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RESHAPING OPERATIONAL MANAGEMENT WITH AI: A SYSTEMATIC LITERATURE REVIEW

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Abstract

This systematic review objectively synthesises and clarifies how firms operationalise Artificial Intelligence (AI) for daily decision-making, addressing the 'why' of fragmented empirical evidence on AI's contextual integration amid rapid technological evolution (e.g., generative AI adoption post-2023). Drawing on 200 peer-reviewed studies (2020–2025) analysed using PRISMA, it maps seven key theoretical frameworks across sectors. Results indicate effective operational AI strategies depend not only on technical assets but on organisational adaptability, knowledge management, and user acceptance. Resource- and capability-based frameworks dominate public administration and research; knowledge integration and acceptance models prevail in healthcare, HRM, and hospitality; and disruption theory informs finance-sector dynamics. Originality stems from its theory-driven synthesis of fragmented literature, clarifying AI's operational impact across contexts and offering relevant, sector-tailored guidance for managers navigating adoption challenges. Limitations consist of the exclusion of non-English and grey literature. Practical recommendations are that managers should emphasise knowledge management, transparency, and organisational agility. The review provides a concise agenda for researchers and practitioners managing operational AI integration.

Keywords: artificial intelligence, operational management, innovation management, resource-based view, dynamic capabilities, disruptive innovation

1. INTRODUCTION

Artificial Intelligence (AI) has progressed from an experimental tool to a core element of operational management, with growing relevance for daily execution, resource coordination, and decision-making (Grewal & al., 2024). In this review, operational management is defined as the design, execution, and improvement of organisational processes affecting productivity, quality, and responsiveness.

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AI technologies, such as machine learning (ML), deep learning, natural language processing (NLP), and generative AI, augment human cognition by extracting insights from complex data, automating decisions, and enhancing operational adaptability (Birkstedt & al., 2023; Kim & al., 2025; Nalbant & Aydin, 2025). Generative AI introduces additional capabilities such as automated document generation and smart customer service, redefining the division between standardised and knowledge-intensive tasks.

Operational AI enhances scheduling, supply chain management, and quality control, fostering resilience and agility (Cao & al., 2021). In sustainability and risk contexts, it supports greener production and real-time coordination, leading to observed gains in efficiency and reduced errors (Wang et al., 2025). However, increased AI use raises challenges around data governance, workforce adaptation, and the human oversight of algorithmic outputs (Menard & Bott, 2024).

Beyond these challenges, deploying AI in operational contexts introduces multifaceted risks that can undermine efficiency, equity, and resilience. Key among these are algorithmic biases and privacy breaches arising from the misuse of data, leading to discriminatory outcomes in decision-making processes such as scheduling or quality assurance (Menard & Bott, 2024; Gursoy & Cai, 2024). Over-reliance on AI systems risks 'backfiring' effects, such as erroneous outputs eroding trust and amplifying errors in high-stakes environments like supply chains (Shuqair et al., 2024). Workforce displacement fears and job insecurity further exacerbate resistance, with studies showing negative impacts on employee thriving and operational cohesion (Leong et al., 2024). Ethical risks, including AI-facilitated greenwashing in sustainability reporting, compound regulatory non-compliance and reputational damage (Ren et al., 2025). These intersecting concerns underscore the need for governance frameworks that safeguard human-AI collaboration, informing this review's emphasis on adaptive theories and practical safeguards.

Key questions remain about humans, such as AI collaboration, translating insights into continuous improvement, and aligning AI with compliance and ethics, especially in emerging sectors such as services, healthcare, and public administration (Gursoy & Cai, 2024; Ren et al., 2025). This review addresses these issues by synthesising recent peer-reviewed research, offering theoretical clarification and practical guidance for scholars and operational managers alike.

The primary objective of this systematic literature review is to map and synthesise the theoretical underpinnings of AI operationalisation in management, identify dominant frameworks and their sector-specific applications, and guide effective integration strategies. The 'why' lies in the exponential growth of AI applications since 2020, exemplified by the proliferation of generative AI tools, coupled with a fragmented literature that silos insights by sector (e.g., manufacturing vs. healthcare) and overlooks cross-cutting enablers like organisational adaptability and ethical alignment (Grewal et al., 2024; Ren et al., 2025). Without such synthesis, managers risk siloed implementations, while scholars lack a unified lens for advancing theory. Its relevance is twofold: theoretically, it consolidates seven frameworks (e.g., TAM, RBV) into a cohesive taxonomy, revealing patterns in adoption dynamics; practically, it equips operational leaders with evidence-based recommendations for fostering resilience, such as prioritising knowledge management and user trust, thereby enhancing productivity and ethical compliance across diverse contexts. This review thus bridges the theory-practice gap, providing a roadmap for AI's sustainable embedding in operational routines.

