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Rethinking Business Model Innovation in the Age of Artificial Intelligence: An Integrative Review

Mr. Kuldeep Goswami, Mr. Pankaj Bhatt, and Mrs. Deepti Raj Verma

Mr Kuldeep Goswami, Assistant Professor- Shriram Institute of Management & Technology, Kashipur
Mr Pankaj Bhatt, Assistant Professor- Shriram Institute of Management & Technology, Kashipur
Mrs Deepti Raj Verma, Assistant Professor- TMIMT, TMU Moradabad

***Abstract*—Business model innovation (BMI) has long been understood as a periodic, deliberate exercise in redesigning how organisations create, deliver, and capture value. The growing presence of artificial intelligence (AI) in organisational life is beginning to unsettle that assumption. Predictive analytics, machine learning, and generative systems allow firms to sense market signals and adjust operations in near real time, which raises the question of whether BMI is becoming a continuous, algorithmically mediated process rather than an episodic one. This paper offers an integrative review of the management, information systems, and strategic innovation literatures to examine how AI is reshaping the theory and practice of BMI. Following the methodological guidance of Whittemore and Knafl (2005) and Torraco (2005), the review synthesises conceptual and empirical work published across leading journals to build a thematic picture of AI-driven value creation, value delivery, and value capture. The analysis shows that while the technical capabilities of AI are well documented, their strategic integration into coherent business models remains fragmented, with most studies treating AI as a tool bolted onto existing structures rather than as a force that reorganises the logic of the business model itself. The review develops a matrix of AI capability archetypes, identifies recurring organisational and ethical tensions, and proposes practical implications for managers and policymakers. It closes with an agenda for future research organised by methodology, context, and level of analysis, intended to guide scholars toward a more integrated theory of AI-enabled business model transformation.**

***Index Terms*—Business Model Innovation, Artificial Intelligence, Value Creation, Dynamic Capabilities, Algorithmic Management, Digital Transformation**

I. INTRODUCTION

BUSINESS model innovation has traditionally been treated as an intentional act, something a management team undertakes when a market shift, a technological breakthrough, or a competitive threat forces a reconsideration of how the firm makes money. Teece (2010) described this as a search process, one in which managers experiment with different configurations of value proposition, cost structure, and revenue architecture until a workable design emerges. That search process has usually unfolded over months or years, punctuated by formal strategy reviews and occasional restructuring.

Artificial intelligence complicates this picture. Systems that can forecast demand, personalise offers, optimise pricing, and even generate new product concepts do not wait for a quarterly strategy meeting. They act continuously, often without direct human intervention at the point of decision. Davenport and Ronanki (2018) noted that most commercial AI applications are narrow in scope, focused on automating specific tasks such as fraud detection or inventory forecasting, yet the cumulative effect of many such applications operating simultaneously across a firm's value chain can amount to something closer to a standing capability for adaptation. This shifts BMI away from a discrete redesign event and toward what might be called algorithmic adaptation, a condition in which the business model is never quite finished because the systems underpinning it keep learning and adjusting.

The problem this review addresses is not whether AI has technical capability. That has been documented extensively in the computer science and operations literature. The problem is that management scholarship has been slower to explain how these capabilities translate into coherent, defensible business models. Studies tend to examine AI adoption in isolated functional areas, such as marketing personalisation or supply chain optimisation, without connecting these applications back to the broader architecture of value creation, value delivery, and value capture that defines a business model in the sense used by Amit and Zott (2001) and Zott and Amit (2010). The result is a literature rich in examples but thin in integrative theory.

This review is guided by three research questions. First, how does the strategic management literature currently conceptualise the relationship between AI capabilities and business model innovation? Second, what recurring patterns of value creation, delivery, and capture emerge from empirical studies of AI-enabled firms? Third, what organisational, ethical, and governance tensions accompany the shift toward more autonomous business model adaptation, and what does this imply for managers and policymakers?

II. THEORETICAL FOUNDATIONS AND CONCEPTUAL BOUNDARIES

Business model innovation sits at the intersection of strategy and organisational design. Teece (2010) defined a business model as the logic by which a firm creates and delivers value to customers, then converts a portion of that value into profit. Amit and Zott (2001) framed it more specifically as a system of interdependent activities that extends beyond the focal firm, spanning suppliers, partners, and customers. Zott and Amit (2010) later developed this into an activity system perspective, arguing that the content, structure, and governance of these activities together determine how much value a business model can generate. BMI, in this tradition, means changing the content, structure, or governance of the activity system, not merely improving efficiency within an existing one.

