process, AI expands the search space and accelerates feedback, while innovation outcomes depend on organizations' interpretive and institutional capacities to convert algorithmic signals into collective strategic learning.

This article offers three theoretical contributions. First, it integrates the literatures on AI-enabled innovation, business model experimentation, and organizational learning into a mechanism-based explanation of AI-driven business model innovation. Second, it clarifies the pathway through which AI influences business model innovation by identifying organizational learning processes as the central mediating mechanism. Third, it distinguishes exploitative and exploratory learning pathways, explaining why AI-supported experimentation sometimes produces incremental refinement of existing business models and, in other cases, enables more transformative innovation. By articulating these mechanisms, the article responds to recent calls for stronger theoretical integration in AI and innovation research (Jorzik et al., 2024; Mariani et al., 2024; Singh et al., 2024).

Finally, the remainder of the paper proceeds as follows. The next section reviews the fragmented theoretical landscape surrounding AI, business model experimentation, and organizational learning. The paper then identifies the conceptual tensions and theoretical gap motivating the study. Building on this diagnosis, it develops an integrative mechanism-based framework explaining how AI-enabled experimentation translates into organizational learning and business model innovation. The study subsequently introduces a conceptual model and research propositions to guide future empirical research before discussing theoretical implications, boundary conditions, and directions for future research. By framing AI-enabled business model experimentation as a problem of multilevel organizational learning, the article advances a clearer theoretical foundation for understanding how organizations learn to innovate with AI (Crossan et al., 1999; Jorzik et al., 2024; Macca et al., 2025).

2. Fragmented Theoretical Landscape

Research on artificial intelligence, innovation, and business model transformation has expanded rapidly across several related literatures. Studies on AI in organizations examine how algorithmic technologies reshape decision-making and capability development, while innovation research emphasizes experimentation as a mechanism for exploring new strategic configurations. Organizational learning research, in contrast, explains how firms convert dispersed insights into shared knowledge and institutionalized routines. Despite addressing related phenomena, these streams largely evolve in parallel, leaving limited theoretical integration regarding how AI-enabled experimentation translates into business model innovation.

The following table synthesizes the three theoretical streams discussed in the literature review and clarifies how the present study integrates them. The structure highlights differences in analytical focus, assumptions, and limitations while positioning the contribution of the article within the broader research landscape.

Table 1. Theoretical Perspectives on AI, Business Model Experimentation, and Organizational Learning

Literature Stream	Core Analytical Focus	Key Assumptions	Main Limitations
AI and Innovation Literature	Examines how artificial intelligence enhances prediction, analytics, and decision-making in organizations.	AI improves analytical capabilities, expands data processing capacity, and supports strategic search and experimentation.	Often treats AI as a technological driver of innovation without specifying the organizational processes through which algorithmic insights become strategic change.
Business Model Experimentation Research	Investigates experimentation as a mechanism for developing and refining business models under uncertainty.	Organizations test hypotheses about value creation, delivery, and capture through iterative experimentation and validation.	Typically assumes human-driven experimentation and pays limited attention to how AI reshapes the generation and evaluation of experimental knowledge.
Organizational Learning Theory	Explains how organizations convert experience and information into shared knowledge and institutionalized routines.	Learning occurs through multilevel processes connecting individual cognition, collective interpretation, and organizational routines.	Rarely integrated into studies of AI-enabled experimentation or business model innovation processes.

Developed by the authors.

Table 1 synthesizes the fragmented theoretical landscape by clarifying how three research streams address related aspects of AI-enabled innovation yet remain weakly integrated. The table positions organizational learning as the missing mechanism linking AI-enabled experimentation with business model innovation outcomes, providing a conceptual bridge across these literatures.

2.1 AI and Innovation Literature

The diffusion of artificial intelligence has stimulated extensive research on how algorithmic technologies influence organizational innovation. Much of this literature conceptualizes AI as a capability-enhancing technology that improves prediction, analytical efficiency, and decision quality in complex environments (Brynjolfsson & McElheran, 2016; Davenport & Ronanki, 2018). Innovation management research further distinguishes between automation and augmentation, where AI may replace human activities or complement managerial cognition and strategic search processes (Raisch & Krakowski, 2021). These perspectives indicate that AI reshapes how organizations explore opportunities and evaluate strategic alternatives during early innovation stages.

Research in artificial intelligence and management also emphasizes the cognitive role of AI in organizational decision-making. AI systems extend managerial cognition through prediction, pattern recognition, and decision augmentation in complex environments (Brynjolfsson & McElheran, 2016; Jarrahi, 2018). From this perspective, AI functions as cognitive infrastructure embedded in socio-technical systems where technological capabilities and organizational practices co-evolve. The strategic value of AI therefore depends not only on technological sophistication but also on organizational capabilities that integrate algorithmic insights into managerial decision processes (Brynjolfsson et al., 2021).

Recent studies further suggest that AI expands the strategic search space for innovation by enabling organizations to process large-scale data and generate previously inaccessible insights. In digital servitization contexts, AI-supported feedback loops between algorithmic systems and organizational actors can accelerate the scaling of new business models (Sjödin et al., 2021). Generative AI research similarly highlights its capacity to produce novel solutions and strategic options that support rapid ideation and experimentation (Holmström & Carroll, 2024; Mariani et al., 2024). These developments position AI as infrastructure enabling continuous experimentation and strategic adaptation.

Despite these advances, the AI and innovation literature primarily emphasizes capability enhancement while paying limited attention to organizational learning processes. Although many studies recognize that AI facilitates experimentation and discovery, they rarely specify how organizations interpret, validate, and institutionalize algorithmic insights. Consequently, the literature explains how AI expands technological possibilities for innovation but provides weaker explanations of how these possibilities translate into enduring strategic outcomes such as business model innovation.

2.2 Business Model Experimentation and Dynamics

Research on business model innovation increasingly emphasizes experimentation as a central mechanism through which firms innovate under uncertainty. Early studies moved beyond static representations of value creation and capture toward dynamic perspectives that highlight iteration, experimentation, and learning in the development of new business models (Foss & Saebi, 2017). Within this view, experimentation allows organizations to test assumptions about customers, value propositions, and revenue mechanisms while gradually reducing uncertainty surrounding emerging strategic configurations. Firms therefore rarely design business models through purely analytical planning; instead, they refine them through cycles of experimentation, validation, and adaptation.

Subsequent research further established experimentation as a key mechanism of strategic learning in business model innovation. Organizations develop viable business models through iterative hypothesis testing that enables the refinement of assumptions about customer needs, value propositions, and revenue mechanisms (McGrath, 2010; Sosna et al., 2010). Empirical studies demonstrate that such experimentation allows firms to progressively adjust and evolve their business models in response to market feedback and organizational learning (Andries & Debackere, 2007; Chesbrough, 2010). These insights reinforce the view that business model innovation unfolds as an ongoing process of strategic learning rather than a discrete strategic event.