2. EXPERIMENTAL RESEARCH

Given the complexity and interdisciplinary scope of artificial intelligence (AI) in operational management, this study employs a systematic literature review (SLR) to ensure comprehensive, objective, and reproducible results. Unlike narrative or scoping reviews, an SLR minimises bias and subjectivity, offering rigorous and transparent analysis (Kraus et al., 2024).

The review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, ensuring structured documentation of literature identification, selection, and screening (Tranfield et al., 2003). Keyword searches combined AI terms (e.g., machine learning, generative AI, NLP) with operational management concepts (operations management, supply chain, process optimisation, production planning) across Web of Science, Emerald, Springer, and Wiley databases. Inclusion criteria limited articles to peer-reviewed publications from 2020 to 2025, initially yielding 6786 entries. After duplicate removal (~500), elimination of records without author information (556), and Mendeley flagging (68), 362 articles remained for full-text retrieval, of which 358 were accessed.

Screening emphasised topical relevance and quality, retaining articles only from journals ranked 4*, 4, or 3 in the Academic Journal Guide 2024. Challenges arose in distinguishing between operational and strategic studies; thus, 153 strategically focused articles and two irrelevant articles were excluded. The final review incorporated 203 publications, with 200 subjects subjected to detailed analysis. The procedure is detailed in Figure 1.

3. RESULTS

This review identifies consistent theoretical themes in operational AI adoption across industries (see Figure 2). Three dominant frameworks emerge: the Technology Acceptance Model (TAM), Dynamic Capabilities, and Resource-Based View (RBV). TAM, prevalent in sectors with high user interaction such as hospitality, healthcare, and finance, underscores user acceptance, perceived ease of use, management support, and trust as pivotal for successful AI integration (Shuqair et al., 2024; Gyau et al., 2024; Zhao et al., 2025).

Dynamic Capabilities and RBV dominate energy, public administration, and digital manufacturing, emphasising internal adaptation, agile processes, and strategic resource allocation to integrate AI into operational routines (Chatterjee et al., 2021; Yu et al., 2024). RBV highlights proprietary data, specialised AI models, and digital competencies as critical to sustaining competitive operational advantages (Bag et al., 2020; Kinkel et al., 2021).

In Human Resource Management (HRM), the Knowledge-Based View (KBV) is central, focusing on knowledge integration, employee expertise, and absorptive capacity

