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Article

Generative Artificial Intelligence in Business Decision-Making: Emerging Frameworks, Applications, and Future Challenges

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Abstract: Enterprise adoption of generative artificial intelligence (GenAI) has outpaced the development of theoretical frameworks capable of explaining why some organizations successfully integrate the technology into decision-making while others fail to realize comparable value, leaving much of the applied literature to borrow, adapt, or extend theoretical apparatus developed for earlier waves of information technology adoption. This paper reviews the theoretical frameworks and applied evidence base for GenAI in enterprise decision-making, organizing the literature around five analytical lenses: individual-level technology acceptance theory, organizational-level technology-organization-environment adoption theory, the dynamic capabilities framework for strategic integration, the prediction-machine economic framework, and the recently formalized "jagged technological frontier" capability-boundary framework. The review synthesizes foundational adoption theory with large-scale field experimental evidence on GenAI's productivity effects, and with the governance and ethical-framework literature addressing accountability and explicability in AI-assisted enterprise decisions. Distinct comparative tables map each framework onto its unit of analysis and central explanatory variable, cross-reference specific business functions against the framework best suited to explain observed adoption patterns in each, and organize the field's principal future challenges by the theoretical gap each challenge exposes. The paper concludes that no single framework adequately explains GenAI's enterprise decision-making effects across all analytical levels, and that individual-, organizational-, and task-level frameworks must be combined rather than treated as competing explanations, identifying multi-level theoretical integration as the central future research prospect.
Keywords: Generative Artificial Intelligence, Enterprise Decision-Making, Technology Adoption, Dynamic Capabilities, Prediction Machines, Jagged Technological Frontier, AI Governance, Business Applications

1. Introduction

Enterprise adoption of generative artificial intelligence has proceeded at a pace that has left much of the theoretical apparatus traditionally used to explain organizational technology adoption straining to keep up, since GenAI differs from prior generations of enterprise software in a specific respect directly relevant to decision-making theory: it does not merely retrieve, store, or structure information but actively generates novel content, recommendations, and analysis, a capability that alters the boundary between what a decision-support tool provides and what a human decision-maker contributes [1], [9]. Davis's technology acceptance model (TAM), developed originally to explain individual employees' adoption of conventional workplace software, proposed that perceived usefulness and perceived ease of use jointly determine an individual's behavioral intention to adopt a new technology, a parsimonious two-construct framework that has since been tested, extended, and applied across four decades of information systems research [2]. Venkatesh and Davis's TAM2 extension incorporated social influence and cognitive instrumental processes as additional determinants of perceived usefulness specifically, while Venkatesh, Morris, Davis, and Davis's Unified Theory of Acceptance and Use of Technology (UTAUT) consolidated TAM and seven competing adoption models into a single framework built around performance expectancy, effort expectancy, social influence, and facilitating conditions, becoming the dominant individual-level technology adoption framework against which subsequent GenAI-specific adoption studies are typically benchmarked [3], [4].

Individual-level adoption theory, however, addresses only one analytical level relevant to enterprise decision-making, and a parallel organizational-level literature has developed to explain why otherwise comparable firms adopt and integrate new technology into strategic decision processes at markedly different rates. Tornatzky and Fleischer's technology-organization-environment (TOE) framework proposed that organizational technology adoption depends jointly on technological context, the availability and relative advantage of the technology itself; organizational context, firm size, structure, and slack resources; and environmental context, industry competitive pressure and regulatory conditions, a three-factor framework subsequently applied extensively to enterprise AI and, more recently, GenAI adoption specifically [5]. Teece's dynamic capabilities framework addresses a related but analytically distinct strategic-management question, not merely whether a firm adopts a new technology but whether the firm possesses the sensing, seizing, and reconfiguring capabilities necessary to translate that technology into sustained competitive advantage through ongoing strategic reconfiguration, a framework with direct relevance to why GenAI adoption alone does not guarantee improved enterprise decision-making without accompanying organizational reconfiguration [6].

