Gordon Institute of Business Science
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A Structured Literature Review on AI-Driven Operations: Exploring Disruption, Human Value, and Implementation Challenges

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A research project submitted to the Gordon Institute of Business Science, University of Pretoria, in partial fulfilment of the requirements for the degree of Master of Philosophy in Evidence-based Management.

30 June 2025

Abstract

This structured literature review explores how artificial intelligence (AI) is reshaping operations management through three interconnected lenses: disruption of traditional operational models, evolving forms of human participation, and the persistent gap between strategic intent and implementation. Drawing on 58 peer-reviewed studies across multiple sectors, the review identifies how AI reconfigures decision-making structures, challenges established routines, and introduces new organisational tensions. It highlights that effective AI integration depends not only on technological readiness but also on trust, governance, contextual alignment, and human capability. The review contributes a nuanced understanding of AI-driven operations and responds to recent calls for operations management scholarship to engage more deeply with the complexities of AI implementation. It concludes by proposing future research directions focused on human-AI collaboration, context-sensitive deployment strategies, and the development of governance models that balance performance, accountability, and adaptability.

Keywords

Artificial Intelligence;
Operations Management;
AI Implementation;
Human-AI Collaboration

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Philosophy in Evidence Based Management at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

30 June 2025

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Name & Surname Signature

Acknowledgements

I am deeply grateful to my supervisors, Professor Anastasia Mamabolo and Dr Kelly Alexander, for their invaluable guidance, thoughtful feedback, and steady encouragement throughout this research journey. Your insight and support have pushed me to think more critically, write more intentionally, and trust the process even when it felt uncertain.

To my friends and family, thank you for standing beside me with unwavering belief. A special thank you to Nthabiseng, your quiet strength, constant reassurance, and faith in me have meant more than words can capture.

I would also like to express my heartfelt thanks to my mentor and boss, Mr Mothupi Modiba. Your leadership has been both inspiring and empowering. Thank you for not only granting me the space to grow professionally, but for challenging me to dream bigger, aim higher, and show up with courage and purpose, even in the face of complexity.

For my father, Linda Ntshalintshali, Nompumelelo (Tsitsi) Ntshalintshali, Hellen (Maye) and Muzimkhulu (Mkulu) Ntshalintshali, niphila kimi. Ngizokwenza niziqhenye ngami kuze kube phakade.

BoNdwandwe, bakwaZwide kaLanga!
Nina baseGudunkomo.
maNtshalintshali Amahle!
Khanuka!

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Chapter 1: Introduction to the review problem

1.1 Introduction

Scholarly interest in artificial intelligence (AI) has intensified within contemporary Operations Management (Dhamija & Bag, 2020a; Kumar et al., 2022), a field traditionally focused on the design, coordination, and improvement of organisational processes in production and service environments (Roth & Menor, 2003). While Operations Management's roots lie in manufacturing and logistics, its scope has expanded to include digital services, knowledge-intensive workflows, and data-driven decision-making (Pilkington & Meredith, 2009). Operations Management now engages with challenges such as supply chain coordination, service optimisation, and operational analytics (M. Li et al., 2025). These require a balance between technical systems, human expertise, and cross-functional collaboration (Taylor & Taylor, 2009).

Within the growing interest in AI integration across contemporary Operations Management (D. T. W. Wong & Ngai, 2025), this review defines AI-driven operations as the strategic application of AI technologies to optimise, augment, or redesign core organisational processes (Borges et al., 2021; Davenport, 2018) in pursuit of improved performance, adaptability, and decision-making (Wamba-Taguimdje et al., 2020). This construct emphasises not only technical integration but also the transformation of operational practices (e.g., workflow automation) and capabilities (e.g., adaptive scheduling) through AI-enabled systems (Benbya et al., 2021; Wei & Pardo, 2022). Rather than representing a purely technical shift, AI adoption often alters decision structures, role boundaries, and the ways in which value is co-created across people, technologies, and processes in Operations Management (Paschen et al., 2020).

Artificial Intelligence refers to technologies capable of performing tasks traditionally associated with human cognition, such as reasoning, learning, and adaptation (Collins et al., 2021). These tools have evolved from early rule-based systems to more sophisticated forms, including generative AI and real-time decision engines, enabling increasingly autonomous, data-driven operations (Haenlein & Kaplan, 2019). In this review, AI is treated not as a fixed toolset, but as a socio-technical system (Mariani, Machado, & Nambisan, 2023) that both shapes and is shaped by the organisational contexts in which it is deployed (Chaudhuri et al., 2024). Techniques such as predictive analytics, natural language processing, and adaptive learning are considered not in isolation, but in terms of how they integrate with human judgment and reshape operational workflows (Chowdhury et al., 2023).

Across operational domains, organisations are increasingly turning to data-informed technologies such as AI to enhance how processes are designed, monitored, and adapted (Huang & Rust, 2018). The role of AI has progressively evolved beyond automation (Barfar et al., 2017), offering upstream value in problem diagnosis, demand forecasting, and strategic decision-making (Xu et al., 2024). In Operations Management, optimisation traditionally refers to the design of processes that achieve maximum efficiency, consistency, and throughput (Chaudhuri et al., 2024). However, in AI-enabled environments, optimisation increasingly involves adaptability, predictive responsiveness, and cross-functional coordination to improve organisational performance, productivity, and efficiency, especially as algorithmic systems influence how performance is defined and pursued (Baptista et al., 2020; Dwivedi et al., 2021).