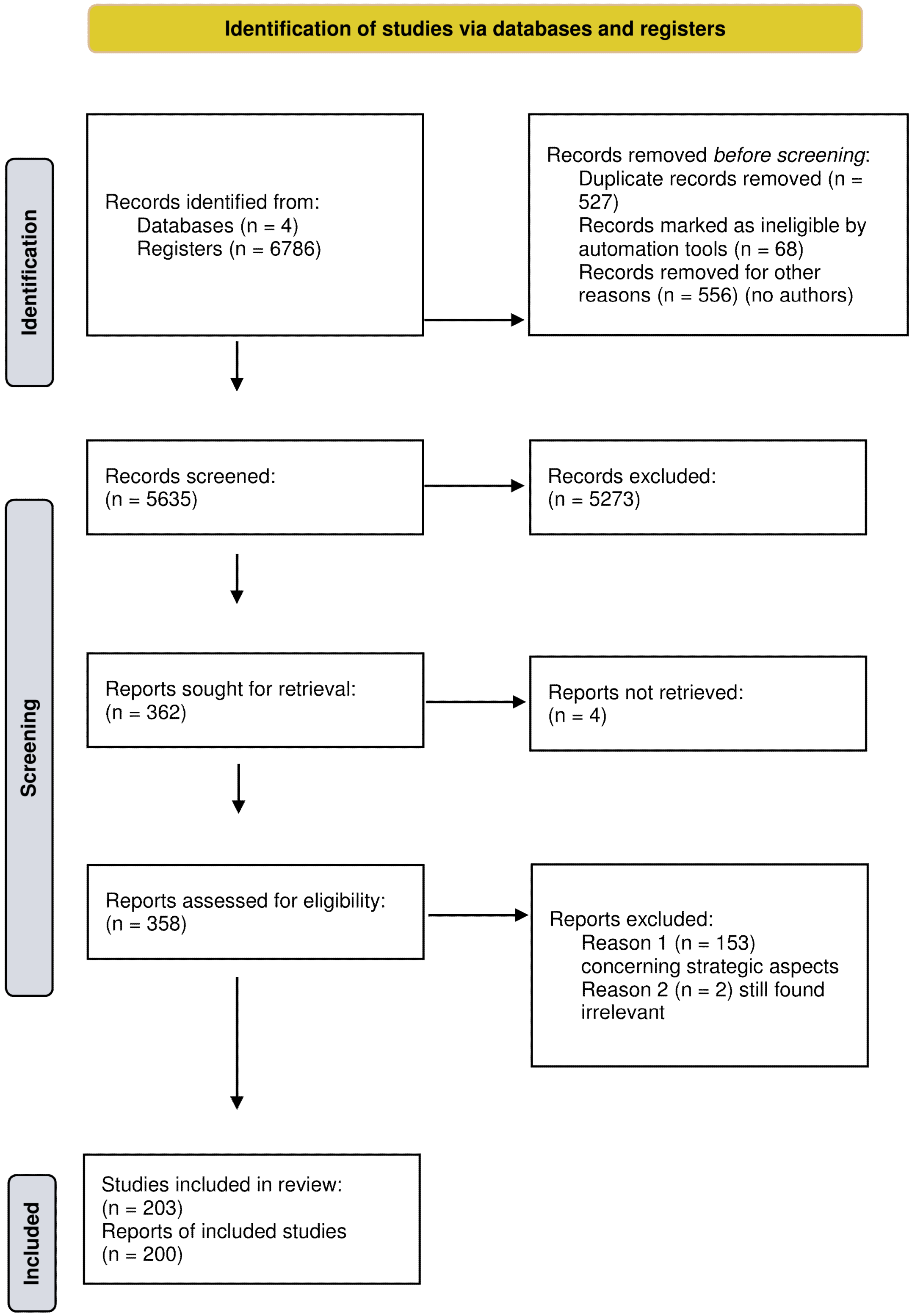

Figure 1. Prisma method of data description

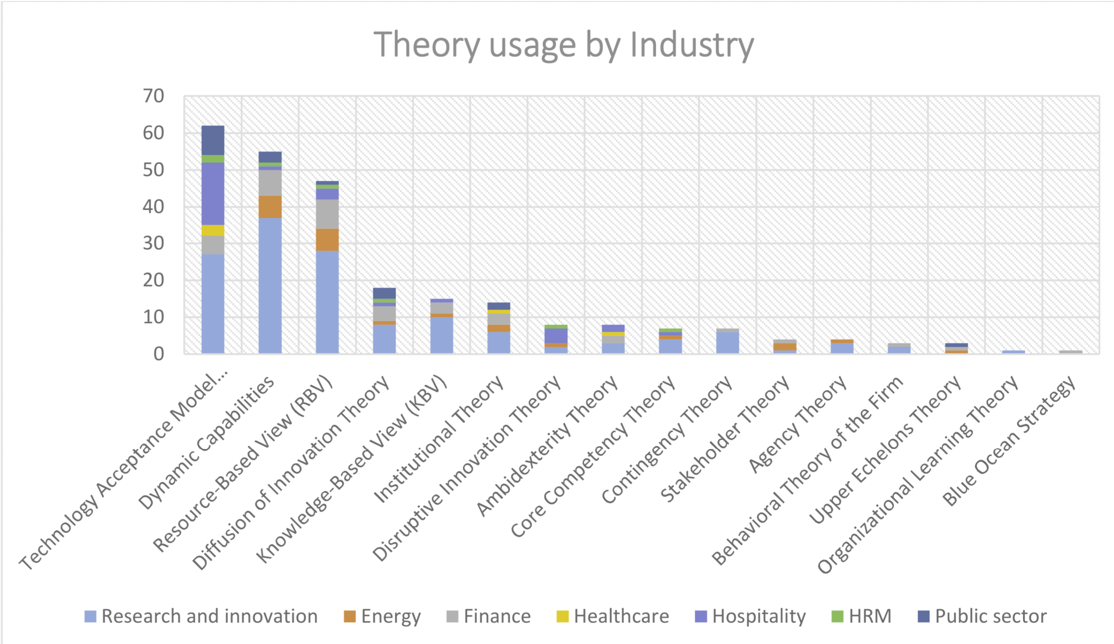

Figure 2. Theory usage total and by category

Table 1. Leading theoretical frameworks of industry-specific studies

Industry	**Leading models**
Research and innovation	Dynamic Capabilities and RBV
Public sector	Dynamic Capabilities and RBV
Energy	TAM and Dynamic Capabilities
Financial	TAM and Disruptive Innovation Theory
HRM	TAM and KBV
Healthcare	TAM and KBV
Hospitality	TAM and KBV

to maximise AI benefits (Chatterjee et al., 2021; Lysø et al., 2024). Disruptive Innovation Theory dominates in finance, reflecting agility and anticipation of technology shifts (Rusthollkarhu et al., 2022; Akhtar et al., 2024).

Other frameworks, including Diffusion of Innovation and Institutional Theory, address scaling, regulatory compliance, and broader implementation contexts, clarifying operational pressures for efficiency and adaptation (Misra et al., 2023; Sienkiewicz-Małyjurek, 2023).

Theoretical distributions (see Table 1) confirm that effective operational AI use depends on harmonising technology, organisational processes, workforce skills, and user engagement

4. DISCUSSION

This section analyses how the adoption and integration of Artificial Intelligence (AI) are interpreted through seven major frameworks: Technology Acceptance Model, Dynamic Capabilities, Resource-Based View, Diffusion of Innovation Theory, Knowledge-Based View, Institutional Theory, and Disruptive Innovation Theory. This analysis evaluates each theory's relevance to AI in operational use, examining its applications, the operational processes it explains, and its key theoretical contributions. In addition, criticisms, conceptual limitations, and emerging extensions of each framework are identified, highlighting their explanatory power and the areas where further research is needed. Evidence from recent operational AI studies is synthesised in Table 2 to illustrate the practical deployment of these theoretical models across diverse organisational contexts.

I Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) remains fundamental for understanding user adoption of AI in operational contexts, emphasising perceived usefulness (expected performance benefit) and ease of use (minimal required effort). These factors significantly influence successful operational integration, with user and employee acceptance playing a key role.