Agrawal, Gans, and Goldfarb's prediction-machine framework reframed the underlying economic question these adoption and capability frameworks address, characterizing AI broadly, and GenAI's synthesis and generation capabilities specifically, as fundamentally a technology that reduces the cost of prediction, and arguing that cheaper prediction should be expected to increase, rather than decrease, the economic value of complementary human judgment, since a decomposed decision task still requires a human or organizational process to attach value to predicted outcomes and select an appropriate action [7]. Dell'Acqua et al.'s large-scale field experiment with Boston Consulting Group consultants provided the most direct empirical test of where this prediction-judgment decomposition succeeds and fails in practice, finding that consultants using GPT-4 for tasks within the model's effective capability frontier significantly outperformed a control group, while consultants applying the same tool to a task specifically designed to exceed that capability underperformed, having extended unwarranted trust to confidently presented but substantively incorrect AI output, a finding the authors formalized as the "jagged technological frontier" [8].

This paper reviews these five analytical frameworks, individual-level acceptance theory, organizational-level TOE adoption theory, dynamic capabilities, prediction-machine economics, and the jagged-frontier capability-boundary model, alongside the applied field-experimental and governance literature, before turning to the specific theoretical and practical challenges that recur across all five frameworks as enterprises scale GenAI-assisted decision-making.

Research Objectives

- To review the individual-level technology acceptance frameworks applied to GenAI adoption in enterprise settings.
- To synthesize organizational-level adoption theory and the dynamic capabilities framework as applied to GenAI strategic integration.
- To examine the prediction-machine economic framework and the jagged technological frontier capability-boundary model.

- To evaluate applied field-experimental evidence on GenAI's business decision-making effects across enterprise functions.
- To identify the central future challenges facing enterprise GenAI decision-making, organized by the theoretical gap each expose.

2. Literature Review

2.1 Individual-Level Technology Acceptance Frameworks

Davis's original TAM proposed that perceived usefulness, the degree to which an individual believes a technology will enhance job performance, and perceived ease of use, the degree to which the technology is perceived as effortless to use, jointly determine adoption intention, and empirical validation across numerous technology contexts consistently found perceived usefulness to be the stronger of the two predictors [2]. Venkatesh and Davis's TAM2 extended this model by specifying the antecedents of perceived usefulness itself, including subjective norm and job relevance, providing a more complete explanatory chain from social and task context through to adoption intention [3]. Venkatesh, Morris, Davis, and Davis's UTAUT consolidated TAM with seven competing frameworks into four core determinants, performance expectancy, effort expectancy, social influence, and facilitating conditions, moderated by gender, age, experience, and voluntariness of use, and has become the standard benchmark framework subsequent GenAI-specific individual adoption studies test against or extend [4].

2.2 Organizational-Level Adoption: The Technology-Organization-Environment Framework

Tornatzky and Fleischer's TOE framework shifted the unit of analysis from the individual employee to the organization, proposing that organizational adoption of a new technology depends on the interaction of technological, organizational, and environmental context factors rather than on individual employee acceptance alone [5]. Applied to GenAI specifically, the TOE framework's technological-context dimension captures firms' assessment of GenAI's relative advantage and compatibility with existing decision workflows, the organizational-context dimension captures firm size, top management support, and absorptive capacity, and the environmental-context dimension captures competitive pressure and regulatory uncertainty, a three-dimensional structure that Chatterjee, Rana, Dwivedi, and Baabdullah's related information-systems survey work on emerging technology adoption found consistently outperforms single-factor adoption explanations when applied to enterprise-level AI adoption decisions specifically [5], [11].

2.3 Dynamic Capabilities and Strategic Integration

Teece's dynamic capabilities framework distinguishes ordinary capabilities, the operational competence to perform current business functions efficiently, from dynamic capabilities, the higher-order capacity to sense emerging opportunities, seize them through resource reconfiguration, and continuously transform the organization to sustain competitive advantage as the environment changes [6]. Teece's subsequent extension of this framework to digital-platform and data-driven business models argued explicitly that data-and-analytics-intensive technologies, a category GenAI extends further than earlier generations of business intelligence software, require particularly strong sensing and seizing capabilities precisely because the technology's capability boundary shifts rapidly, meaning that a firm's dynamic capability to reassess and reconfigure its GenAI-assisted decision processes matters more for sustained advantage than the initial adoption decision itself [9]. Warner and Wäger's empirical study of digital transformation through a dynamic capabilities lens found that firms successfully navigating digital disruption exhibited a consistent sensing-seizing-transforming cycle, with organizational inertia and a lack of digital leadership identified as the most common barriers preventing firms from progressing from initial technology sensing to genuine strategic reconfiguration, a barrier pattern directly relevant to why GenAI adoption alone frequently fails to translate into improved enterprise decision-making [12].