This shift introduces a conceptual tension (Jarrahi, 2018), while optimisation has traditionally been treated as a technical goal, AI-enabled environments reveal it to be a negotiated, context-dependent process (Berente et al., 2021). Moreover, as organisations increasingly adopt AI or scale from pilot projects to enterprise-wide systems, implementation failures have emerged as a critical barrier to operational value (Mariani, Machado, & Nambisan, 2023), partly because AI does not simply support existing systems but reconfigures the very meaning of optimisation, reshaping how it is conceptualised and measured (Dwivedi et al., 2021).

In the literature, implementation (including adoption and integration) is not merely a technical challenge but a dynamic, context-dependent process shaped by how organisational actors interpret, adapt, and negotiate the role of AI in practice (Engström et al., 2024; Maragno et al., 2023). Contrary to linear deployment models (Veale & Brass, 2019), this review adopts a non-linear perspective, positioning implementation as an ongoing sociotechnical negotiation shaped by contextual dynamics, actor interpretations, and iterative adaptation (Glaser et al., 2021; Lee et al., 2023). AI systems disrupt stable routines, redefine workflows, and recalibrate human–machine collaboration (Fogliato et al., 2022). These evolving dynamics prompt new questions about how optimisation is enacted, who participates in its success, and what trade-offs emerge when operational systems are reorganised around algorithmic reasoning. This review examines scholarly perspectives on AI-driven operations in Operations Management, with particular attention to how disruption, human participation, and implementation tensions have been framed, explained, and theorised across the literature.

1.2 Background

Operations Management is undergoing a paradigm shift as AI enables more responsive approaches to uncertainty and complexity (Spieske & Birkel, 2021). Accelerated by digital transformation, post-pandemic volatility, and competitive pressures, this transition is fundamentally reshaping process design and execution (Ghobakhloo et al., 2023). Where traditional operational models prioritised standardised efficiency (Yigitcanlar et al., 2024), AI introduces predictive capabilities and dynamic problem-solving that challenge conventional practices (Karatas et al., 2022). However, persistent gaps remain between AI's theoretical promise and operational reality, often due to implementation barriers such as change resistance, skills deficits, data limitations, and system misalignment (Dogru & Keskin, 2020; Kraus et al., 2022; Paschen et al., 2020).

Algorithmic approaches like Ant Colony Optimization (ACO), inspired by the collective foraging behaviour of real ant colonies (S. Li et al., 2018), have demonstrated measurable success in structured operational domains such as mechanical engineering, particularly in inventory management and production scheduling (Mahat et al., 2023). AI-driven models have been effectively applied to churn prediction and personalised pricing strategies in telecommunications (Ortakci & Seker, 2024). However, implementation becomes significantly more challenging in dynamic service operations characterised by high variability, knowledge-intensive work, or customer interaction (Mariani & Borghi, 2024). Here, traditional assumptions of stability and linear causality (Rust & Huang, 2012) often fail to hold, while organisational barriers, including change resistance, data limitations, and functional silos, compound technical challenges (Bienhaus & Haddud, 2018).

Effective AI implementation is not merely a technical rollout but a driver of organisational transformation (Barrett et al., 2012), requiring reinterpretation of performance criteria (e.g., balancing efficiency with service empathy) (Hult et al., 2022), negotiation of decision-making boundaries, and alignment of implementation approaches with operational realities (Merhi, 2023). Current literature tends to examine either technical performance or human factors in isolation, leaving critical gaps in understanding their interaction during real-world adoption (Lee et al., 2023; Orlikowski, 1992).

These gaps become visible when examining how operational actors, from managers interpreting AI recommendations to frontline staff adapting workflows, co-construct optimisation in practice, often deviating from purely technical designs (Engström et al., 2024). For instance, studies optimising logistics AI ignore how dispatchers override ‘ideal’ route due to local knowledge (Álvarez et al., 2024). Similarly, research on how workers adapt to AI often doesn’t connect their behaviour to technical problems, like when people stop using a system due to delays in software updates (Makridis & Han, 2021). This siloing obscures why technically sound AI fails in practice, and how human-machine tensions might be resolved.

Taken together, these developments highlight the need to move beyond static accounts of AI capability toward a situated understanding of how optimisation unfolds in practice. Organisational factors such as readiness, interpretation, and competing priorities shape implementation outcomes (Kraus et al., 2022), yet these dynamics remain underexplored. This review addresses this gap by examining how the human and technical dimensions of AI-driven operations are conceptualised across the literature.

1.3 Problem statement

Despite growing interest in AI for operational optimisation, conceptual tension persists in the literature, most notably, a tendency to prioritise technical capability (such as automation potential) while under-theorising the messy, context-sensitive dynamics of human-machine collaboration and implementation (Chowdhury et al., 2022; Dwivedi et al., 2021; Shaw et al., 2019). This gap is particularly pressing as AI moves from strategic considerations to operational reality (Cao et al., 2021). With rapid advancements in generative AI and escalating competitive pressures, organisations face urgent demands to adopt AI technologies yet lack evidence-based frameworks for sustainable implementation (Chowdhury et al., 2022). Despite growing investment, many organisations continue to struggle with execution, underscoring the need for scholarship that addresses the cluttered, interpretive work of implementation (Lee et al., 2023).

This review responds to these limitations by examining how AI-driven operations are framed and operationalised across the literature, with attention to three neglected yet interrelated areas: (1) how AI disrupts and reconfigures traditional operational models, generating new theoretical insights; (2) how human participation (including interpretation, adaptation, and resistance) shapes the realisation of value; and (3) how implementation unfolds as a dynamic, context-sensitive process mediated by organisational structures and priorities. By treating implementation not as a linear deployment phase but as a contested, ongoing negotiation between human and technical systems, the review offers both conceptual and practical contribution to the field of Operations Management (Cao et al., 2021; Chowdhury et al., 2022). The review deliberately confines itself to the intersection of AI capability and organisational implementation (Dwivedi et al., 2021), emphasising interpretive, contextual, and structural challenges that mediate AI's impact on operational optimisation (Stouten et al., 2018; Volberda et al., 2021).