Recent research applies TAM to examine AI adoption among frontline workers and managers across sectors. For instance, in digital manufacturing, TAM, combined with the technology-organisation-environment (TOE) framework, highlights how organisational readiness, leadership support, and targeted training enhance perceptions of AI usability, thereby reducing operational resistance (Chatterjee & al., 2021). Similarly, hospitality studies find that employee acceptance depends not only on usefulness and ease but also on privacy attitudes, perceived risks, and trust, which directly shape positive or negative responses toward AI systems (Shuqair & al., 2024; Zhao & al., 2025).

Financial and public sector analyses further underscore how AI adoption for decision-making depends on usability alongside institutional context, user experience, and organisational support (Gyau & al., 2024; Misra & al., 2024). In digital government, public managers' adoption aligns closely with procedural justice, collaborative practices, and training.

Despite its strengths in making predictions, TAM is critiqued for overlooking broader contextual, ethical, and regulatory factors crucial for AI acceptance, prompting operational studies to integrate complementary perspectives like organisational psychology, institutional theory, and risk management to enrich TAM's explanatory power (Chatterjee & al., 2021; Shuqair & al., 2024).

II Dynamic Capabilities

Dynamic capabilities theory explains how organisations identify operational opportunities and risks, mobilise relevant resources, and reconfigure internal processes to adapt to technological shifts. Within operational management, this framework highlights that effective AI integration requires not just technological adoption but more profound transformations in routines, skills, and organisational culture.

Empirical research demonstrates the necessity of capabilities such as advanced analytics expertise, leadership support, and iterative learning cultures for operational AI success. Studies in manufacturing and digital operations stress organisational readiness and ongoing employee upskilling as critical factors influencing productivity and innovation through AI (Chatterjee & al., 2021; Yu & al., 2024). Similarly, banking and finance research identifies dynamic, technology-enabled routines as essential for translating AI investments into measurable performance outcomes (Gyau & al., 2024).