2.4 The Prediction-Machine Economic Framework

Agrawal, Gans, and Goldfarb's prediction-machine framework decomposes any decision task into a prediction component, forecasting an uncertain future state, and a judgment component, assigning value or payoff to different predicted outcomes and selecting an action accordingly, arguing that AI's comparative advantage lies specifically in the prediction component, and that as prediction becomes cheaper, the economic value of the complementary human judgment component should be expected to rise rather than fall [7]. This framework directly informs how enterprise decision-making should be redesigned around GenAI: rather than treating GenAI as a general decision-automation tool, the framework implies decision processes should be explicitly decomposed so that GenAI handles the prediction and synthesis sub-tasks while accountable human decision-makers retain the judgment sub-task, a decomposition principle that anticipates the empirical capability-boundary findings reviewed in Section 2.6 [7], [8].

2.5 Field Experimental Evidence on Enterprise Applications

Brynjolfsson, Li, and Raymond's large-scale field experiment within a Fortune 500 software company's customer support function found that access to a generative AI conversational assistant increased resolved-issues-per-hour productivity by roughly 14 percent on average, with the effect concentrated overwhelmingly among newer and lower-skilled agents, a skill-distribution pattern the authors attribute to the tool's capacity to accelerate the transfer of organizational best practices that experienced agents had already internalized [13]. Noy and Zhang's controlled experiment on professional writing tasks found a closely parallel pattern, with generative AI's largest productivity gains accruing to relatively lower-performing participants, evidence the authors interpret as a knowledge-leveling rather than uniformly amplifying effect [14]. Peng et al.'s controlled study of software developers using GitHub Copilot found a 55.8 percent faster completion rate on a standardized programming task, extending the productivity evidence base into a technical decision-making domain with its own distinct evaluation criteria from customer service or consulting [15]. Chui et al.'s McKinsey Global Institute analysis estimated that generative AI could add trillions of dollars in annual value to the global economy, concentrated in customer operations, marketing and sales, software engineering, and research and development functions, a cross-functional distribution the authors attribute to these functions' comparatively high proportion of language-based, prediction-and-synthesis-heavy tasks, directly consistent with the prediction-machine framework's task-decomposition logic [7], [16].

2.6 The Jagged Technological Frontier

Dell'Acqua et al.'s BCG consultant field experiment found that consultants using GPT-4 for tasks within the model's effective capability frontier completed 12.2 percent more tasks on average and produced work rated 40 percent higher in quality by blind evaluators, while consultants applying the same tool to a task specifically designed to exceed that capability underperformed a control group, having extended unwarranted trust to the model's confidently presented but substantively incorrect output, a pattern the authors term a false-sense-of-confidence effect [8]. This capability-boundary finding, subsequently termed the "jagged technological frontier" because AI capability does not expand uniformly across task types but advances unevenly and unpredictably, represents the field's most direct empirical evidence that GenAI's enterprise decision-making value is conditional on task-model fit rather than unconditionally positive, a finding with direct implications for how the TOE framework's technological-context dimension and the dynamic capabilities framework's sensing function should be operationalized specifically for GenAI, since both frameworks require an accurate, continuously updated assessment of where a given task sits relative to the model's shifting capability frontier [5], [6], [8].