Chesbrough (2010) added an important qualifier: business model innovation is difficult precisely because it requires

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overturning assumptions that were once useful and have since become taken for granted. Firms that succeed at incremental innovation often struggle at business model innovation because the latter demands a willingness to cannibalise existing revenue streams or organisational routines. This tension between exploitation of the current model and exploration of a new one has been a persistent theme in the literature, echoing the dynamic capabilities framework that Teece (2007, 2018) developed to explain how firms sense opportunities, seize them, and reconfigure resources accordingly.

Digital transformation and AI-driven business model innovation are related but distinct phenomena, and the review treats them as such. Vial (2019) characterised digital transformation as a process in which digital technologies trigger significant changes to organisational properties, generally through the accumulation of digital capabilities such as cloud infrastructure, data platforms, and connected devices. This process is largely about digitising existing activities: moving paper processes online, connecting previously siloed systems, and building the data infrastructure that later enables analytics. AI-driven BMI presupposes much of this digital groundwork but goes further. It concerns what happens once a firm has the data and computational capacity to let algorithms make or heavily influence decisions that used to require human judgement, whether in pricing, product recommendations, or operational scheduling. Digital transformation builds the plumbing. AI-driven BMI changes who, or what, turns the taps.

To make this distinction more precise, the review borrows a widely used taxonomy of analytic capability, distinguishing descriptive, predictive, prescriptive, and autonomous dimensions of AI (Davenport & Ronanki, 2018; Mikalef & Gupta, 2021). Descriptive analytics summarise what has already happened, offering dashboards and reports that inform human decision-makers. Predictive analytics estimate what is likely to happen next, using historical patterns to forecast demand, churn, or risk. Prescriptive analytics go a step further, recommending a specific course of action given a forecast and a set of constraints. Autonomous systems close the loop entirely, acting on their own recommendations with limited or no human review, as seen in automated bidding systems, dynamic pricing engines, and certain forms of robotic process automation embedded in supply chains. Business models built primarily on descriptive and predictive capability tend to preserve existing decision structures, with AI serving as an advisory layer. Models that incorporate prescriptive and autonomous capability begin to alter the locus of decision-making itself, which is where the sharpest theoretical and governance questions arise.

III. METHODOLOGY: INTEGRATIVE REVIEW FRAMEWORK

This paper follows an integrative review design, chosen because the subject matter spans conceptual, empirical, and practitioner-oriented literature that a narrower systematic review method would struggle to accommodate. Whittemore and Knafl (2005) described the integrative review as suited to topics where the aim is to summarise past theoretical and empirical work in order to provide a more comprehensive understanding of a phenomenon, rather than to test a single hypothesis. Torraco (2005) similarly argued that integrative reviews are appropriate when a topic is emerging and would benefit from a fresh conceptual synthesis, which fits the current state of AI-driven BMI research, where empirical studies are accumulating faster than integrative theory.

The review followed a five-stage process consistent with Whittemore and Knafl's framework: problem identification, literature search, data evaluation, data analysis, and presentation. The literature search was conducted across Scopus and Web of Science, supplemented by targeted searches in Google Scholar to capture recent working papers and practitioner reports not yet indexed in the main databases. Search terms combined variants of "business model innovation," "artificial intelligence," "machine learning," "algorithmic management," and "digital transformation," connected using Boolean operators and restricted to English-language publications.

Inclusion criteria required that a source engage substantively with either the conceptual architecture of business models (value proposition, value creation, value delivery, or value capture) or the strategic application of AI at the organisational level, and that it appear in a peer-reviewed journal, an edited scholarly volume, or a widely cited practitioner outlet such as Harvard Business Review or MIT Sloan Management Review. Exclusion criteria removed purely technical papers focused on algorithm design without organisational context, single-case studies with no theoretical generalisation, and sources published before 2000, since the review is concerned with the contemporary intersection of AI and BMI rather than the earlier history of information systems research.