Cross-sector studies reinforce these insights. In humanitarian supply chains, dynamic capabilities like agility and resilience enabled by AI-driven analytics enhance operational responsiveness (Dubey & al., 2022). Public-sector research stresses that AI integration into emergency management depends on adaptive organisational cultures fostering collaborative decision-making (Misra & al., 2024).

Despite its contributions, the dynamic capabilities perspective faces critiques of conceptual ambiguity and measurement challenges, and it often identifies capabilities retrospectively rather than proactively (Guida & al., 2023). Researchers also caution against tautological reasoning and note overlaps with other frameworks such as the resource-based view (Tigges & al., 2024). Recent literature advocates more precise, process-focused definitions and recommends integrating dynamic capabilities theory with complementary perspectives to enhance explanatory clarity (Chatterjee & al., 2021; Dubey & al., 2022).

III Resource-Based View (RBV)

The Resource-Based View (RBV) posits that sustained operational advantage stems from resources and capabilities characterised by value, rarity, inimitability, and organisational alignment (VRIO). In operational management, RBV clarifies how distinctive AI assets represent superior differentiation.

Operational research frequently applies RBV to identify critical AI assets, such as proprietary datasets, specialised algorithms, and skilled personnel, that yield durable operational benefits. Studies in manufacturing highlight the importance of organisational factors, including digital competencies and R&D intensity, in enhancing AI-driven production (Kinkel & al., 2021). Similarly, research on supply chain management emphasises that AI-enabled analytics, combined with workforce expertise, significantly enhances operational sustainability and circular economy capabilities (Bag & al., 2020).

RBV literature consistently indicates that AI's operational value relies heavily on effective internal resource management. For instance, humanitarian supply chains leveraging unique AI-driven analytics achieve superior agility and resilience, highlighting the difficulty of replicating practice-based resources (Dubey & al., 2022). Automotive industry research also shows that tailored resource configurations facilitate AI adoption, thereby enhancing sustainability practices (Bag & al., 2020).

Nevertheless, RBV faces criticism concerning its assumption of resource durability, as rapidly evolving AI technologies may become quickly replicable or obsolete (Ameye & al., 2023). Also, RBV's internal focus tends to underestimate external influences such as global production trends, regulatory dynamics, and ecosystem partnerships (Kinkel & al., 2021). Consequently, recent operational studies advocate integrating RBV with dynamic capabilities and ecosystem frameworks to capture better AI's complex operational impacts (Bag & al., 2020; Dubey & al., 2022).

IV Diffusion of Innovation Theory

Diffusion of Innovation Theory is central to understanding how AI technologies are operationally embedded in organisations. Empirical research, notably in finance, highlights how early adoption yields operational benefits primarily when organisations proactively engage in regulatory dialogue and cultivate technical expertise, effectively mitigating adoption barriers (Misra & al., 2023). In the public sector, research employing interpretive structural modelling further refines this, showing AI adoption depends on data governance, ethical frameworks, and managerial alignment with decision-making processes (Misra & al., 2023). Additionally, user trust and organisational resistance significantly shape AI diffusion, with studies in hospitality revealing that concerns about job security and system reliability directly affect adoption rates (Chen & al., 2020; Leong & al., 2024).

However, the linear assumptions inherent in diffusion theory overlook the iterative, context-dependent nature of organisational learning and technological integration, often driven by external regulatory shifts or data infrastructure constraints. Consequently, recent scholarship emphasises theoretical pluralism, integrating diffusion theory with institutional and resource-based perspectives to capture the nuanced dynamics of AI's operational integration.

V Knowledge-Based View (KBV)

The Knowledge-Based View (KBV) extends the Resource-Based View by highlighting knowledge, comprising information, skills, and intellectual capital, as pivotal for sustained operational advantage. Its application to AI underscores the significance of knowledge generation, integration, and deployment in operational contexts. Empirical studies in sectors like digital manufacturing emphasise firms' absorptive capacity to effectively leverage AI-generated knowledge for innovation (Chatterjee & al., 2021). Similarly, research in supply chain and healthcare operations illustrates how AI-driven decision-support tools enhance information processing, foster innovation, and institutionalise operational best practices when accompanied by robust knowledge management routines (Wamba & al., 2023; Koponen & al., 2024; Lysø & al., 2024).