2.7 Governance and Explicability Frameworks

Shrestha, Ben-Menahem, and von Krogh's typology of organizational decision-making structures in the age of artificial intelligence distinguished full human control, hybrid human-AI decision-making, and full AI automation, arguing that the appropriate structure for a given enterprise decision depends on decision frequency, stakes, and how well specified the underlying prediction task is, with hybrid structures recommended for the large majority of consequential business decisions given current AI capability [17]. Berente, Gu, Recker, and Santhanam's framework for managing artificial intelligence in organizations identified the opacity of generative models' internal reasoning as a distinct organizational management challenge, since managers integrating GenAI into decision workflows must establish appropriate trust and oversight levels without the ability to fully audit the system's reasoning process the way they could audit a human subordinate's stated rationale [18]. Floridi et al.'s AI4People framework articulated beneficence, non-maleficence, autonomy, justice, and explicability as guiding ethical principles for responsible AI deployment, with explicability, the capacity to understand and articulate why an AI system produced a given output, carrying particular relevance for enterprise decisions involving legal or fiduciary accountability that a decision-maker cannot fully explain if reliant on an opaque generative model [19]. Kaplan and Haenlein's broader conceptual framework for understanding AI's evolution and business implications situated GenAI's decision-support role within a longer historical progression from analytical to intuitive AI capability, arguing that enterprise decision-making frameworks must be periodically reassessed as AI capability itself evolves, rather than treating any single framework, including the frameworks reviewed above, as a fixed and permanent description of the technology's decision-making role [1].

2.8 Research Gap

While individual-level acceptance theory, organizational-level TOE adoption theory, and dynamic capabilities theory have each been extensively validated for prior generations of enterprise technology, and the prediction-machine and jagged-frontier frameworks have been developed and empirically tested specifically for GenAI, comparatively few studies integrate these individual-, organizational-, and task-level frameworks within a single explanatory model of enterprise GenAI decision-making, leaving open how, for instance, an individual employee's TAM-predicted adoption intention interacts with an organization's TOE-predicted adoption readiness and the task-level capability-boundary constraints Dell'Acqua et al. documented [2], [5], [8]. This review addresses this gap by organizing the reviewed frameworks within a comparative structure spanning unit of analysis, central explanatory variable, and applicability to specific enterprise decision-making contexts.

3. Methodology

This study adopts a qualitative, descriptive, and comparative research design synthesizing peer-reviewed information systems, strategic management, and applied economics literature addressing GenAI's role in enterprise decision-making. Reviewed frameworks and studies were compared along four axes: unit of analysis (individual, organization, or task); theoretical lineage (technology acceptance, organizational adoption, strategic management, or economic); evidence type (survey-based construct validation, field experiment, or conceptual/theoretical framework); and whether the framework addresses adoption, strategic integration, or task-level capability boundaries specifically.

4. Results and Discussion

4.1 Frameworks Mapped by Unit of Analysis and Central Explanatory Variable

Table 1 organizes the reviewed frameworks by their unit of analysis, a structure that clarifies which analytical level each framework is best suited to explain rather than presenting them as competing, mutually exclusive theories.

Table 1. Enterprise GenAI Frameworks by Unit of Analysis and Central Explanatory Variable

Framework	Unit of Analysis	Central Explanatory Variable(s)	Key Source
Technology Acceptance Model (TAM) / TAM2	Individual employee	Perceived usefulness, perceived ease of use	Davis [2]; Venkatesh & Davis [3]
UTAUT	Individual employee	Performance/effort expectancy, social influence, facilitating conditions	Venkatesh et al. [4]

Technology-Organization-Environment (TOE)	Organization	Technological, organizational, and environmental context	Tornatzky & Fleischer [5]
Dynamic Capabilities	Organization/firm strategy	Sensing, seizing, and reconfiguring capability	Teece [6], [9]
Prediction Machines	Decision task	Cost of prediction relative to value of complementary judgment	Agrawal, Gans & Goldfarb [7]
Jagged Technological Frontier	Individual task-model pairing	Task position relative to model's effective capability boundary	Dell'Acqua et al. [8]
AI4People / Explicability	Governance/ethics (cross-level)	Explicability, accountability, non-maleficence	Floridi et al. [19]

4.2 Business Functions Mapped to Explanatory Framework and Evidence

Table 2 shifts from framework-level comparison to specific enterprise decision-making functions, mapping each to the framework the reviewed evidence indicates is most explanatory for that function's observed adoption or productivity pattern.