1.4 Prior studies and review rationale

While interest in AI for operational optimisation has grown (Al Amin et al., 2024), much of the existing review literature remains bounded by either domain-specific or function-specific concerns, limiting its contribution to broader organisational inquiry, particularly around implementation. Numerous structured literature reviews have examined AI across domains such as healthcare (Al-Assaf et al., 2024; Jocelyn Chew & Achananuparp, 2022), public administration (Babšek et al., 2025; Caiza et al., 2024), and services (Bock et al., 2020; Gkioka et al., 2023), but these studies remain largely fragmented. While each contributes useful perspectives on adoption, ethics, or system capabilities (Jocelyn Chew & Achananuparp, 2022; Zhao et al., 2021), and even fewer engage meaningfully with implementation as an organisational process (Dwivedi et al., 2021; Wamba-Taguimdje et al., 2020).

Notably, Lee et al. (2023) have synthesised high-level insights into AI implementation across organisational contexts, a disciplinary and theoretical gap remains. Despite growing research on adoption of AI across operational domains, no systematic literature review to date has explicitly examined implementation as a core conceptual and analytical focus within the discipline of Operations Management (Dhamija & Bag, 2020b; Mithas et al., 2022; Venkatesh et al., 2024). A targeted review of both peer-reviewed and grey literature revealed only limited and often peripheral engagement with implementation, typically situated outside Operations Management journals and rarely grounded in Operations Management-specific theories (Liu et al., 2024). As such, existing reviews tend to treat implementation as a technical stage of system rollout rather than as a dynamic organisational process shaped by human interpretation, adaptation, and resistance (Zhou et al., 2022).

In sum, while prior reviews offer valuable perspectives on adoption, ethics, performance, and theory development, few engage implementation as a dynamic, contested organisational process (Stouten et al., 2018; Volberda et al., 2021). Most treat it as a technical phase to be completed, rather than a condition that shapes AI's long-term effectiveness (Newell & Marabelli, 2015). This review addresses that gap by positioning implementation not as an endpoint, but as a lens for reinterpreting the meaning, value, and evolution of AI-driven operations in practice.

1.5 Purpose and review questions

The purpose of this structured literature review is twofold. Academically, it seeks to consolidate, critique, and advance scholarly understanding of AI-driven operations by examining its implementation dynamics. Practically, it aims to generate insight into the organisational conditions and trade-offs that shape whether AI implementations deliver their intended value. To this end, the review is guided by three interrelated review questions:

1. **RQ1:** How has AI disrupted traditional operational models, and what new theoretical insights have emerged from these disruptions?
2. **RQ2:** How does human participation shape value creation in AI-driven operations, and what trade-offs arise?
3. **RQ3:** What tensions exist between the goals of AI-driven operations and the operational realities of implementation across different organisational contexts?

Together, these questions support the review's overarching aim: to understand how AI-driven operations are being implemented, where conceptual advances have occurred, and where further theoretical and practical development is needed.

1.6 Structure of the review

The remainder of this review is organised as follows. Chapter 2 outlines the methodology, including the review protocol, search strategy, and selection criteria. Chapter 3 presents the findings from the literature, offering a descriptive and thematic overview of the selected studies. Chapter 4 synthesises the literature, drawing out conceptual patterns and tensions. Finally, Chapter 5 identifies questions for future research and concludes the review.