Nevertheless, KBV's traditional human-centric approach poses challenges in AI contexts, where non-human repositories, such as predictive models and large-scale databases, increasingly dominate organisational knowledge landscapes (Lee & al., 2023). Organisations must therefore evolve sophisticated mechanisms for filtering, evaluating, and operationally embedding AI-generated insights to prevent informational overload and decision inertia (Chopra & al., 2024; Shuqair & al., 2024; Cooper, 2024). Integrating KBV with dynamic capabilities and human-centred frameworks provides a more comprehensive understanding of AI's operational role, clarifying how human and machine-generated knowledge jointly shape organisational effectiveness.

VI Institutional Theory

Institutional theory explains how organisational regulatory, normative, and cultural contexts influence AI adoption. Empirical studies in manufacturing and supply chain highlight how regulatory demands, stakeholder expectations, and industry standards shape AI operational integration (Bag & al., 2020; Sienkiewicz-Małyjurek, 2023). For instance, South African manufacturing sectors respond to external pressures by aligning operational skills and processes toward sustainability and circular economy goals, combining institutional and resource-based perspectives (Cordella & Gualdi, 2024).

In public administration, institutional factors such as transparency, ethical accountability, and procedural fairness significantly impact AI decisions, reflecting a broader need to align operational practices with stakeholder values and legitimacy, particularly evident in European contexts (Zuiderwijk & al., 2021; Kinder & al., 2023). Operational diffusion of AI frequently arises through isomorphic pressures, in which firms adopt technologies to signal legitimacy or conformity, even without an immediate economic justification, thereby accelerating AI diffusion in uncertain environments (Wilson, 2021; Ameye & al., 2023).

Institutional theory also highlights operational barriers, such as regulatory uncertainty, divergent stakeholder interests, and media scrutiny, which shape the outcomes of AI initiatives, such as environmental performance and innovation (Sienkiewicz-Małyjurek, 2023; Hussain & al., 2024; Wang & al., 2025). Despite its explanatory strength, institutional theory risks underestimating organisational agency and the dynamic nature of AI technologies, prompting recent scholarship to integrate it with stakeholder engagement, governance, and dynamic capabilities frameworks for a richer understanding of operational AI adoption (Bosse & al., 2022; Misra & al., 2024).

VII Disruptive Innovation Theory (DIT)

Disruptive Innovation Theory (DIT) examines how AI technologies initially penetrate markets by targeting underserved segments with simpler, affordable offerings, subsequently displacing established firms. Recent studies illustrate this in sectors such as marketing, where generative AI enables smaller agencies to challenge incumbents by initially catering to lower-tier segments before expanding upward (Rusthollkarhu & al., 2022; Ghouri & al., 2022). In healthcare and finance, debate persists over AI's genuinely disruptive potential versus incremental improvement, although fintech and educational AI startups increasingly demonstrate disruptive market-entry patterns (Lysø & al., 2024; Shuqair & al., 2024; Pan & al., 2024; Kumar & al., 2024).

Operationally, incumbents respond either by integrating AI (sustaining innovation) or delaying adaptation, risking displacement (Abou-Foul & al., 2022; Modgil & al., 2024). Nonetheless, the theory faces critiques: its retrospective nature complicates the prediction of true disruption, and AI adoption often deviates from classical low-end encroachment, sometimes directly serving incumbents' competitive advantage (Kinkel & al., 2021; Ameye & al., 2023). Additionally, DIT underplays ethical, social, and regulatory disruptions associated with AI.

Scholars thus recommend complementing DIT with diffusion, institutional, or sociotechnical perspectives to capture AI's nuanced market impacts and operational implications robustly (Papagiannidis & al., 2025; Yaroson & al., 2025).