An initial search returned several hundred candidate sources. After removing duplicates and screening titles and abstracts for relevance, a smaller set of sources was retained for full-text review. From this set, the sources cited throughout this paper were selected on the basis of theoretical influence within the strategic management and information systems fields, methodological rigour, and direct relevance to the three value dimensions structuring the thematic synthesis. Data analysis proceeded thematically, with sources coded according to which value dimension they primarily addressed, which AI capability level they described, and which organisational tensions or governance issues they raised. These codes form the basis for the matrix and figures presented in the following section.

IV. THEMATIC SYNTHESIS: THE AI-DRIVEN BUSINESS MODEL MATRIX

The literature reviewed for this paper clusters naturally around the three value dimensions that Amit and Zott (2001) and later Zott and Amit (2010) placed at the centre of business model theory: value creation, value delivery, and value capture. AI does not affect these dimensions uniformly. It tends to enter value creation through new forms of product and service design, value delivery through the reorganisation of operational and logistical processes, and value capture through changes to how firms' price and monetise what they offer. Treating the three dimensions separately, while keeping their interdependence in

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view, provides a workable structure for synthesising a literature that has so far developed somewhat unevenly across them.

A. Value Creation

Value creation concerns what a firm offers and how that offering is generated. In an AI-enabled context, this increasingly means algorithmic product-service systems, in which software continuously adjusts features, content, or recommendations based on user behaviour rather than shipping a fixed product and waiting for the next release cycle. Streaming platforms, navigation applications, and many software-as-a-service products now operate this way, with the underlying model learning from usage patterns and adjusting what is presented to each user. Paschen, Wilson, and Ferreira (2020) described a related development in business-to-business contexts, where AI systems assist human sales and account teams by surfacing relevant information and next-best-action suggestions, a pattern they termed collaborative intelligence rather than full automation.

A second strand concerns autonomous or semi-autonomous research and development. Firms in pharmaceuticals, materials science, and software engineering have begun using generative and predictive models to propose candidate compounds, designs, or code, narrowing the search space that human researchers must then evaluate. This does not eliminate human judgement from the innovation process, but it changes where that judgement is applied, shifting from generating options to evaluating and selecting among a larger and faster-moving set of AI-generated possibilities. Von Krogh (2018) argued that this kind of phenomenon calls for what he termed phenomenon-based theorising, since existing innovation management theory was largely built around human-centred ideation processes that do not map cleanly onto machine-assisted discovery.

A third strand involves customer co-creation through generative tools. Where earlier digital platforms allowed customers to configure products from a fixed menu of options, generative AI allows a much wider and less structured form of participation, in which customers describe what they want in natural language and the system produces a tailored output, whether that is a piece of marketing copy, a design concept, or a personalised learning plan. This blurs the boundary between producer and consumer that had already been loosened by earlier platform business models, and it raises fresh questions about intellectual property, quality control, and the value that firms can reasonably claim to have added.

B. Value Delivery

Value delivery concerns how an offering reaches the customer and how the underlying operations are organised to make that possible. The clearest development here involves intelligent supply chains, in which predictive models forecast demand at increasingly granular levels, sometimes down to individual store locations or delivery windows, and prescriptive systems then adjust procurement, warehousing, and logistics routing accordingly. Iansiti and Lakhani (2020) described how firms that rebuild their operations around this kind of continuous data feedback loop tend to develop a different organisational shape altogether, one oriented around algorithms and data pipelines as much as around traditional functional departments such as procurement or logistics.

Hyper-personalisation at scale represents a second development within value delivery. Retailers, media firms, and financial services providers increasingly tailor not just product recommendations but pricing, service level, and even the sequence of interactions a customer experiences, all generated automatically for each individual rather than for a small number of predefined segments. This extends earlier mass customisation strategies considerably further, since the personalisation is generated in real time rather than selected from a limited catalogue of variants prepared in advance.

Automated operational orchestration is the third development, referring to the use of AI systems to coordinate activity across previously separate functions, such as linking customer service chatbots directly to inventory systems so that a promise made to a customer is automatically checked against real stock levels, or connecting maintenance scheduling in manufacturing to real-time sensor data from equipment on the factory floor. Mikalef and Gupta (2021) found empirical support for the idea that this kind of cross-functional AI integration, rather than AI use in any single department, was more strongly associated with improved firm performance, suggesting that the value of AI for delivery lies substantially in its capacity to connect functions that were previously managed independently.