Chapter 2: Methodology

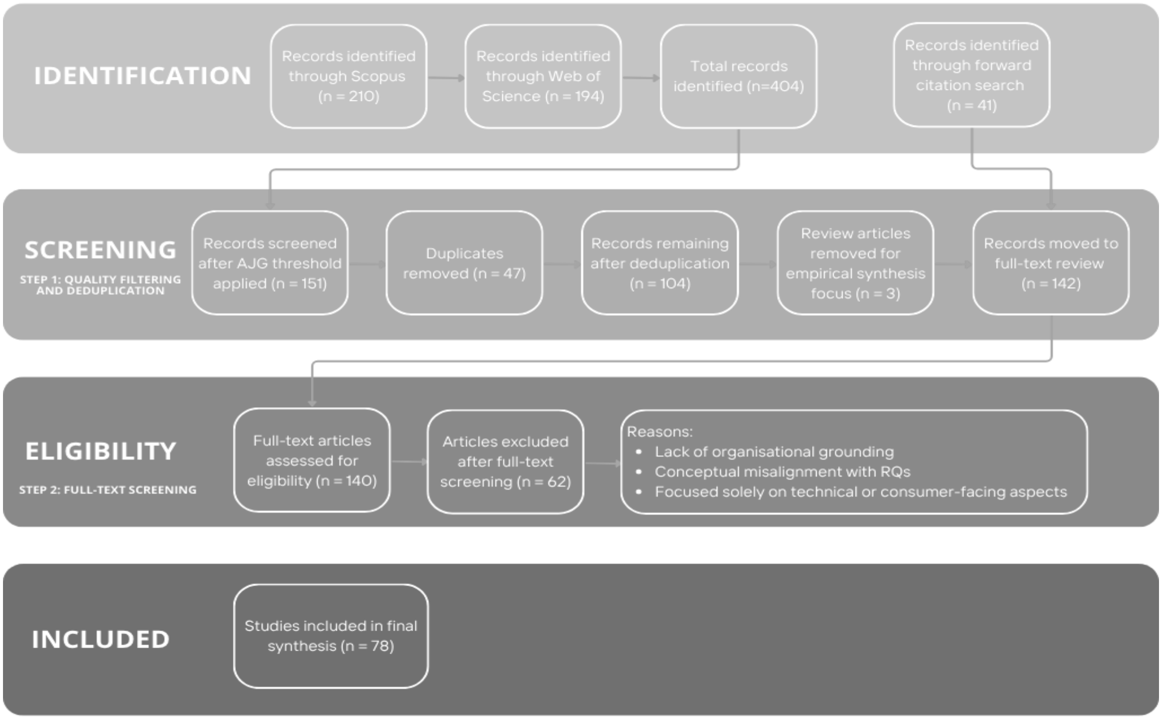
2.1 Introduction

This study adopts a Structured Literature Review (SLR), following the methodological framework of Kitchenham (2009), as a systematic and replicable approach to synthesising fragmented knowledge across disciplines. This method is particularly suited to investigating how the implementation of AI for operational optimisation reshapes, disrupts, or reinforces operational work models (Mariani, Machado, & Nambisan, 2023), because of the rapid evolution and cross-functional nature of the topic. Situated within contemporary Operations Management, the review defines AI-driven operations as the strategic application of AI technologies to optimise, augment, or redesign core organisational processes (Borges et al., 2021; Davenport, 2018) in pursuit of improved performance, adaptability, and decision-making (Wamba-Taguimdje et al., 2020).

To ensure rigour and transparency, this review adhered to the 2020 PRISMA guidelines (Page et al., 2021), adapted for use in management research. The process followed four PRISMA stages (identification, screening, eligibility, and inclusion) as illustrated in the flow diagram (Figure 1). These stages were operationalised through the following four methodological steps: (1) Identification: A structured search protocol was developed across Scopus and Web of Science, yielding 404 records. An additional 41 records were identified through forward citation tracking. (2) Screening: Records were screened using explicit inclusion and exclusion criteria, including journal quality thresholds (AJG 3-star and above), and duplicates were removed. (3) Eligibility: Full-text articles were assessed for conceptual alignment with the review questions and organisational relevance. (4) Inclusion: A final sample of 78 high-quality empirical studies was selected and subjected to critical appraisal to support synthesis and thematic integration.

In accordance with PRISMA's expectations regarding bias assessment, potential risks were addressed through the application of clear inclusion criteria (Zarate et al., 2022), a transparent selection process, and manual validation of the final sample to ensure conceptual alignment and analytical integrity (Polychronopoulos & Nguyen-Duc, 2024).

Figure 1: 2020 PRISMA-adapted flow diagram



Source: (Page et al., 2021; Zarate et al., 2022)

The remainder of this section details the review process. Section 2.2 presents the guiding review questions and explains their development. Sections 2.3 to 2.7 outline the search strategy, screening procedures, and methods for assessing quality and synthesising findings. Section 2.8 concludes by acknowledging the methodological limitations of the study.

2.2 Review questions

The purpose of this Structured Literature Review (SLR) is twofold. Academically, it seeks to consolidate, critique, and advance scholarly understanding (Selçuk, 2019) of AI-driven operations by examining how implementation processes reshape organisational systems (Chaudhuri et al., 2024). Practically, it aims to generate insight into the conditions and trade-offs that determine whether AI delivers its intended value in real-world settings (Chen et al., 2015). To support this purpose, the review is guided by three interrelated questions developed through a systematic interrogation of existing reviews in the field.

These review questions were not developed in isolation. Rather, they emerged through a detailed synthesis of prior SLRs, as outlined in Section 1.4. The analysis identified common limitations, including a tendency to prioritise technical and system-oriented perspectives, abstract discussions of integration, and insufficient attention to the realities of organisational implementation (Anjulo Lambebo & Chen, 2024; Fescioglu-Unver & Yıldız Aktaş, 2023; Jain et al., 2021; Kalnaovakul & Promsivapallop, 2023). Because these gaps reflect a disconnect between AI's potential and how it is actually operationalised in practice, this review poses three guiding questions.

First, how has AI disrupted traditional operational models, and what new theoretical insights have emerged from these disruptions? This question establishes a foundation by surfacing the paradigmatic shifts and innovation patterns prompted by AI. Second, how does human participation shape value creation in AI-driven operations, and what trade-offs arise? This question centres the human element, because prior reviews have rarely examined how individuals and teams influence or constrain implementation processes. Third, what tensions exist between the goals of AI-driven operations and the operational realities of implementation across different organisational contexts? This final question addresses the structural frictions, misalignments, and institutional constraints that shape whether AI initiatives succeed or stall.

Together, these questions reflect a coherent response to the limitations identified in prior research. They frame this review not as a technical inventory of AI capabilities, but as a theoretically informed investigation into how AI-driven operations unfold in practice, and what this means for both scholarship and organisational strategy.

2.3 Search strategy

To identify relevant literature, a structured search was conducted across two major academic databases: Web of Science (WoS) and Scopus. These databases were selected because they provide extensive coverage of high-quality peer-reviewed journals, particularly in the fields of management, operations research, and business studies, areas directly aligned with the review's organisational and implementation-focused aims (Christofi et al., 2021). Their inclusion also ensured disciplinary diversity and comprehensive retrieval of both conceptual and empirical work on AI in operational contexts.