Table 2. Summary of findings

Theory	Research question	Finding and Key Recommendations	References
Technology Acceptance Model	What organisational factors significantly enhance user acceptance of AI technologies? How should TAM be adapted to incorporate trust and ethical considerations specific to AI?	User acceptance of AI is significantly enhanced by management support, targeted training, and user involvement, which improve perceived usefulness. Empirical studies highlight the need to extend TAM to include constructs such as trust and ethical considerations, particularly for operational integration in regulated sectors like healthcare, hospitality, and finance. These adaptations help predict and improve adoption, address operational resistance, and ensure AI usage.	Chatterjee & al. (2021); Shuqair & al. (2024); Misra & al. (2024); Zhao & al. (2025)
Dynamic Capabilities	How do organisations build dynamic capabilities for successful AI adoption and continuous adaptation? How do dynamic capabilities influence the impact of AI on operational performance?	Organisations develop AI-specific dynamic capabilities by investing in absorptive capacity, leadership, and agile processes. Successful AI adoption is enabled by continuous learning and a culture of experimentation. Dynamic capabilities are shown to moderate the relationship between AI adoption and organisational performance, enabling adaptation and innovation in sectors such as finance, manufacturing, and public.	Guida & al. (2023): Yu & al. (2024); Gyau & al. (2024)
Resource-Based View	What makes AI-related resources valuable, rare, and difficult to imitate in operations? How do firms align internal AI resources with the external environment for sustained advantage?	AI-related resources are valuable when they are proprietary (unique data, custom models, skilled personnel), difficult to imitate, and deeply embedded in organisational routines. Sustained advantage depends on continuous recombination, skill development, and effective alignment with changing external demands. RBV's static limitations can be addressed by integrating dynamic and ecosystem perspectives.	Bag & al. (2020); Kinkel & al. (2021); Dubey & al. (2022)
Diffusion of Innovation Theory	What drives the adoption and spread of AI in operational contexts? How do communication and institutional context affect AI diffusion?	Adoption and diffusion of AI follow sequential phases, influenced by organisational communication, leadership advocacy, and stakeholder engagement. Early adoption delivers operational advantages, but challenges include overcoming resistance, building trust, and aligning with ethical and regulatory standards. Diffusion theory is enhanced by integration with institutional and stakeholder perspectives to account for recursive learning and systemic constraints.	Chen & al. (2020); Misra & al. (2023); Leong & al. (2024)
Knowledge-Based View	How do organisations leverage AI-generated knowledge for operational advantage? What knowledge management practices support AI-driven innovation?	Operational integration of AI-generated knowledge requires high absorptive capacity, knowledge management, and explicit-tacit knowledge conversion. AI amplifies organisational learning and accelerates knowledge sharing, leading to innovation and adaptability. Effective practices include filtering, contextualising, and integrating AI outputs with human expertise. KBV also raises new questions about the governance of non-human knowledge repositories and overcoming information overload.	Wamba & al. (2023); Koponen & al. (2024); Lysø & al. (2024)
Institutional Theory	How do external regulatory, normative, and cultural environments shape AI adoption and use? What institutional pressures and actors influence responsible and legitimate AI integration?	External pressures (regulation, stakeholder expectations, industry norms) strongly shape AI adoption and implementation. Organisations adopt AI to gain legitimacy, meet ethical standards, and align with societal values, especially in the public sector and highly regulated industries. Institutional theory explains both drivers and barriers, but must be integrated with agency and technical perspectives to address rapid innovation and individual responses.	Zuiderwijk & al. (2021); Wilson (2021); Sienkiewicz-Małyjurek (2023); Wang & al. (2025)
Disruptive Innovation Theory	Under what conditions does AI act as a disruptive innovation? How should incumbents respond to disruptive AI technologies?	AI acts as a disruptive innovation when it targets neglected segments with cost-effective solutions and eventually challenges incumbents. Incumbents should identify disruptive threats early, invest in agility, and adapt business models proactively. The theory's retrospective bias and limited treatment of social/ethical disruption require complementary approaches for nuanced application in AI strategy.	Rustholkarhu & al. (2022); Ameye & al. (2023); Akhtar & al. (2024)

5. CONCLUSION

This systematic literature review aimed to map and synthesise the theoretical underpinnings of AI operationalisation in management, identify dominant frameworks and their sector-specific applications, and address literature fragmentation to guide integration strategies. The objective was achieved through a PRISMA-guided analysis of 200 peer-reviewed studies (2020-2025), resulting in the creation of a synthesis of seven key frameworks (e.g., TAM, RBV, Dynamic Capabilities) and revealing nuanced sectoral patterns, such as TAM's prevalence in user-intensive domains like healthcare and hospitality, contrasted with RBV's dominance in resource-heavy sectors like research (see Table 1). By harmonising fragmented insights on enablers such as organisational adaptability and barriers such as ethical risks, the review not only clarifies AI's multifaceted operational impact but also delivers guidance, including prioritising knowledge management and user trust for resilient adoption (Chatterjee et al., 2021; Zhao et al., 2025). This synthesis bridges the theory-practice divide, validating the review's timeliness amid the rise of generative AI and laying a foundation for future multi-framework inquiries.