C. Value Capture

Value capture concerns how a firm translates the value it creates and delivers into revenue and profit, and this is where AI's effects on business models are arguably most visible to customers, since they are the ones who encounter the resulting prices. Dynamic pricing algorithms, long used in airline and hotel booking, have spread into retail, ride-hailing, and even some business-to-business contexts, adjusting prices continuously based on demand signals, competitor behaviour, and individual customer characteristics. This represents a significant departure from the periodic pricing reviews that characterised most industries even a decade ago.

Outcome-based revenue models represent a second pattern, in which firms charge customers based on measured results rather than on the product or service delivered. Industrial equipment manufacturers increasingly sell “power by the hour” rather than the equipment itself, using sensor data and predictive maintenance models to guarantee uptime, with revenue tied directly to that guarantee. This model depends heavily on the predictive and prescriptive AI capabilities described earlier in this paper, since it requires the firm to forecast and manage risk that it previously passed on to the customer at the point of sale.

Data-monetisation loops form a third pattern, referring to business models in which the data generated through use of a product or service becomes a resource that the firm can apply to improve the product, sell as a separate offering, or use to train models that support entirely new lines of business. Kiron and Unruh (2018) observed that firms pursuing this kind of strategy often find that the data asset accumulates value more slowly than expected and requires sustained governance investment before it becomes genuinely monetisable, a finding that tempers some of the more optimistic accounts of data as a costless byproduct

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of digital operations. Table I and Table II, together with the two conceptual figures presented below, summarise how these three value dimensions interact with the descriptive, predictive, prescriptive, and autonomous capability levels introduced in Section II, and they form the basis for the discussion of organisational tensions and strategic implications that follows.

V.STRUCTURED EMPIRICAL AND CONCEPTUAL TABLES

TABLE I
EVOLUTION OF BUSINESS MODEL DIMENSIONS: TRADITIONAL VS DIGITAL VS AI-DRIVEN PARADIGMS

Dimension	Traditional View	Digital/Platform View	AI-Driven Autonomous View	Key Theoretical Shifts
Value Proposition	Fixed product or service specification, revised infrequently through formal planning cycles	Configurable offering, personalised through segmentation and rule-based recommendation engines	Continuously adapted offering, generated or adjusted in real time for the individual user	Shift from designed to emergent value propositions (Amit & Zott, 2001; Zott & Amit, 2010)
Value Architecture	Vertically integrated internal processes with clear functional boundaries	Modular architecture connecting internal systems to external platforms and APIs	Interconnected, self-adjusting architecture in which algorithms coordinate activity across functions	Reconfiguration of activity systems as dynamic rather than static structures (Teece, 2018)
Value Network	Linear supply chain with defined roles for suppliers, the firm, and customers	Multi-sided network with platform intermediaries and data-sharing arrangements	Networked ecosystem in which autonomous agents transact and coordinate with limited human mediation	Extension of the activity system beyond the focal firm (Zott & Amit, 2010)
Revenue Model	Fixed pricing set through periodic review, typically tied to unit sales	Tiered or subscription pricing supported by usage data and customer segmentation	Dynamic, outcome-based, or usage-contingent pricing generated continuously by algorithms	Movement from static to algorithmically negotiated value capture (Chesbrough, 2010)

Source: Table constructed by the author from the synthesis of Amit and Zott (2001), Zott and Amit (2010), Teece (2018), and Chesbrough (2010).

TABLE II
SYNTHESIS OF AI CAPABILITIES AND ASSOCIATED BUSINESS MODEL ARCHETYPES

AI Capability Archetype	Functional Mechanism	Target Industry Example	Primary Operational Risk	Representative Literature
Descriptive analytics	Aggregates historical data into dashboards and reports for human review	Retail sales reporting and performance dashboards	Limited strategic value if not connected to decision workflows	Davenport & Ronanki (2018)
Predictive forecasting	Estimates future demand, churn, or risk from historical patterns	Demand forecasting in fast-moving consumer goods	Model drift and degraded accuracy as conditions change	Mikalef & Gupta (2021)
Prescriptive optimisation	Recommends or ranks specific actions given a forecast and constraints	Dynamic pricing in travel and ride-hailing	Opaque recommendations that are difficult for staff to interpret or challenge	Iansiti & Lakhani (2020)
Autonomous orchestration	Executes decisions directly with minimal human review, closing the feedback loop	Automated bidding and inventory replenishment in e-commerce	Reduced human oversight and delayed detection of systemic error	Paschen, Wilson, & Ferreira (2020)

Source: Table constructed by the author, synthesising the capability taxonomy introduced by Davenport and Ronanki (2018) with empirical archetypes drawn from Mikalef and Gupta (2021), Iansiti and Lakhani (2020), and Paschen, Wilson, and Ferreira (2020).