The search strategy was carefully designed to surface literature capable of addressing the review's three guiding questions, which span technological disruption, human participation, and implementation tension. To achieve this, keywords were clustered around five conceptual anchors: (1) core AI technologies ("artificial intelligence" OR

"AI" OR "machine learning" OR "algorithm*"), (2) implementation processes (implement* OR adoption OR deployment OR "technology integration"), (3) operational domains ("operations management" OR "operational process*" OR "business operations" OR "service operations" OR "supply chain"), (4) organisational context (organization* OR firm* OR enterprise OR business), and (5) human and relational dimensions (manager* OR employee* OR user* OR practitioner* OR decision-maker* OR stakeholder* OR participat* OR interact* OR interpret* OR sensemaking OR engagement OR resistance OR trust OR perception OR behaviour). Boolean operators and truncation techniques were applied to accommodate disciplinary variation and maximise relevant retrieval.

Although the search strings do not include the phrase 'AI implementation' as a standalone clause, the Boolean combinations intentionally intersect 'AI' terminology with implementation-related constructs (e.g., implement*, adoption, deployment, integration). This approach aligns with best-practice SLR design by maximising coverage of both direct and adjacent terminology (Boell & Cecez-Kecmanovic, 2015; Snyder, 2019). Moreover, the search terms were clustered to reflect the conceptual overlap between implementation activity and operational integration, rather than limiting results to narrow phrase matches.

Initial searches were conducted without restrictions on time or region to allow for a comprehensive scan of the field. In later stages, refinements were introduced to ensure methodological and conceptual quality, limiting results to English-language studies published in peer-reviewed journals ranked three-star or higher on the Academic Journal Guide (Walker et al., 2019). The AJG is widely used in management scholarship to assess journal quality and disciplinary relevance (Coupe et al., 2010). These restrictions addressed concerns raised in earlier reviews about the inclusion of low-quality or non-comparable sources (Tranfield et al., 2003).

Domain-level filters were also applied in WoS and Scopus to limit results to relevant research areas (e.g., Business Economics, Operations Research/Management Science), excluding studies from computer science or engineering unless they directly addressed organisational implementation (Davenport & Ronanki, 2018). The subsequent screening and inclusion process is detailed in section 2.4.

2.4 Inclusion and exclusion criteria

The inclusion and exclusion criteria were developed to ensure that selected studies were conceptually aligned with the review's guiding questions and methodologically appropriate for a synthesis grounded in organisational inquiry (Bernerth & Aguinis, 2016). Because the aim of this review is to move beyond technical framings and into the socio-technical dimensions of AI implementation (Alvesson & Sandberg, 2011; Faraj et al., 2018) these criteria were structured to prioritise relevance, depth, and contextual insight over technical specificity or volume (Gioia et al., 2013).

2.4.1 Inclusion criteria

Studies were included if they met multiple criteria aligned with the review's dual focus on conceptual synthesis and practical relevance. First, only articles published in peer-reviewed journals rated three-star or higher on the AJG Journal List were considered (Walker et al., 2019). As outlined in the Academic Journal Guide Chartered Association of Business Schools (2024), these journals are recognised for their methodological rigour, conceptual contribution, and academic influence. This threshold was applied to ensure quality and address prior concerns about including studies lacking transparency or theoretical depth (Bernerth & Aguinis, 2016; Gioia et al., 2013; Page et al., 2021). Second, only English-language publications were included, consistent with database accessibility and standard academic practice (Chavarro et al., 2018).

Third, studies had to examine AI in relation to internal organisational operations, including service delivery, workflow coordination, supply chain management, or back-end decision-making (Linnenluecke et al., 2020). Both empirical and review articles were included. Finally, studies were required to demonstrate relevance to at least one of the review questions: disruption, human participation, or implementation tensions (Alexander, 2020).

2.4.2 Exclusion criteria

Exclusion criteria were developed to align with the review's conceptual scope and methodological aims (vom Brocke et al., 2015). Studies were excluded if they were not published in peer-reviewed journals ranked three-star or higher on the AJG Journal List (Walker et al., 2019), or if they failed to engage meaningfully with at least one of the review questions. Articles focused solely on algorithm development, system architecture, or engineering evaluations, without reference to organisational implementation, were excluded (Jaakkola, 2020). Similarly, studies situated in marketing, clinical, or public-sector contexts were removed unless they addressed internal operational processes (Grossnickle, 2016). Publications were also excluded during full-text screening if they lacked sufficient empirical or theoretical contribution, as defined in the inclusion parameters. This ensured that the final sample reflected both methodological rigour and conceptual relevance.

2.5 Screening and selection process

The screening and selection process followed a structured, two-stage approach to ensure conceptual relevance, methodological rigour, and alignment with the review's implementation focus (Jaakkola, 2020; vom Brocke et al., 2015). Given the aim to synthesise literature engaging critically with AI adoption in operational contexts, screening retained only studies that could meaningfully contribute to this synthesis (Xiao & Watson, 2019).

Following the search strategy outlined in Section 2.3, a total of 104 articles were retrieved after deduplication. These were reviewed across two stages: sectoral and disciplinary relevance (Stage 1) and conceptual fit (Stage 2), following the layered review logic recommended by Kitchenham (2009).

To address potential omissions due to indexing or keyword variability, a forward citation search was conducted using (Dubey et al., 2020), a highly cited anchor study with strong AJG standing and a direct focus on AI's operational impact. This process yielded 41 additional articles, which were screened for AJG ranking and conceptual fit, resulting in a broader and more representative sample.