More recent research conceptualizes business model experimentation as part of broader processes of business model dynamics. Entrepreneurial experimentation enables firms to explore alternative configurations of value creation while iteratively refining strategic assumptions through repeated testing (Sanasi, 2023). Similarly, experimentation is embedded within sequences of validation, scaling, and strategic pivots that collectively shape the evolution of business models over time (Macca et al., 2025). This stream of research positions experimentation as a learning mechanism through which organizations gradually identify viable configurations of resources, activities, and value propositions.

Despite these advances, the literature has only recently begun to consider how AI-enabled technologies reshape experimentation processes. Most studies implicitly assume experiments occur through human-driven hypothesis testing, market trials, or controlled pilot projects. Increasing use of AI in analytics, customer interaction, and predictive modeling suggests experimentation is becoming data-intensive, algorithmically mediated, and continuous. Yet existing research rarely conceptualizes AI as an epistemic infrastructure shaping how organizations generate, interpret, and evaluate experimental knowledge. Consequently, while business model dynamics research provides a strong foundation for understanding experimentation as a strategic process, it remains underdeveloped in explaining how AI reshapes the production and diffusion of experimental knowledge within organizations.

2.3 Organizational Learning Theory

Organizational learning theory provides a critical lens for integrating research on AI-enabled innovation and business model experimentation by explaining how organizations transform dispersed experiences into shared knowledge and coordinated action. Foundational studies emphasize that learning involves more than accumulating information; it requires individuals and groups to develop shared interpretations, adjust behaviors, and institutionalize new practices within organizational structures (Fiol & Lyles, 1985). This perspective links individual cognition with collective routines and decision processes, highlighting how organizations convert experimental outcomes into enduring capabilities and strategic renewal.

Subsequent research further demonstrates that learning processes enable organizations to adapt to complex and uncertain environments by transforming experience into knowledge and action (Levitt & March, 1988; Argote & Miron-Spektor, 2011). Learning unfolds across multiple organizational levels and involves both cognitive and behavioral change within organizations. These processes are particularly salient in innovation contexts where firms must continuously update their knowledge structures in response to new information and environmental feedback (Argote, 2013). Organizational learning theory therefore provides a useful framework for understanding how firms translate experimental insights into strategic capabilities and sustained competitive advantage.

One influential framework conceptualizes learning as a multilevel process connecting individual cognition with collective routines. The 4I model proposed by Crossan et al. (1999) describes learning as a dynamic sequence of intuiting, interpreting, integrating, and institutionalizing through which insights become embedded in organizational practices. Complementing this view, Argyris and Schön (1978) distinguish between single-loop learning, which adjusts actions within existing assumptions, and double-loop learning, which revises the underlying assumptions guiding organizational behavior. This distinction is particularly relevant in experimentation contexts where learning may either refine existing practices or enable deeper strategic transformation.

Applying this perspective to AI-enabled innovation highlights that algorithmic insights alone do not generate innovation outcomes. Organizations must interpret and integrate such insights into collective decision processes before they influence strategic change. The impact of AI on business model innovation therefore depends not only on technological capabilities but also on the learning mechanisms through which organizations interpret signals, evaluate experimental outcomes, and institutionalize new value creation logics. Yet organizational learning remains insufficiently integrated into studies of AI-enabled business model experimentation. Consequently, the literatures on AI innovation, business model experimentation, and organizational learning provide complementary insights but remain conceptually fragmented, motivating the theoretical tensions examined in the next section.

3. Conceptual Tensions and Theoretical Gaps

Although prior research recognizes the growing role of artificial intelligence in innovation and business model development, the literature remains theoretically fragmented. Studies often examine AI capabilities, experimentation practices, or organizational learning processes separately rather than explaining how these elements interact to produce business model innovation. This fragmentation obscures the mechanisms through which AI-enabled experimentation translates into strategic transformation. Three conceptual tensions illustrate these limitations and reveal the theoretical gap addressed in this study.

3.1 Tension 1: Data-Rich Experimentation versus Meaning-Poor Learning

The integration of artificial intelligence into organizational processes has dramatically expanded firms' capacity to generate and analyze data during innovation activities. AI systems support rapid experimentation through predictive analytics, algorithmic simulations, and real-time digital feedback, producing large volumes of information about customer behavior, operational performance, and market dynamics (Raisch & Krakowski, 2021; Holmström & Carroll, 2024). These capabilities appear to strengthen firms' ability to evaluate strategic alternatives and refine emerging business models.

However, the availability of data does not automatically produce organizational learning. Organizational learning theory emphasizes that information becomes knowledge only when it is interpreted, integrated into shared cognitive frames, and embedded in collective decision-making processes (Crossan et al., 1999; Fiol & Lyles, 1985). AI therefore expands analytical capacity without guaranteeing the interpretive processes required for strategic understanding.

This distinction exposes a central tension in AI-enabled experimentation. Organizations may generate sophisticated insights through machine learning models yet struggle to translate these insights into shared interpretations about how value creation, delivery, and capture should evolve. Evidence from AI adoption studies shows that algorithmic outputs often challenge established mental models and organizational routines, making interpretation difficult (Raisch & Krakowski, 2021). AI-enabled experimentation may therefore become data-rich but meaning-poor, producing extensive analytical signals without generating the shared understanding required for business model innovation.

3.2 Tension 2: Adaptive Optimization versus Business Model Transformation

A second tension concerns the difference between incremental improvement and fundamental business model transformation. Many organizational applications of AI focus on optimizing existing activities such as pricing, segmentation, operational automation, or demand forecasting. These applications enhance efficiency and decision accuracy within established value creation and revenue structures (Brynjolfsson & McElheran, 2016; Davenport & Ronanki, 2018). Such improvements represent adaptive optimization, where organizations refine existing processes without questioning the underlying logic of the business model.

Business model transformation requires deeper reconsideration of value creation and capture mechanisms. Organizations must reassess questions such as who the customer is, how value is delivered, and which revenue models sustain the firm. Organizational learning theory explains this process through double-loop learning, where firms revise the assumptions guiding their strategies rather than merely adjusting actions within existing frameworks (Argyris & Schön, 1978).

Despite growing interest in AI-enabled innovation, the literature rarely explains how AI-driven experimentation triggers these deeper learning processes. AI can detect patterns and generate predictive insights, but it does not automatically prompt organizations to reconsider the core logic of their business models. Consequently, existing research struggles to explain why AI-supported experimentation sometimes produces incremental optimization while in other cases enabling more transformative business model change.

This tension aligns with a long-standing distinction in organizational learning and strategic management between exploration and exploitation. March (1991) conceptualized organizations as balancing the search for new knowledge with the refinement of existing capabilities. Later research introduced the concept of organizational ambidexterity, where firms simultaneously pursue exploratory and exploitative innovation (O'Reilly & Tushman, 2013; Gupta et al., 2006). AI-enabled experimentation intensifies this tension because algorithmic systems can support both forms of learning depending on how organizations interpret and apply experimental insights.

3.3 Tension 3: Individual insight versus organizational institutionalization

A third tension concerns the relationship between localized insights and organization-wide learning. In many organizations, AI tools operate within specialized units such as data analytics teams, digital innovation groups, or product development functions. These units often generate valuable insights about customer behavior, operational improvements, or new service opportunities through AI-supported analysis.