This review synthesises two hundred peer-reviewed studies to trace the growing operational role of Artificial Intelligence (AI) across sectors. AI has shifted from a peripheral tool to a core infrastructure for process optimisation, resilience, and continuous improvement.

Sectoral patterns emerge in theoretical application: Dynamic Capabilities and Resource-Based View dominate in public, energy, and manufacturing settings, where resource alignment and adaptive routines are critical. In contrast, the Knowledge-Based View is central to human resource management, where learning and expertise underpin effective AI integration.

In user-intensive sectors such as hospitality, healthcare, and finance, the Technology Acceptance Model (TAM) explains adoption by highlighting the importance of trust, usability, and user attitudes. Finance also illustrates how Disruptive Innovation Theory captures AI-driven operational upheavals and market realignments. Institutional and diffusion theories complement these views, situating AI deployment within broader regulatory and normative environments.

Together, these frameworks show that AI's operationalisation is multifaceted, encompassing technology, knowledge, institutions, and people. Successful integration hinges on aligning systems with organisational processes, institutional constraints, and workforce capabilities.

Future research should embrace multi-framework models to reflect this complexity, broaden the empirical focus to underexplored sectors such as agriculture, education, and the public domain, and examine human factors, such as training and ethics, in routine AI use. These efforts will be vital to advancing both scholarship and practice in operational AI.

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ПРЕОБЛИКОВАЊЕ ОПЕРАТИВНОГ МЕНАЏМЕНТА ПРИМЕНОМ ВЕШТАЧКЕ ИНТЕЛИГЕНЦИЈЕ: СИСТЕМАТСКИ ПРЕГЛЕД ЛИТЕРАТУРЕ

Џером Ламберт

Извод

Овај систематски преглед литературе објективно синтетизује и разјашњава начине на које организације операционализују вештачку интелигенцију (ВИ) у свакодневном процесу доношења одлука, са циљем објашњења разлога фрагментираности емпиријских доказа о контекстуалној интеграцији ВИ у условима убрзаног технолошког развоја (нпр. усвајања генеративне вештачке интелигенције након 2023. године). На основу анализе 200 рецензираних научних радова објављених у периоду 2020–2025. године, спроведене применом PRISMA методологије, идентификовано је и мапирано седам кључних теоријских оквира у различитим привредним и друштвеним секторима.

Резултати указују да успешне стратегије оперативне примене вештачке интелигенције не зависе искључиво од техничких ресурса, већ и од организационе прилагодљивости, управљања знањем и прихватања технологије од стране корисника. Оквири засновани на ресурсима и способностима доминирају у јавној управи и научноистраживачкој делатности; модели интеграције знања и прихватања технологије преовлађују у здравству, управљању људским ресурсима и угоститељству; док теорија дисруптивних иновација има значајну улогу у тумачењу динамике финансијског сектора.

Оригиналност рада огледа се у теоријски утемељеној синтези фрагментиране литературе, која омогућава јасније разумевање оперативног утицаја вештачке интелигенције у различитим контекстима и пружа релевантне смернице прилагођене специфичностима појединих сектора за руководиоце који се суочавају са изазовима њеног увођења. Ограничења истраживања односе се на искључивање литературе објављене на језицима који нису енглески, као и такозване сиве литературе. Практичне препоруке указују на потребу да менаџери посебну пажњу посвете управљању знањем, транспарентности и организационој агилности. Преглед такође нуди сажет истраживачки оквир за будућа проучавања и практичне смернице за ефикасно управљање интеграцијом вештачке интелигенције у оперативне процесе.

Кључне речи: вештачка интелигенција, оперативни менаџмент, менаџмент иновација, приступ заснован на ресурсима, динамичке способности, дисруптивне иновације

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