2.5.1 Stage 1: Sectoral and disciplinary alignment

In the first stage, studies were reviewed for their relevance to the review's organisational and operational focus. Articles situated in a variety of domains (including healthcare, education, and public administration) were retained where they engaged substantively with internal organisational processes and AI implementation (Xiao & Watson, 2019). Studies were excluded only if they focused exclusively on technical architectures, algorithm development, or consumer-facing applications without organisational grounding (Jaakkola, 2020). This approach ensured that sectoral diversity was included where appropriate, while maintaining alignment with the review's conceptual scope

2.5.2 Stage 2: Conceptual fit

The second screening stage involved full-text review of all remaining articles to assess their conceptual alignment with the review's guiding questions, namely, AI-driven disruption, human participation, and implementation tensions (Thomé et al., 2016; Xiao & Watson, 2019). Articles were retained if they addressed the adoption, integration, or transformation of AI in operational contexts, with emphasis on organisational process change, role redefinition, or decision-making dynamics (Barnett-Page & Thomas, 2009). Studies that focused solely on abstract theory, consumer behaviour, or system performance without organisational grounding were excluded. Full-text screening provided sufficient granularity to assess relevance and quality. This resulted in a final inclusion set of 78 empirical and review studies, each directly contributing to the analytical scope of the review and situated within the broader field of Operations Management and organisational research. These studies form the basis for the data extraction and synthesis procedures detailed in the sections that follow.

2.6 Data extraction and coding

Data extraction and coding were conducted to support a thematic synthesis aligned with the review's overarching aim: to surface how AI implementation is experienced, interpreted, and shaped within organisational operations. Because the review is focused on organisational dynamics, such as workflow transformation, human-machine interaction, and implementation trade-offs, coding was designed to capture both manifest and latent themes across the selected literature (Gao et al., 2023; Gioia et al., 2013). A structured codebook (Appendix B) was developed directly from the three review questions, each of which reflects a distinct conceptual lens: disruption, human participation, and implementation tensions (Guest et al., 2012). This deductive anchor provided initial structure, but the coding process remained open to inductive emergence of subthemes and contextual nuance.

Table 1. Trading studies used to train Intentional AI Model in ATLAS.ti

Study ID / Citation	Selected for	Review Question(s)	Notes on Selection
(Al-Surmi et al., 2022)	Theory-oriented contribution	RQ1	Examines AI-related transformation within operations, contributing to theoretical perspectives on organisational change.
(Roux et al., 2023)	Multi-RQ alignment	RQ1, RQ2, RQ3	Addresses all three review questions through a multi-level analysis; conceptually aligned with the review's focus.
(Hasija & Esper, 2022)	Human dynamics focus	RQ2	Offers empirical reflection related to trust, reliance, and ethical considerations in AI–human interaction.
(Fosso Wamba et al., 2023)	Analytical framing on implementation	RQ3	Explores organisational barriers and integration challenges associated with AI implementation.
(Le & Behl, 2024)	Multi-level focus	RQ1, RQ3	Investigates strategic alignment, operational disruption, and resilience-focused implementation frameworks.

Source: Author

To mitigate interpretive bias and ensure analytical consistency, a hybrid thematic analysis approach was employed, combining machine-assisted coding using ATLAS.ti's Intentional AI feature with manual refinement (Gao et al., 2023). The analysis progressed through three distinct stages: initial coding, where researcher-defined criteria guided the tagging of relevant excerpts; category development, in which similar codes were grouped based on conceptual affinity; and theme generation, where broader patterns were identified in relation to the review questions (Guest et al., 2012). To support reliability, five conceptually rich studies were selected for AI training, as outlined in Table 1, ensuring the model was exposed to diverse perspectives aligned with the study's analytical aims (Atlas.ti, 2025; Friese et al., 2018). All machine-generated outputs were manually reviewed to remove redundancies, verify consistency, and refine boundary cases.

In line with data quality principles, the process incorporated an audit trail via ATLAS.ti's coding exports, and alignment checks with the review questions to maintain validity (Nowell et al., 2017). Although coding was conducted by a single researcher, reliability was supported through prolonged engagement with the data and systematic review of coded outputs (Guest et al., 2012). This combination of machine learning and researcher-guided synthesis strengthened the transparency and rigour of the findings (Friese et al., 2018). The final coded dataset forms the analytical foundation for the thematic synthesis presented in the next section.

2.7 Limitations

This review aimed to balance conceptual breadth with methodological rigour, but several limitations must be acknowledged. First, the study was limited to peer-reviewed journal articles indexed in Scopus and Web of Science and ranked three-star or higher on the AJG list (Chartered Association of Business Schools, 2024). While this threshold supported quality assurance, it may have excluded innovative or regionally relevant work published in less-established outlets or grey literature (Briscoe et al., 2020).

Second, only English-language studies were included. This reflects practical constraints related to language fluency and indexing coverage, but introduces a potential bias toward Anglophone perspectives in a globally relevant field (Martín-Martín et al., 2021). Third, while the review followed a rigorous coding process using a predefined framework, the study was coded by a single researcher. Despite efforts to ensure consistency, this introduces a degree of interpretive subjectivity and limits inter-coder reliability (Braun & Clarke, 2023).

Fourth, the exclusion of technical and consumer-facing studies, as well as macro-level policy discussions, narrows the lens to organisational implementation. This focus, while intentional, may omit external forces shaping operational dynamics in practice. Fifth, the synthesis draws on secondary data from published studies, meaning the quality, framing, and transparency of the primary sources shape the strength of the conclusions. While quality filters were applied, the limitations of the original studies may affect generalisability and thematic clarity (Xiao & Watson, 2019).

Lastly, the field of AI implementation remains emergent and conceptually fluid. The evolving nature of definitions and overlapping constructs presented challenges during search string design, screening, and synthesis, particularly in distinguishing between AI implementation, adoption, and integration, terms often used interchangeably but with different theoretical and practical implications (Dwivedi et al., 2021; Mariani, Machado, Magrelli, et al., 2023). These limitations do not undermine the validity of the review but should guide cautious interpretation of the findings, particularly in applying them to real-world implementation scenario (Braun & Clarke, 2023).