However, insights generated in these localized contexts do not automatically diffuse across the organization. Organizational learning theory suggests that such diffusion requires mechanisms that translate individual or team-level insights into shared routines, structures, and decision processes (Crossan et al., 1999). Without these mechanisms, valuable insights remain confined to specific teams rather than influencing broader strategic practice.

This challenge becomes particularly visible in business model experimentation. Innovation teams may identify promising opportunities for new value propositions or revenue mechanisms through experimentation, yet these insights may remain limited to pilot projects if they are not integrated into organizational decision-making processes. Without institutionalization through governance structures, strategic frameworks, or operational routines, experimentation generates episodic learning rather than sustained organizational change. The impact of AI-enabled experimentation therefore depends not only on generating insights but also on embedding them in organizational structures and strategic logic.

3.4 Core Theoretical Gap

Taken together, these tensions reveal a central theoretical gap at the intersection of AI, experimentation, and business model innovation. Although research increasingly acknowledges that artificial intelligence can support innovation and enable new business model configurations, existing studies offer limited explanation of how AI-enabled experimentation becomes organizational learning that shapes strategic outcomes.

Specifically, the literature lacks a coherent account of how algorithmic insights generated through experimentation are interpreted, retained, and institutionalized across organizational levels to support business model validation, scaling, and transformation. Without this explanation, AI is often treated as a technological driver of innovation rather than as part of broader organizational learning processes.

Recent reviews reinforce this limitation. Studies of AI-driven business model innovation emphasize the fragmented nature of the field and call for stronger theoretical integration (Jorzik et al., 2024). Research on business model experimentation similarly highlights the need to understand how experimentation interacts with organizational capabilities and learning mechanisms in shaping business model dynamics (Sanasi, 2023; Macca et al., 2025). Addressing this gap requires a framework that integrates insights from AI research, experimentation studies, and organizational learning theory to explain how AI-enabled experimentation produces both incremental and transformative business model innovation.

4. Toward an Integrative Mechanism-Based Framework

AI-enabled business model experimentation requires a theoretical explanation linking technological capability with organizational learning. Existing research often frames AI as an innovation driver but rarely specifies how experimentation produces strategic knowledge. A mechanism-based framework therefore explains how AI-generated insights become collective interpretation and organizational routines that shape business model innovation. Figure 1 illustrates this mechanism-based core by showing how AI-enabled experimentation becomes organizational learning rather than a purely technical process. Innovation emerges as organizations translate algorithmic variation into shared interpretation, validation, and institutional embedding.

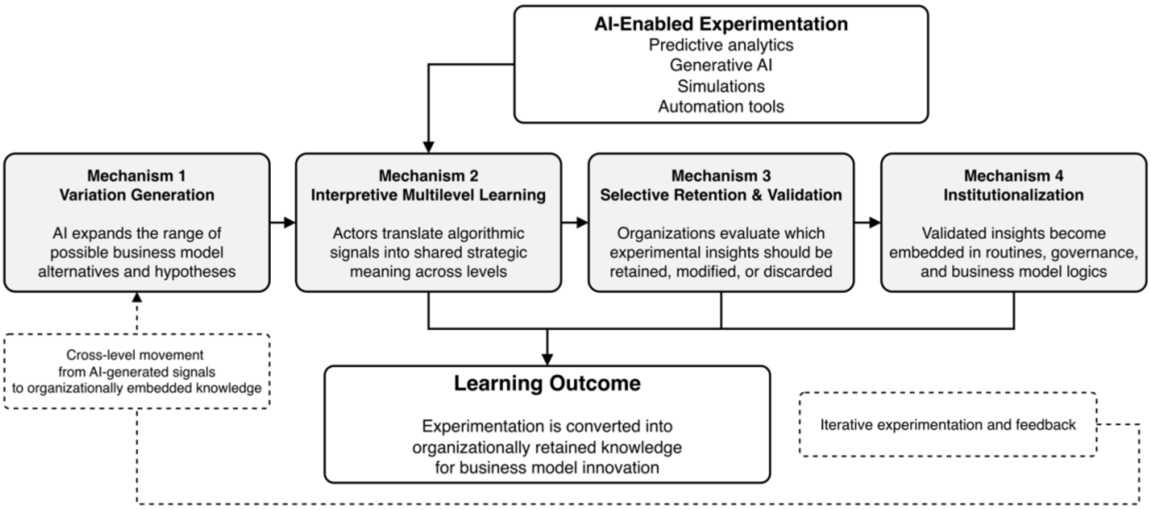

Figure 1. Organizational Learning Mechanisms in AI-Enabled Business Model Experimentation
Source: Author's conceptualization

As illustrated in Figure 1, the framework organizes AI-enabled experimentation as a four-stage learning process moving from variation generation to institutionalization. Figure 1 supports the article's argument by making explicit that business model innovation depends on interpretive and organizational mechanisms that convert algorithmic outputs into retained and embedded strategic knowledge.

4.1 Foundational Assumptions

This framework rests on three assumptions explaining how AI-enabled experimentation contributes to business model innovation through organizational learning mechanisms. These assumptions clarify the role of AI in generating experimental insights and how organizations convert those insights into strategic change.

First, AI should be understood as a learning enabler rather than a direct determinant of business model innovation. AI technologies enhance the capacity to generate insights, detect patterns, and simulate strategic alternatives, but they do not autonomously produce innovation. Their impact depends on how organizations interpret algorithmic outputs and integrate them into collective decision processes. AI therefore expands the informational basis for learning without replacing the interpretive and institutional processes required for organizational adaptation (Raisch & Krakowski, 2021; Holmström & Carroll, 2024).

Second, business model experimentation represents a multilevel learning process rather than a simple trial-and-error technique. Experiments involving value propositions, revenue models, or ecosystem structures are episodes within broader processes through which organizations generate variation, interpret feedback, and institutionalize strategic insights. Organizational learning theory emphasizes that these processes unfold across individual, group, and organizational levels through iterative cycles of interpretation and integration (Crossan et al., 1999). Viewing experimentation through this perspective explains how AI-generated insights gradually reshape organizational understanding of value creation and capture.

Third, the impact of AI-enabled experimentation depends on an organization's capacity to translate algorithmic outputs into collective interpretation and institutionalized knowledge. AI systems can generate predictions, simulations, and recommendations, but these outputs influence innovation only when actors interpret them, debate their implications, and embed them in strategic routines. The central challenge therefore lies not in generating analytical insights but in developing learning mechanisms that allow those insights to reshape how the organization conceptualizes and operationalizes its business model.

4.2 Mechanism 1: AI-Enabled Variation Generation

The first mechanism is variation generation, which refers to the creation of alternative ideas, hypotheses, or strategic configurations that can be evaluated through experimentation. AI technologies expand this process by enabling organizations to explore a broader range of possibilities than traditional analytical approaches allow.

Advanced analytics, machine learning models, and generative AI systems simulate market scenarios, identify emerging customer segments, and generate new product or service concepts. These capabilities enable firms to produce diverse business model configurations that can be tested through experimentation. Predictive analytics may reveal emerging demand patterns, while generative AI can support the design of novel service concepts or platform interactions.