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VI. CONCEPTUAL VISUALISATIONS

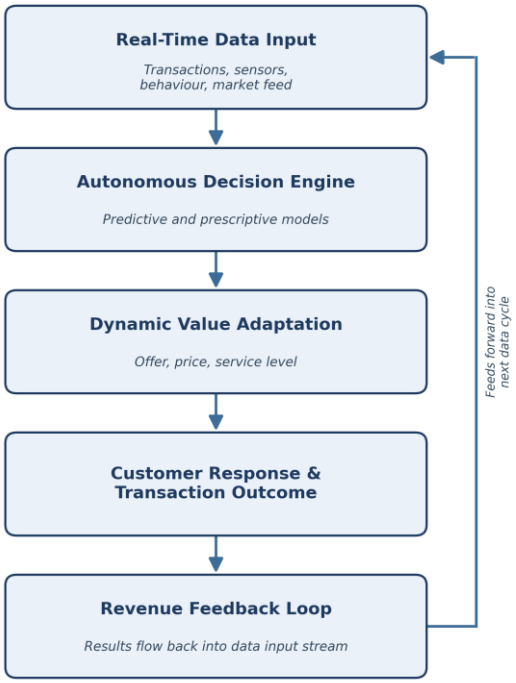

Fig. 1. The Continuous AI-BMI Feedback Loop.

Source: Fig. 1 illustrates the recursive process described conceptually by Teece (2018) and empirically by Iansiti and Lakhani (2020), in which operational outcomes are continuously re-absorbed as new data inputs.

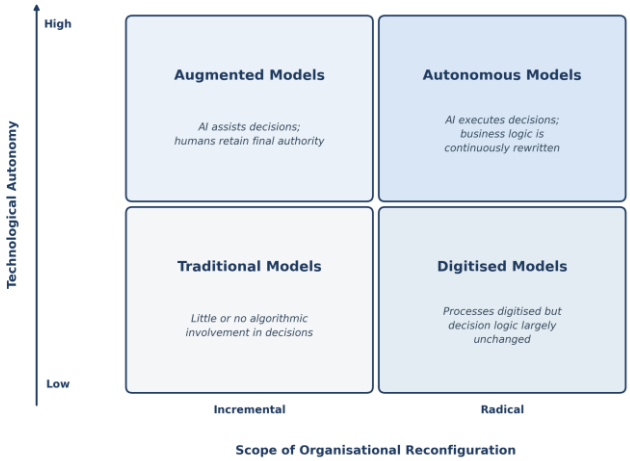

Fig. 2. Strategic Adoption Matrix of AI in Business Model Transformation

Source: Fig. 2 adapts the distinction between digital transformation and AI-driven reconfiguration developed by Vial (2019) and the capability taxonomy discussed in Section II, following Davenport and Ronanki (2018).

VII. CRITICAL TENSIONS, ETHICAL GOVERNANCE, AND ORGANISATIONAL BARRIERS

The literature reviewed points to three recurring sources of friction as firms move toward AI-driven business models. The first is strategic inertia. Established firms often carry legacy architecture, meaning software systems, reporting structures, and data stores that were built for a slower, more manually governed business model. Teece (2018) argued that dynamic capabilities depend on a firm's ability to reconfigure resources quickly, yet legacy architecture tends to work against exactly this kind of reconfiguration, since data needed for a new AI application is frequently locked inside departmental systems that were never designed to share it. Data silos of this kind are not simply a technical inconvenience. They reflect organisational boundaries, incentive structures, and historical rivalries between departments, which means that removing a silo is as much a political undertaking as a technical one.

A second tension concerns algorithmic bias, explainability, and compliance. Shrestha, Ben-Menahem, and von Krogh (2019) observed that decision-making structures built around AI often struggle to reconcile the statistical logic of a model with the accountability expectations placed on human decision-makers, particularly where a decision affects a customer's access to credit, pricing, or service. Kellogg, Valentine, and Christin (2020) described how algorithmic systems introduce new forms of workplace control that are frequently invisible to the employees subject to them, which can erode trust even when the system is technically accurate. Explainability, in this sense, is not only a technical requirement but a governance obligation. Regulators in several jurisdictions have begun to require that firms be able to articulate why an automated system reached a particular decision, and firms that cannot do so face both compliance risk and reputational exposure if customers perceive the system as arbitrary or unfair.