Table 2. Enterprise Decision-Making Functions Mapped to Explanatory Framework

Business Function	Reported Evidence	Most Explanatory Framework	Supporting Source
Customer support/operations	~14% productivity gain, concentrated among lower-skilled agents	Prediction Machines (task decomposition); TAM (individual adoption variation)	Brynjolfsson, Li & Raymond [13]; Agrawal, Gans & Goldfarb [7]
Management consulting	+12.2% tasks completed; quality gains in-frontier, losses out-of-frontier	Jagged Technological Frontier	Dell'Acqua et al. [8]
Software engineering	55.8% faster task completion	Prediction Machines; TOE (technological context)	Peng et al. [15]
Cross-functional strategic planning	High estimated economic potential concentrated in language-intensive functions	Dynamic Capabilities (sensing/seizing); TOE (organizational context)	Chui et al. [16]; Teece [6]
High-stakes/accountable decisions (legal, financial sign-off)	Governance and explicability concerns dominate over productivity findings	AI4People/Explicability; Managing AI framework	Floridi et al. [19]; Berente et al. [18]
Organization-wide digital transformation	Sensing-seizing-transforming cycle; inertia as primary barrier	Dynamic Capabilities	Warner & Wäger [12]

4.3 Future Challenges Organized by Theoretical Gap

Table 3 organizes the field's principal future challenges not by topic but by the specific theoretical gap in Sections 2.1 through 2.7 that each challenge exposes, directly connecting the challenges discussed in Section V below to the frameworks reviewed above.

Table 3. Future Challenges Organized by Underlying Theoretical Gap

Challenge	Theoretical Gap Exposed	Relevant Framework(s)
Capability-boundary drift over time	Frameworks assume a static technological context; GenAI capability shifts unevenly and continuously	Jagged Technological Frontier [8]; TOE [5]
Multi-level model integration	Individual, organizational, and task-level frameworks developed largely in isolation from one another	TAM/UTAUT [2], [4]; TOE [5]; Prediction Machines [7]
Explicability under opaque model reasoning	Governance frameworks presuppose auditability that generative models do not straightforwardly provide	AI4People [19]; Managing AI [18]
Dynamic capability development lag	Firms sense GenAI opportunity faster than they build reconfiguration capability	Dynamic Capabilities [6], [9], [12]
False-confidence/automation bias in judgment allocation	Prediction-judgment decomposition assumes accurate human calibration of AI reliability	Prediction Machines [7]; Jagged Frontier [8]
Skill-distribution and workforce equity effects	Adoption frameworks do not account for differential productivity effects across skill levels	Field experimental evidence [13], [14], [15]

4.4 Discussion

Taken together, the evidence in Tables 1 through 3 supports treating GenAI enterprise decision-making theory as a multi-level problem rather than one adequately addressed by any single framework in isolation. Table 1 establishes that TAM, UTAUT, TOE, and dynamic capabilities theory each explain a genuinely distinct analytical level, individual, organizational, or strategic, while the prediction-machine and jagged-frontier frameworks address the task level specifically, a level largely absent from the technology-adoption literature these frameworks predate [2], [4], [5], [6], [7], [8]. Table 2's function-level mapping indicates that no single framework explains observed enterprise outcomes uniformly across functions: customer support outcomes are best explained by prediction-machine task decomposition combined with individual-level adoption variation, while consulting outcomes are best explained specifically by the jagged frontier's capability-boundary logic, and cross-functional strategic planning outcomes require the dynamic capabilities framework's sensing-seizing lens that the task-level frameworks do not address [6], [7], [8], [13], [15], [16]. This functional heterogeneity directly motivates Table 3's reframing of future challenges as theoretical gaps rather than merely practical obstacles: the capability-boundary-drift challenge exposes the TOE framework's implicit assumption of a relatively static technological context, an assumption the jagged frontier's continuously shifting capability boundary directly violates, while the explicability challenge exposes a tension between Berente, Gu, Recker, and Santhanam's opacity concern and Floridi et al.'s explicability principle that none of the individual-, organizational-, or task-level frameworks reviewed in Sections 2.1 through 2.6 was designed to resolve [5], [8], [18], [19]. This pattern suggests that the field's most pressing theoretical need is not a replacement framework but a genuinely integrative one, combining individual adoption variables, organizational readiness variables, and task-level capability-boundary variables within a single explanatory structure.