Generative AI particularly expands organizations' exploratory capabilities by producing multiple strategic alternatives and reducing cognitive constraints associated with human-driven ideation (Holmström & Carroll, 2024). AI-enabled innovation research shows that algorithmic systems support exploration by revealing patterns within complex data environments and identifying opportunities that would otherwise remain hidden (Singh et al., 2024). AI therefore functions as a variation engine that expands the search space for business model experimentation.

Digital innovation research similarly emphasizes how digital infrastructures broaden organizational search processes. Digital technologies enable modular recombination of technological components and data resources, thereby expanding the space of potential innovation opportunities (Yoo et al., 2010; Nambisan et al., 2017). AI extends these capabilities by generating predictive insights and design alternatives that support systematic exploration of business model opportunities.

4.3 Mechanism 2: Interpretive learning and hypothesis refinement

AI can generate numerous experimental possibilities, but these possibilities become strategically meaningful only when organizational actors interpret them. The second mechanism therefore concerns interpretive learning and hypothesis refinement.

Organizational learning theory describes interpretation as a social and cognitive process through which actors construct shared meaning from new information. Within the 4I framework, interpretation and integration connect individual insights with collective understanding and coordinated action (Crossan et al., 1999). In AI-enabled experimentation, interpretive learning occurs when managers and analysts evaluate algorithmic outputs and examine their implications for customer value, competitive positioning, and revenue logic.

Experimental insights often challenge assumptions about how the business model operates. Predictive insights may reveal unexpected customer behaviors, while AI simulations may expose alternative configurations of value creation within digital ecosystems. Through discussion, debate, and iterative testing, these signals are translated into refined strategic hypotheses that guide further experimentation. Without such interpretive processes, AI-generated insights remain analytical observations rather than drivers of strategic change.

4.4 Mechanism 3: Selective Retention and Business Model Validation

The third mechanism involves selective retention, which refers to evaluating experimental outcomes and determining which insights should be retained, modified, or discarded. In business model experimentation this stage corresponds to validation of emerging strategic configurations.

AI technologies assist evaluation by detecting patterns in customer responses, identifying performance changes associated with specific interventions, and simulating long-term strategic outcomes. These analytical capabilities allow organizations to assess experimental results more systematically than traditional methods.

Retention decisions, however, remain shaped by managerial judgment rather than algorithmic outputs alone. Strategic priorities, governance structures, and dominant mental models influence how organizations interpret experimental outcomes. Selective retention therefore represents the interface between experimentation and strategic decision-making, where firms determine whether experimental insights support incremental improvements or justify deeper changes in value creation, delivery, and capture mechanisms.

4.5 Mechanism 4: Institutionalization of Learned Business Model Logics

The final mechanism concerns institutionalization, through which validated insights become embedded in organizational routines, structures, and decision architectures. Institutionalization transforms episodic learning from experiments into durable organizational capabilities.

Within the 4I framework, institutionalization occurs when insights are incorporated into governance structures, performance metrics, operational processes, and digital platforms (Crossan et al., 1999). In business model innovation this stage may involve formalizing revenue mechanisms, restructuring organizational processes, or redefining ecosystem relationships with partners and customers.

Institutionalization is critical because experimentation alone rarely produces strategic transformation. Organizations often conduct numerous experiments that generate valuable insights yet fail to influence broader strategic practices when confined to pilot projects. Institutionalization ensures that successful experiments reshape the organization’s operating logic and become embedded in its enduring business model architecture.

4.6 Outcome Differentiation: Exploitative versus Exploratory Pathways

The mechanisms described above generate different innovation outcomes depending on how organizations interpret and institutionalize experimental insights. AI-enabled experimentation may therefore follow exploitative or exploratory learning pathways.

This figure clarifies how AI-enabled experimentation can lead to two distinct innovation trajectories depending on the type of organizational learning that occurs during experimentation. The structure highlights the analytical distinction between exploitative and exploratory learning pathways and their corresponding business model innovation outcomes.

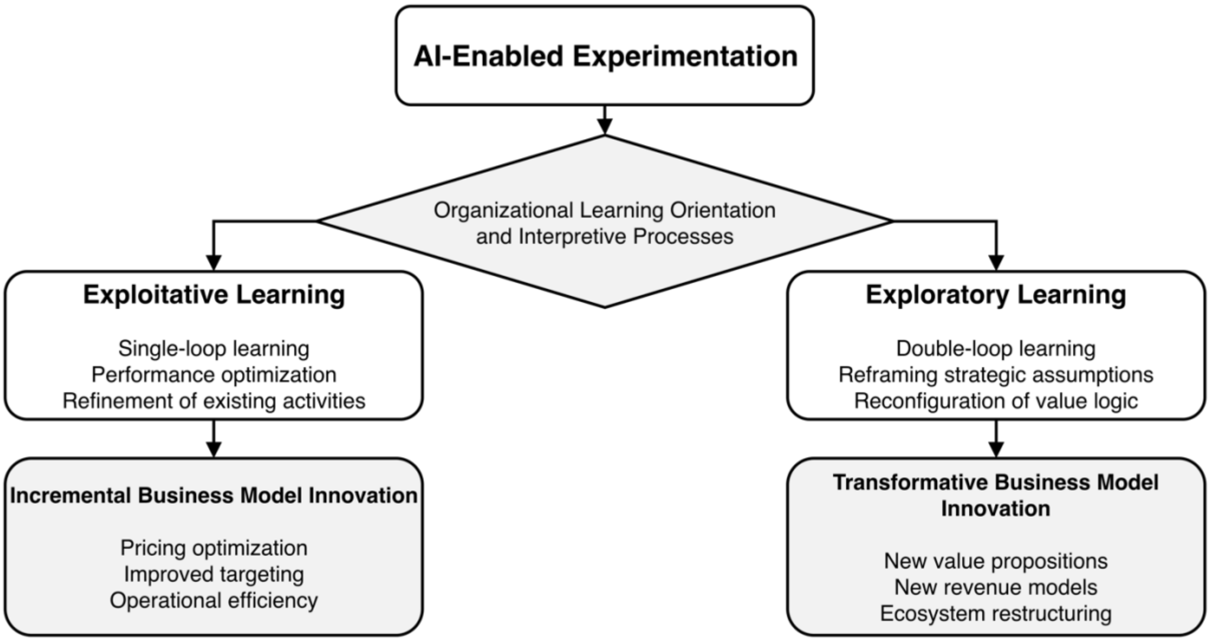

Figure 2. Learning Pathways in AI-Enabled Business Model Experimentation
Author's conceptualization

Figure 2 explains why AI-enabled experimentation generates different innovation outcomes by distinguishing alternative organizational learning trajectories. The model identifies two pathways: exploitative learning, which refines existing routines and produces incremental improvements to the current business model, and exploratory learning, which challenges strategic assumptions and enables transformative reconfiguration of value creation and capture. This distinction reinforces the argument that the innovation impact of artificial intelligence depends on how organizations interpret and institutionalize experimental insights.