The third tension concerns the balance between human judgement and autonomous agentic decision-making. As Section IV showed, the shift from prescriptive to fully autonomous AI capability changes not just how decisions are made but who, or what, is accountable when a decision goes wrong. Firms adopting autonomous business models, in the sense used in Fig. 2, must decide how much authority to delegate to algorithms and at what point human review becomes mandatory rather than optional. Brynjolfsson and McAfee (2017) suggested that the firms managing this transition most successfully tend to treat the boundary between human and machine authority as a deliberate design choice, revisited regularly, rather than as something that settles automatically once a system proves accurate in testing. Left unmanaged, this boundary tends to drift toward greater automation over time, simply because automated decisions are cheaper and faster, even when the underlying case for full autonomy has not been properly made.

VIII. STRATEGIC IMPLICATIONS FOR MANAGERS AND POLICYMAKERS

For managers, the review suggests several practical priorities. Leadership teams should treat the descriptive, predictive, prescriptive, and autonomous capability levels introduced in Section II as a deliberate sequence rather than a target to reach as quickly as possible. Moving to prescriptive or autonomous capability before an organisation has resolved its data silos and governance gaps tends to amplify existing weaknesses rather than solve them. It is generally more productive to secure reliable descriptive and predictive capability first, since this

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builds the data infrastructure and organisational trust needed for later stages.

Firms should also assign clear ownership for the boundary between human and algorithmic authority described in Section VII, rather than allowing it to be set implicitly by whichever system happens to be easiest to automate. This means building review points into prescriptive and autonomous systems where a human can intervene, and resourcing those review points properly rather than treating them as a formality. Cross-functional integration, shown in Section IV to be strongly associated with performance gains (Mikalef & Gupta, 2021), should be prioritised over isolated departmental pilots, since the value of AI in this review's synthesis consistently comes from connecting functions rather than optimising any single one.

For policymakers, the review points to a need for regulatory frameworks that address accountability at the level of the business model rather than only at the level of individual algorithms. Dynamic pricing, outcome-based contracts, and data-monetisation practices, all discussed in Section IV, raise questions about fair competition and consumer protection that are not fully captured by existing data protection or consumer law, which tend to focus on data handling rather than on the pricing or contractual outcomes that AI-driven models generate. Policymakers should also consider requirements for explainability that are proportionate to the stakes of a decision, since a uniform standard applied equally to low-stakes recommendations and high-stakes decisions such as credit or insurance pricing is likely to be either too weak in the latter case or unworkably burdensome in the former.

IX. AGENDA FOR FUTURE RESEARCH

Three categories of gap emerge from this review. The first concerns methodology. Much of the empirical literature synthesised here relies on single-firm case studies or cross-sectional surveys, which document that AI adoption correlates with performance change but rarely establish the mechanism or direction of causality. Longitudinal studies that track a firm's business model architecture before and after the introduction of prescriptive or autonomous AI capability would help clarify whether the value dimensions identified in Section IV change sequentially or simultaneously, and whether the organisational tensions described in Section VII tend to resolve over time or persist.

The second category concerns context. Existing studies concentrate heavily on large technology firms and a small number of well-resourced industries such as retail, finance, and travel. Far less is known about how smaller firms, public sector organisations, or firms in emerging economies adapt their business models under similar technological pressure but with more limited data infrastructure and governance capacity. Given that Kiron and Unruh (2018) found data assets to be slower and more costly to monetise than commonly assumed, research into how resource-constrained organisations manage this cost would be particularly valuable.

The third category concerns level of analysis. This review has focused primarily on the firm level, following the activity system tradition established by Amit and Zott (2001). Less attention has been paid to how AI-driven business model change affects entire industries or ecosystems, particularly where autonomous systems from different firms interact directly with one another, as in automated bidding markets or algorithmically coordinated supply chains. Research connecting firm-level business model theory to ecosystem-level and institutional-level analysis would help address the fragmentation identified in the introduction to this paper, and would move the field closer to a genuinely integrative theory of AI-driven business model innovation.

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