Chapter 3: Findings from the literature review

3 Introduction

This section presents the key findings of the structured literature review, organised according to the three guiding research questions. Each theme synthesises patterns across the literature to illuminate how AI is disrupting operational models, reshaping human roles, and exposing challenges in implementation.

3.1 Descriptive profile of the literature

This section offers a descriptive overview of the 58 peer-reviewed academic articles included in the final review sample (Appendix A). The analysis highlights patterns in publication characteristics, methodological choices, disciplinary and sectoral orientations, and theoretical foundations. These patterns provide insight into how the topic of AI-driven operations is being studied across different contexts and inform the interpretive synthesis that follows in Section 3.3.

3.1.1 Source and publication trends

All articles in the final sample were published in reputable, peer-reviewed journals, with the majority appearing in journals rated 3-star or higher on the Academic Journal Guide (AJG) list. These include top-tier publications in Operations Management, Information Systems, and Supply Chain Management, reflecting methodological rigour and disciplinary breadth. The spread of sources illustrates the cross-functional nature of AI implementation and signals a growing convergence between operations and digital technologies, particularly in contexts where AI is deployed to reshape organisational processes and decision structures.

Table 2. Academic journal distribution

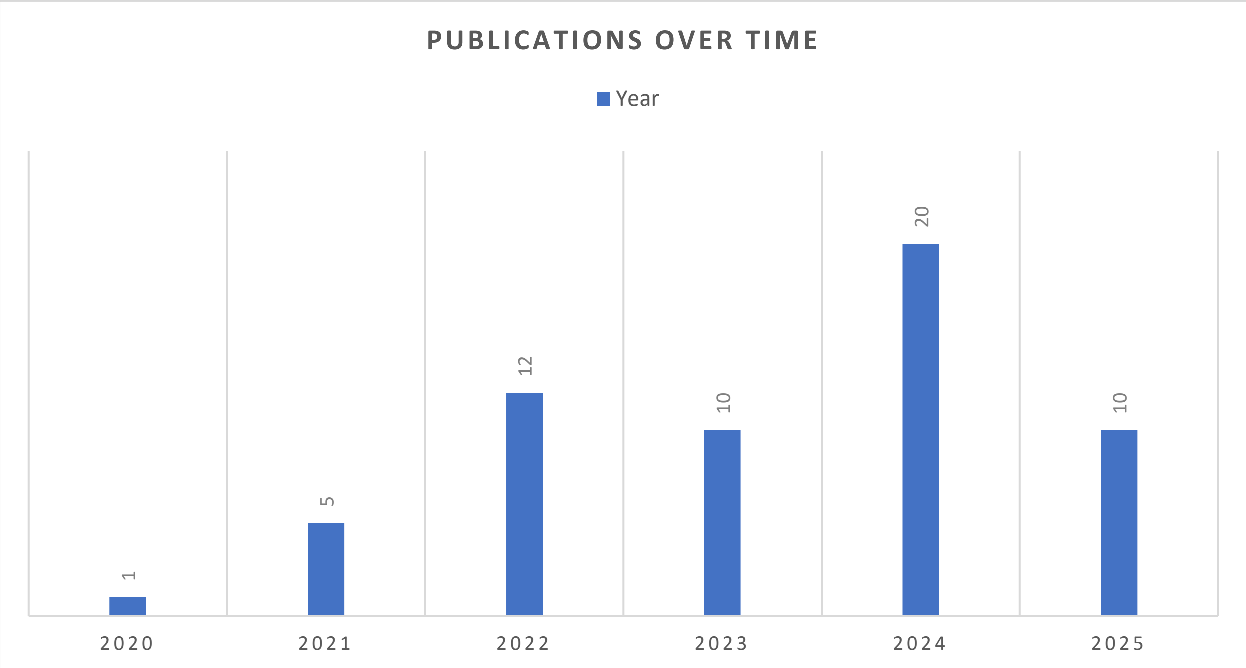
Journal Title	Disciplinary Area	No. of Articles
Technological Forecasting & Social Change	Technology	10
International Journal of Production Research	Production	9
International Journal of Production Economics	Production	8
Journal of Business Research	Business Management	5
Annals of Operations Research	Operations	3
Industrial Marketing Management	Marketing	5
IEEE Transactions on Engineering Management	Engineering Management	3
Production Planning & Control	Production	3
Journal of Business Logistics	Business Management	1
Business Strategy and the Environment	Business Management	1

Technovation	Technology	1
Journal of Supply Chain Management	Supply Chain	1
Information Systems Frontiers	Information Systems	1
Information & Management	Information Systems	1
The TQM Journal	Management Sciences & Operations	1
Supply Chain Management: An International Journal	Supply Chain	1
Energy Economics	Energy Economics & Finance	1
International Journal of Operations & Production Management	Operations and Production	1
Production and Operations Management	Operations and Production	1
European Journal of Information Systems	Information Systems	1
Total		**N = 58**

Source: Author

Of the 58 reviewed articles, the majority were published in Operations and Productions Management journals (n = 25), followed by Information Systems (n = 3) and Technology & Innovation Management (n = 11).