In exploitative pathways, AI enhances efficiency and optimization within the existing business model. Firms use AI-enabled experimentation to refine pricing strategies, improve customer targeting, automate operations, and optimize service delivery. These improvements increase performance without fundamentally altering the logic of value creation and capture.

Exploratory pathways emerge when experimentation challenges assumptions underlying the existing business model. Organizations may redefine value propositions, restructure ecosystem relationships, or introduce new revenue mechanisms. These changes reflect deeper learning processes resembling double-loop learning in organizational learning theory.

Generative AI can support both forms of innovation depending on how organizations integrate algorithmic capabilities into experimentation processes (Singh et al., 2024). The impact of AI on business model innovation therefore depends less on technological sophistication and more on the learning pathways through which organizations interpret, validate, and institutionalize experimental insights.

5. Integrative Conceptual Model

Building on the mechanisms developed earlier, this study proposes an integrative conceptual model explaining how AI-enabled experimentation leads to business model innovation through organizational learning processes. The model assumes that AI affects innovation indirectly by shaping how organizations generate experimental variation, interpret signals, validate strategic hypotheses, and institutionalize learned value logics. AI therefore functions as an enabling infrastructure that amplifies experimentation and learning rather than directly producing innovation outcomes. Business model innovation is conceptualized as the result of AI-enabled organizational learning dynamics rather than a direct technological effect.

This figure consolidates the article's theoretical argument into an integrative architecture linking AI-enabled experimentation with organizational learning and business model innovation outcomes. The structure emphasizes that artificial intelligence influences innovation indirectly by shaping experimentation processes that activate multilevel learning mechanisms within organizations.

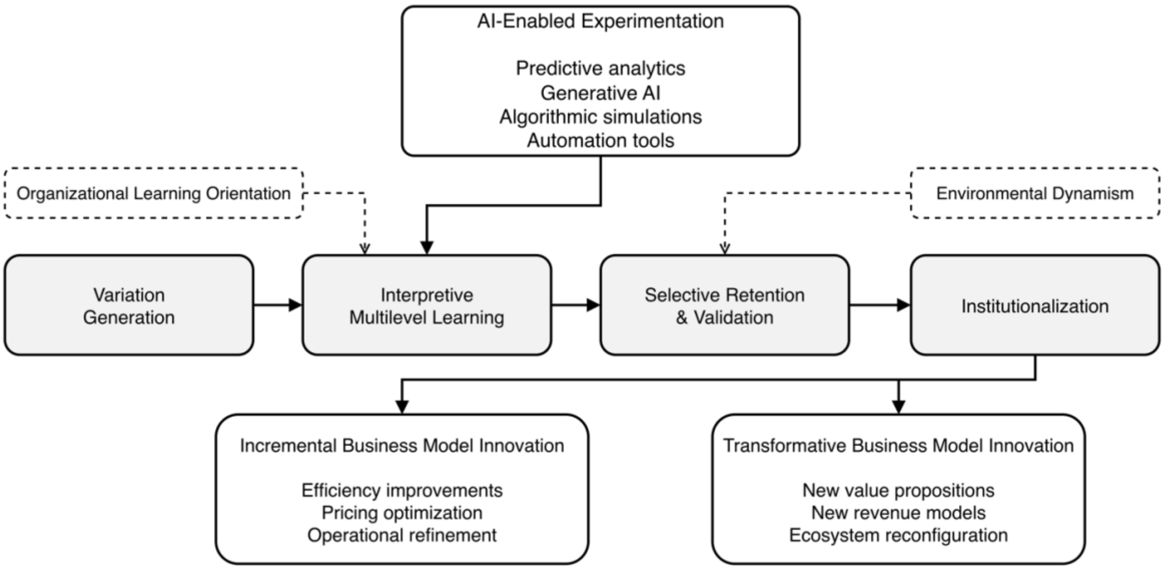

Figure 3. Integrative Conceptual Model of AI-Enabled Business Model Innovation
Author's conceptualization

Figure 3 presents an integrative framework explaining how artificial intelligence influences business model innovation through organizational learning rather than direct technological effects. The model positions AI-enabled experimentation as the infrastructure generating analytical signals and experimental insights that initiate organizational learning processes. These processes include variation generation, multilevel interpretive learning, selective retention and validation, and institutionalization, through which organizations convert algorithmic insights into strategic knowledge. The framework also distinguishes incremental and transformative business model innovation outcomes and identifies contextual conditions, including organizational learning orientation and environmental dynamism, that influence the effectiveness of these learning processes.

The model begins with AI-enabled experimentation inputs representing the technological infrastructures through which organizations generate experimental insights. These inputs include advanced analytics, generative AI systems, predictive algorithms, and automation tools that allow firms to collect data, simulate strategic alternatives, and evaluate potential business model configurations. Research shows that such technologies expand organizations' capacity to explore complex problem spaces and detect patterns in customer behavior, operational processes, and market dynamics (Holmström & Carroll, 2024; Raisch & Krakowski, 2021). These capabilities provide the informational foundation for experimentation by increasing the volume, speed, and diversity of insights generated during innovation processes.

The model then specifies four organizational learning mechanisms linking experimentation to business model innovation. The first mechanism, variation generation, reflects the ability of AI systems to expand the range of strategic alternatives available for experimentation. Through predictive modeling, simulations, and generative design tools, organizations can identify new value propositions, customer segments, pricing mechanisms, and ecosystem configurations. This stage corresponds to the search phase of experimentation, where organizations formulate multiple hypotheses about how value creation and capture may be reconfigured.

The second mechanism, interpretive multilevel learning, describes how organizational actors interpret experimental signals and connect them to existing assumptions about the business model. Individuals and teams engage in sensemaking processes that translate algorithmic outputs into strategic meaning. Drawing on the multilevel learning framework proposed by Crossan et al. (1999), interpretation occurs through interactions across individual, group, and organizational levels. Through this process, managers and analysts transform analytical observations into shared organizational understanding that informs subsequent experimentation.

The third mechanism, selective retention and validation, concerns the evaluation of experimental outcomes and the selection of viable strategic configurations. Organizations assess whether experiments produce economically and strategically viable results. AI technologies support this process by enabling systematic analysis of experimental data and detection of performance patterns across multiple experiments. However, retention decisions ultimately depend on managerial judgment and strategic priorities. Through this stage, organizations validate certain configurations of value creation and capture while abandoning others.

The fourth mechanism, institutionalization, occurs when validated insights become embedded in organizational routines and structures. Institutionalization involves incorporating experimental learning into governance mechanisms, operational processes, performance metrics, and strategic frameworks. At this stage, insights generated during experimentation evolve into enduring components of the organization's business model architecture. Consistent with the institutionalizing stage of organizational learning theory, this process transforms episodic experimentation into sustained organizational capability (Crossan et al., 1999).