5. Future Challenges

The theoretical gaps organized in Table 3 translate into five specific challenges enterprises and researchers must address as GenAI-assisted decision-making scales beyond the pilot projects and controlled field experiments that dominate the current evidence base. First, capability-boundary drift means that a task correctly classified as within a model's effective frontier today may fall outside it, or a previously excluded task may fall within it, as underlying models are updated, requiring enterprises to treat capability-boundary assessment as a continuous monitoring function rather than a one-time classification exercise, a requirement current TOE-based adoption assessments do not typically build in [5], [8]. Second, the absence of multi-level theoretical integration means that enterprises currently lack validated guidance for reconciling individual employee adoption resistance or enthusiasm, per TAM and UTAUT, with organizational readiness assessments, per TOE, when the two point in different directions, a reconciliation problem the field's siloed framework development has not yet addressed [2], [4], [5]. Third, explicability requirements clash directly with the opacity Berente, Gu, Recker, and Santhanam identify as characteristic of generative models specifically, a tension particularly acute for the high-stakes, accountable decisions Table 2 identifies as requiring governance frameworks rather than pure productivity frameworks, and one that current explainability research has not resolved for large generative models to the standard Floridi et al.'s framework implies [18], [19]. Fourth, dynamic capability development, per Teece and Warner and Wäger, appears to lag behind firms' initial sensing of GenAI opportunity, meaning that the productivity gains documented in controlled field experiments may not generalize to firms that adopt the technology without the accompanying organizational reconfiguration the dynamic capabilities framework identifies as necessary for sustained advantage [6], [9], [12], [13]. Fifth, the skill-distribution pattern documented across the field-experimental evidence, productivity gains concentrated among lower-skilled or lower-performing employees, raises a workforce-equity and human-capital-development challenge that none of the adoption, capability, or economic frameworks reviewed in Section 2 was designed to address directly, since these frameworks predict aggregate adoption or productivity outcomes rather than their distribution across a firm's existing workforce [13], [14], [15].

6. Conclusion

This paper has reviewed the theoretical frameworks and applied evidence base for generative AI in enterprise decision-making, synthesizing individual-level technology acceptance theory, organizational-level TOE adoption theory, the dynamic capabilities framework, the prediction-machine economic framework, and the jagged technological frontier capability-boundary model within a single comparative structure. The evidence indicates that no single framework adequately explains GenAI's enterprise decision-making effects across the individual, organizational, and task levels these frameworks separately address, and that the field's most consistently reported empirical findings, skill-distribution effects in productivity gains and capability-boundary-dependent performance effects, are best explained by combining frameworks rather than selecting among them. The future challenges this evidence exposes, capability-boundary drift, multi-level theoretical integration, explicability under model opacity, dynamic capability development lag, and workforce-equity effects, each trace back to a specific gap in the reviewed frameworks rather than constituting a separate, unrelated set of practical obstacles, suggesting that theoretical integration and practical implementation guidance are, in this field, substantially the same research problem.

7. Future Work

Future research should prioritize developing and empirically testing an integrated, multi-level framework combining TAM/UTAUT individual-adoption variables, TOE organizational-readiness variables, and jagged-frontier task-level capability-boundary variables within a single model, since the current literature has developed and validated these three levels largely in isolation from one another. Further work is needed to develop continuous, rather than one-time, capability-boundary assessment methodologies that enterprises can operationalize as part of ongoing dynamic-capability sensing, extending Dell'Acqua et al.'s consulting-specific finding into a general-purpose organizational monitoring practice applicable across the business functions summarized in Table 2. Continued research should also examine whether explicability requirements can be operationalized for generative models through process-level rather than output-level transparency, given that Berente, Gu, Recker, and Santhanam's opacity concern applies most directly to a model's internal reasoning rather than to the surrounding decision workflow an enterprise designs around that model. Finally, future work should extend the skill-distribution findings reviewed in Section 2.5 into longitudinal workforce-development research, examining whether the productivity-leveling effect documented in controlled short-term field experiments persists, narrows, or reverses as lower-skilled employees' baseline competence rises through sustained GenAI-assisted work, a question current cross-sectional field experiments cannot answer.

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