The model further proposes two contextual moderators influencing the effectiveness of these learning mechanisms: organizational learning orientation and environmental dynamism. Organizational learning orientation reflects the extent to which firms promote experimentation, knowledge sharing, and reflective inquiry in strategic decision-making. Organizations with strong learning orientations are more likely to collectively interpret experimental signals and institutionalize insights derived from experimentation. Environmental dynamism represents volatility and uncertainty in the competitive environment. In highly dynamic contexts, organizations face stronger incentives to pursue exploratory experimentation and reconsider existing business model assumptions.

The model distinguishes between two business model innovation outcomes emerging from these learning processes. Incremental business model innovation occurs when experimentation produces refinements within the existing value logic of the organization. These changes may involve improved pricing strategies, customer segmentation, or delivery efficiency enabled by AI-driven analytics. Transformative business model innovation occurs when experimentation challenges underlying assumptions of the existing business model and leads to deeper reconfigurations of value creation, delivery, or capture mechanisms. Examples include new revenue models, redesigned ecosystem relationships, or platform-based value architectures.

Figure 1 summarizes the integrative conceptual model. The figure begins with AI-enabled experimentation inputs that initiate a sequence of organizational learning mechanisms: variation generation, interpretive learning, selective retention and validation, and institutionalization. Feedback loops connect these mechanisms, reflecting the iterative nature of experimentation and learning processes. Two learning pathways, exploitative and exploratory learning, illustrate how experimentation may either optimize existing business models or generate fundamentally new configurations. These pathways lead to two innovation outcomes: incremental business model innovation and transformative business model innovation. By integrating AI-enabled experimentation with multilevel organizational learning processes, the model clarifies how AI influences business model innovation through organizational learning dynamics rather than direct technological effects.

6. Research Propositions

Building on the conceptual framework developed earlier, this study proposes a set of research propositions explaining how AI-enabled experimentation contributes to business model innovation through organizational learning mechanisms. These propositions translate the theoretical framework into testable relationships that can guide future empirical research. Consistent with the integrative model, the propositions focus on three interconnected dimensions: the role of AI in generating experimental variation, the mediating role of organizational learning, and contextual conditions shaping whether experimentation leads to incremental or transformative business model innovation.

P1. AI-enabled variation generation in business model experimentation

The first proposition concerns the role of AI in expanding the range of strategic alternatives available during business model experimentation. AI technologies such as predictive analytics, machine learning, and generative AI enable firms to analyze large data sets, simulate market scenarios, and generate novel configurations of products, services, and value propositions. These capabilities expand the search space for experimentation by revealing patterns and opportunities that traditional managerial analysis may overlook (Raisch & Krakowski, 2021; Holmström & Carroll, 2024).

From an organizational learning perspective, variation generation represents the initial stage of adaptive learning. Innovation requires the creation of multiple alternatives that can be evaluated through experimentation and feedback (March, 1991). AI accelerates this process by generating experimental hypotheses and identifying opportunities for reconfiguring business model elements. Firms that integrate AI extensively into experimentation processes are therefore likely to generate a broader and more diverse set of potential business model configurations.

Proposition 1 (P1): *The greater a firm's use of AI in business model experimentation, the greater its capacity to generate a wider and more diverse set of business model variations.*

P2. Organizational learning as a mediating mechanism

AI-generated insights do not automatically translate into strategic innovation. Organizational learning theory suggests that knowledge emerges through processes of interpretation, integration, and institutionalization that transform individual insights into shared organizational understanding (Crossan et al., 1999). In AI-enabled experimentation, algorithmic outputs must therefore be interpreted and discussed by managers and teams before they influence strategic decisions.

Multilevel learning processes enable organizations to translate analytical signals into shared interpretive schemas that guide experimentation and adaptation. Through collective sensemaking and discussion, actors connect experimental insights to the organization's value creation and revenue logic. Without such interpretive processes, AI-generated insights remain isolated analytical observations rather than catalysts for strategic change.

Proposition 2 (P2): *The relationship between AI-enabled experimentation and business model innovation is mediated by multilevel organizational learning processes that translate algorithmic outputs into shared interpretive schemas.*

P3. Exploitative learning and incremental business model innovation

The third proposition examines conditions under which AI-enabled experimentation produces incremental improvements rather than fundamental transformation. Many organizations initially deploy AI to optimize existing processes, improve decision accuracy, and enhance operational efficiency. These applications correspond to exploitative learning, where experimentation focuses on refining established routines and improving performance within existing strategic assumptions (March, 1991).

From an organizational learning perspective, such processes resemble single-loop learning, in which organizations adjust actions without questioning underlying strategic assumptions (Argyris & Schön, 1978). In these situations, AI-enabled experimentation primarily improves pricing strategies, customer targeting, and service delivery. Although these changes enhance efficiency, they typically preserve the core logic of the existing business model.

Proposition 3 (P3): *AI-enabled experimentation is more likely to produce exploitative business model innovation when learning processes remain focused on performance optimization within existing strategic assumptions.*

P4. Exploratory learning and transformative business model innovation

AI-enabled experimentation can also stimulate deeper learning processes that challenge fundamental assumptions of the business model. These processes correspond to exploratory learning, where organizations search for new ways of creating and capturing value (March, 1991). Exploratory learning often emerges when experimental insights contradict established strategic beliefs.

Within organizational learning theory, this process resembles double-loop learning, in which organizations question and revise the assumptions guiding their strategies (Argyris & Schön, 1978). Under these conditions, experimentation may lead firms to redefine value propositions, restructure ecosystem relationships, or introduce new monetization mechanisms. These changes represent transformative business model innovation rather than incremental improvement.

Proposition 4 (P4): *AI-enabled experimentation is more likely to produce transformative business model innovation when organizations engage in double-loop learning that challenges assumptions about value creation, delivery, and capture.*

P5. Institutionalization and the scaling of business model innovation

Experimental insights influence strategic outcomes only when they become embedded in organizational structures and routines. Institutionalization refers to the process through which learning from experimentation is incorporated into governance mechanisms, operational procedures, and decision architectures. Through this process, temporary insights evolve into enduring organizational capabilities.

Institutionalization also enables organizations to scale successful experimental initiatives by aligning resources, incentives, and decision processes with the newly learned business model logic. Without institutionalization, experimentation may generate episodic insights that fail to influence broader organizational practices. The extent to which firms embed experimental learning into formal routines therefore shapes whether AI-enabled experimentation produces sustained business model innovation.

Proposition 5 (P5): *The positive effect of AI-enabled experimentation on business model innovation is strengthened when organizations institutionalize experimental learning into routines, governance mechanisms, and decision architectures.*

P6. Environmental dynamism and exploratory learning outcomes

The final proposition considers contextual conditions shaping the outcomes of AI-enabled experimentation. Environmental dynamism, characterized by technological change, evolving customer preferences, and competitive uncertainty, encourages organizations to pursue exploratory learning and reconsider existing business model assumptions (Teece, 2018). In dynamic environments, firms are more likely to interpret AI-generated insights as signals for strategic transformation.

Organizations operating in stable environments often prioritize efficiency and risk reduction, leading them to focus on exploitative experimentation. Organizational rigidity, such as reliance on entrenched routines or dominant strategic beliefs, may further inhibit the translation of exploratory insights into transformative innovation. Environmental dynamism and organizational flexibility therefore influence whether experimentation produces incremental improvements or more radical business model transformation.

Proposition 6 (P6): *Environmental dynamism strengthens the effect of exploratory AI-enabled learning on transformative business model innovation, while organizational rigidity weakens it.*

The following table summarizes the research propositions derived from the conceptual framework and clarifies the relationships between key constructs in the study. Presenting the propositions in a structured format helps readers quickly identify the theoretical logic linking AI-enabled experimentation, organizational learning processes, and business model innovation outcomes.

Table 2. Research Propositions on AI-Enabled Business Model Innovation

	Proposition & Relationship	**Expected Outcome**
P1	AI use in experimentation → greater variation generation	Broader set of potential business model configurations
P2	Organizational learning processes mediate AI-enabled experimentation	AI insights translated into shared strategic interpretation
P3	Exploitative learning during experimentation	Incremental business model innovation
P4	Exploratory (double-loop) learning during experimentation	Transformative business model innovation
P5	Institutionalization of experimental insights	Scaling and stabilization of new business model logics
P6	Environmental dynamism moderates exploratory learning	Stronger likelihood of transformative innovation

Source: Author's conceptualization.

Table 2 organizes the propositions into analytically testable relationships. The table shows that AI-enabled experimentation influences business model innovation indirectly through organizational learning processes. Contextual factors determine whether experimentation produces incremental improvements or transformative business model change.

7. Discussion

This study develops a mechanism-based explanation of how artificial intelligence influences business model innovation through organizational learning processes embedded in experimentation. Prior research often links AI adoption to improved analytics, prediction, or decision support, yet provides limited insight into the organizational processes through which algorithmic insights become strategic change. By integrating AI-enabled experimentation with multilevel organizational learning theory, the framework clarifies how firms transform analytical signals into validated business model logics. The discussion interprets these findings by highlighting the article's theoretical contributions, outlining directions for future empirical research, and specifying boundary conditions that shape the applicability of the framework.

7.1 Theoretical Contributions

This article advances research on artificial intelligence and business model innovation by offering a mechanism-based explanation of how AI-enabled experimentation contributes to organizational learning and strategic change. Much existing research treats AI primarily as a technological antecedent that improves analytical capability or decision accuracy (Raisch & Krakowski, 2021; Holmström & Carroll, 2024). The framework proposed here instead conceptualizes AI as a learning infrastructure that reshapes how organizations generate, interpret, and institutionalize experimental knowledge. This shift redirects attention from technological capability alone toward the organizational learning mechanisms that determine whether AI-enabled experimentation produces meaningful innovation outcomes.

The study also contributes to the literature on business model experimentation by conceptualizing experimentation as a multilevel learning process rather than a sequence of isolated tests. Prior studies emphasize the role of experimentation in business model dynamics and entrepreneurial innovation (Foss & Saebi, 2017; Sanasi, 2023), yet the learning processes linking experimentation to strategic transformation remain underdeveloped. Drawing on organizational learning theory and the multilevel 4I framework (Crossan et al., 1999), the framework shows how insights generated through AI-enabled experimentation evolve from individual analytical observations into shared interpretations and institutionalized business model logics.

A third contribution lies in clarifying why AI-enabled experimentation may produce different innovation outcomes. Existing studies acknowledge that AI can support both incremental improvements and more radical innovation (March, 1991; Singh et al., 2024), but the mechanisms behind these divergent outcomes remain unclear. The framework shows that outcomes depend on the learning pathways through which experimental insights are interpreted and institutionalized. When learning remains oriented toward performance optimization within existing strategic assumptions, experimentation produces exploitative improvements in existing business models. When organizations engage in deeper interpretive processes that challenge underlying assumptions about value creation, delivery, and capture, experimentation can generate transformative business model innovation. This mechanism-based explanation contributes to ongoing debates on how AI shapes organizational innovation and strategic renewal.

7.2 Implications for Future Research

The conceptual framework and propositions proposed in this study open several avenues for empirical research. Longitudinal studies of business model innovation processes could examine how AI-enabled experimentation evolves over time and how experimental insights are interpreted, validated, and institutionalized within organizations. Such approaches are particularly suited to capturing the iterative and cumulative nature of experimentation and learning.

Comparative case studies across industries may also generate valuable insights into how organizations deploy AI-enabled experimentation under different technological and competitive conditions. Cross-industry comparisons can clarify how contextual factors such as ecosystem complexity, technological turbulence, and organizational structure influence the learning mechanisms identified in the framework.

Large-scale survey research provides another promising avenue for empirical testing. Multi-respondent organizational surveys could examine relationships between AI-enabled experimentation practices, organizational learning processes, and different forms of business model innovation. Such designs would allow researchers to test the mediating and moderating relationships proposed in the conceptual model.

Digital trace data and platform-based experimentation systems also offer new opportunities for studying AI-enabled experimentation empirically. Data generated through online platforms, digital product testing systems, and AI-supported innovation infrastructures can reveal how experimentation unfolds in real time and how organizations respond to experimental feedback.

Future research may also refine the operationalization of the framework's core constructs. AI use intensity may be measured through the breadth and depth of AI applications employed in experimentation activities. Interpretive learning quality may be captured through indicators of cross-functional sensemaking and knowledge integration. Institutionalization depth may be operationalized through the extent to which experimental insights become embedded in routines, governance mechanisms, or performance systems. Innovation outcomes can also be empirically differentiated between exploitative improvements, such as incremental pricing or service adjustments, and exploratory transformations, such as new revenue models or ecosystem roles.

7.3 Boundary conditions

Although the proposed framework provides a general explanation of how AI-enabled experimentation contributes to business model innovation, its applicability varies across organizational contexts. The framework is particularly relevant for data-intensive organizations that rely heavily on analytics, digital technologies, and algorithmic decision systems to generate strategic insights. In such environments, AI-enabled experimentation becomes a central mechanism through which firms explore opportunities and refine emerging business models.

The framework is also especially applicable in digital and service-oriented industries, where innovation processes frequently rely on continuous experimentation with customer interactions, digital platforms, and data-driven service delivery models. AI technologies in these settings function as core infrastructures that enable organizations to test alternative value propositions and service configurations at scale. The framework is likewise most relevant in dynamic environments characterized by technological change and strategic uncertainty, where firms must frequently revise business model assumptions.

Conversely, the framework may be less applicable in contexts with limited data availability or low technological adoption, where experimentation depends primarily on managerial judgment rather than AI-supported analysis. In stable environments with limited competitive change, organizations may face weaker incentives to engage in exploratory experimentation or to challenge existing business model assumptions. Organizations that lack the interpretive capabilities required to translate algorithmic insights into shared strategic understanding may also struggle to realize the learning processes described in this framework. Under such conditions, AI may improve operational efficiency without necessarily generating deeper organizational learning or business model innovation.

8. Conclusion

This study explains how artificial intelligence contributes to business model innovation by examining organizational learning in AI-enabled experimentation. Prior research recognizes AI as a driver of innovation and strategic adaptation but rarely specifies how AI-generated insights translate into business model transformation. The framework positions AI as an infrastructure for experimentation and learning. AI-enabled experimentation influences business model innovation through four mechanisms: variation generation, multilevel interpretive learning, selective retention and validation, and institutionalization. These mechanisms convert algorithmic insights into shared strategic understanding and embed validated insights into new business model logics.

The framework advances three contributions. First, it reframes AI as a catalyst that reshapes organizational learning processes underlying business model experimentation. Second, it conceptualizes experimentation as a multilevel learning process where individual insights, collective interpretation, and institutionalized routines interact to produce strategic change. Third, it explains heterogeneous innovation outcomes by distinguishing exploitative learning pathways that optimize existing models from exploratory pathways that enable transformative reconfiguration of value creation and capture. Integrating research on AI, business model dynamics, and organizational learning clarifies how firms learn to innovate with AI.

The propositions open directions for empirical research. Longitudinal studies can examine how AI-enabled experimentation unfolds across business model innovation processes. Comparative case studies may explore cross-industry variation in experimentation practices, while survey-based studies can analyze organizational learning capabilities supporting experimentation. Future research may also investigate differences in firms' capacity to interpret and institutionalize AI-generated insights, as well as the influence of contextual factors such as ecosystem complexity, technological turbulence, and governance structures on these learning processes.

The framework emphasizes a central insight. AI does not innovate business models independently. Innovation emerges when organizations learn through AI-enabled experimentation, translate analytical signals into shared interpretation, and institutionalize validated insights into new value logics. Explaining these learning processes is essential for understanding how firms convert expanding AI capabilities into strategic transformation in a data-driven economy.

References

Andries, P., & Debackere, K. (2007). Adaptation and performance in new businesses: Understanding the moderating effects of independence and industry. *Small Business Economics, 29*(1–2), 81–99. https://doi.org/10.1007/s11187-005-5602-1

Argote, L. (2013). *Organizational learning: Creating, retaining and transferring knowledge* (2nd ed.). Springer. https://doi.org/10.1007/978-1-4614-5251-5

Argote, L., & Miron-Spektor, E. (2011). Organizational learning: From experience to knowledge. *Organization Science, 22*(5), 1123–1137. https://doi.org/10.1287/orsc.1100.0621

Argyris, C., & Schön, D. A. (1978). *Organizational learning: A theory of action perspective*. Addison-Wesley.

Autio, E., Nambisan, S., Thomas, L. D. W., & Wright, M. (2018). Digital affordances, spatial affordances, and the genesis of entrepreneurial ecosystems. *Strategic Entrepreneurship Journal, 12*(1), 72–95. https://doi.org/10.1002/sej.1266

Brynjolfsson, E., & McElheran, K. (2016). The rapid adoption of data-driven decision-making. *American Economic Review, 106*(5), 133–139. https://doi.org/10.1257/aer.p20161016

Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics, 13*(1), 333–372. https://doi.org/10.1257/mac.20180386

Chesbrough, H. (2010). Business model innovation: Opportunities and barriers. *Long Range Planning, 43*(2–3), 354–363. https://doi.org/10.1016/j.lrp.2009.07.010

Crossan, M. M., Lane, H. W., & White, R. E. (1999). An organizational learning framework: From intuition to institution. *Academy of Management Review, 24*(3), 522–537. https://doi.org/10.5465/amr.1999.2202135

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108–116.

Fiol, C. M., & Lyles, M. A. (1985). Organizational learning. *Academy of Management Review, 10*(4), 803–813. https://doi.org/10.5465/amr.1985.4279103

Foss, N. J., & Saebi, T. (2017). Fifteen years of research on business model innovation. *Journal of Management, 43*(1), 200–227. https://doi.org/10.1177/0149206316675927

Gupta, A. K., Smith, K. G., & Shalley, C. E. (2006). The interplay between exploration and exploitation. *Academy of Management Journal, 49*(4), 693–706. https://doi.org/10.5465/amj.2006.22083026

Holmström, J., & Carroll, N. (2024). Generative AI and the future of innovation management. *California Management Review*. https://doi.org/10.1177/00081256241200000

Jarrahi, M. H. (2018). Artificial intelligence and the future of work. *Business Horizons, 61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Jorzik, J., Sjödin, D., Parida, V., & Kohtamäki, M. (2024). Artificial intelligence–driven business model innovation: A systematic review and research agenda. *Technological Forecasting and Social Change, 200*, 123114. https://doi.org/10.1016/j.techfore.2023.123114

Levitt, B., & March, J. G. (1988). Organizational learning. *Annual Review of Sociology, 14*, 319–338. https://doi.org/10.1146/annurev.so.14.080188.001535

Macca, M., Santoro, G., & Papa, A. (2025). Business model experimentation and innovation dynamics: A systematic perspective. *Technological Forecasting and Social Change*. https://doi.org/10.1016/j.techfore.2024.123500

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science, 2*(1), 71–87. https://doi.org/10.1287/orsc.2.1.71

Mariani, M. M., Perez-Vega, R., & Wirtz, J. (2024). Generative artificial intelligence in business and management research. *Journal of Business Research, 172*, 114365. https://doi.org/10.1016/j.jbusres.2023.114365

McGrath, R. G. (2010). Business models: A discovery driven approach. *Long Range Planning, 43*(2–3), 247–261. https://doi.org/10.1016/j.lrp.2009.07.005
Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital innovation management. *MIS Quarterly, 41*(1), 223–238. https://doi.org/10.25300/MISQ/2017/41:1.03
Nambisan, S., Zahra, S. A., & Luo, Y. (2019). Global platforms and ecosystems. *Journal of International Business Studies, 50*(9), 1464–1486. https://doi.org/10.1057/s41267-019-00262-4
O'Reilly, C. A., & Tushman, M. L. (2013). Organizational ambidexterity. *Academy of Management Perspectives, 27*(4), 324–338. https://doi.org/10.5465/amp.2013.0025
Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management. *Academy of Management Review, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072
Sanasi, S. (2023). Entrepreneurial experimentation and business model innovation. *Research Policy, 52*(4), 104713. https://doi.org/10.1016/j.respol.2023.104713
Singh, J., Faraj, S., & Pachidi, S. (2024). Human–AI collaboration and organizational innovation. *Organization Science*. https://doi.org/10.1287/orsc.2023.1725
Sjödin, D., Parida, V., Kohtamäki, M., & Wincent, J. (2021). An agile co-creation process for digital servitization. *Journal of Business Research, 121*, 473–484. https://doi.org/10.1016/j.jbusres.2020.08.038
Sosna, M., Trevinyo-Rodríguez, R. N., & Velamuri, S. R. (2010). Business model innovation through trial-and-error learning. *Long Range Planning, 43*(2–3), 383–407. https://doi.org/10.1016/j.lrp.2010.02.003
Teece, D. J. (2018). Business models and dynamic capabilities. *Long Range Planning, 51*(1), 40–49. https://doi.org/10.1016/j.lrp.2017.06.007
Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). Research commentary: The new organizing logic of digital innovation. *Information Systems Research, 21*(4), 724–735. https://doi.org/10.1287/isre.1100.0322