Figure 2. Publications over time



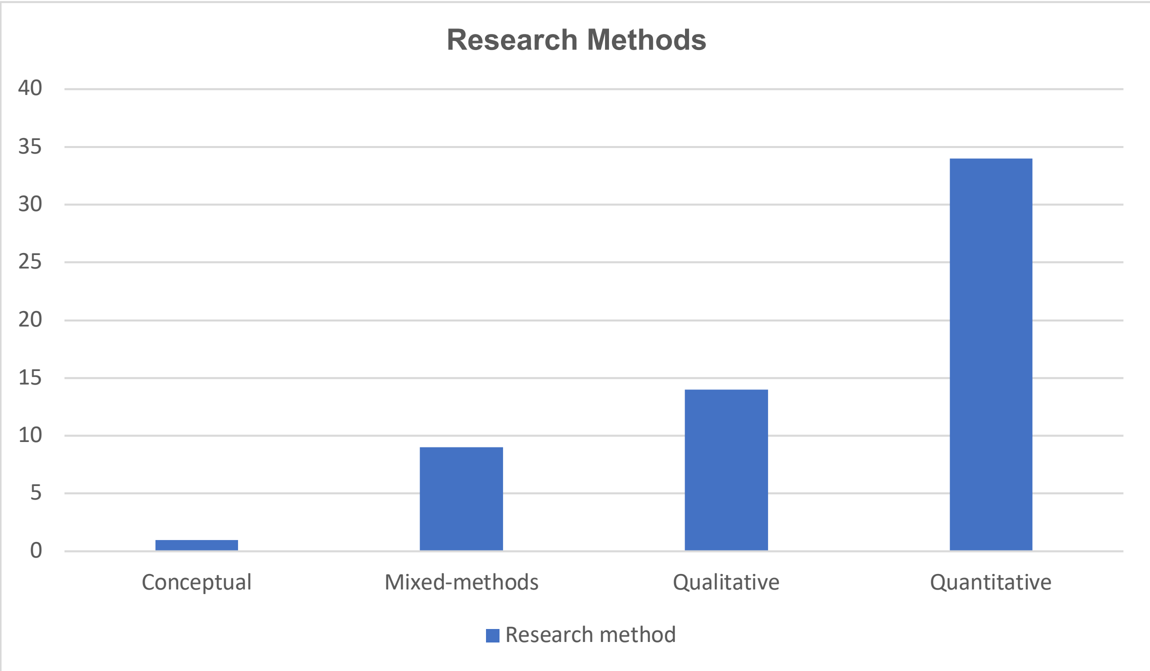
Source: Author

3.1.2 Research methods and trends

The reviewed literature reflects a diverse mix of methodological approaches. Quantitative empirical studies form the majority of the sample, with survey-based designs commonly used to analyse patterns in AI adoption, performance outcomes, and integration enablers. Qualitative case studies offer contextuality, providing insight on the organisational dynamics of implementation, such as cultural, structural, and leadership-related influences.

Conceptual papers, though fewer in number, contribute important theoretical advancements, particularly in emerging areas like algorithmic governance, human-machine interaction, and operational transparency. This methodological distribution underscores the field's growing trend of multi-method inquiry (Figure 3.) to capture both systemic and situated dimensions of AI-driven change.

Figure 3. Research methods



Source: Author

3.1.3 Sectoral and geographic distribution

AI-driven operations research is concentrated in a limited set of sectors, most notably manufacturing, logistics, and healthcare, where operational complexity, digital maturity, and data infrastructure are relatively advanced. These sectors offer fertile ground for integrating AI into core operational functions such as supply chain coordination, scheduling, resource optimisation, and patient or asset flow management. However, studies also appear in education, retail, public sector, and humanitarian contexts, suggesting broader interest in AI's operational applicability across diverse environments

Geographically, the literature is weighted toward Asia, especially China and India, followed by Europe. Notably, African-based studies constitute 10% of the final sample, a significant representation given the global distribution of research output and technological infrastructure. This underscores emerging interest and growing capabilities in AI adoption within African operational contexts. In contrast, North American specific studies were limited. Regional patterns largely reflect disparities in digital infrastructure, policy readiness, and the balance between public and private research investment.

Table 3. Sector and geographical focus

Sector	No. of Studies
Agriculture/Food Supply Chain	3
Construction / Real Estate	2
Education	1
Finance	1
Healthcare	2
Humanitarian	1
ICT/Tech	1
Manufacturing	13
Retail	1
Transportation/Electric Vehicles	1
Services	2
Cross-sector / Unspecified	30
Total	**N = 58**

Geographical Focus	No. of Studies
Brazil	1
China	11
France	1
Finland	1
Ghana	1
India	8
Italy	1
Japan	1
Jordan	1
Malaysia	2
Thailand	1
South Africa	3
US	1
UK	4
Vietnam	2
Cross-country / Unspecified	19
Total	**N = 58**

Source: Author

3.1.4 Theoretical foundations

A wide range of theoretical frameworks underpin the studies reviewed, reflecting the conceptual diversity of AI implementation research. While some papers adopt AI-specific or emerging frameworks, others draw from established theories commonly used in organisational research. Table 4 summarises the most frequently cited theoretical foundations across the sample, including the Resource-Based View (RBV), Technology Acceptance Model (TAM), Dynamic Capabilities, Institutional Theory, and Sociotechnical Systems Theory. These frameworks are employed to explore various dimensions of AI integration, from strategic alignment and capability development to employee adoption behaviours and socio-technical interactions. Their application supports deeper insight into how AI reshapes operational practices and decision-making routines.

Although diverse frameworks are evident, the concentration around a few core theories highlights both convergence and future opportunities. As AI-driven operations continue to evolve, there is scope to extend theoretical engagement through more integrated, operations-oriented perspectives on AI implementation.

Table 4. Key theoretical frameworks

Theoretical Framework	No. of Studies
Resource-Based View (RBV)	2
Organizational Information Processing Theory (OIPT)	4
Dynamic Capabilities	5
Service-Dominant Logic (SDL)	2
Theory of Acceptance and Use of Technology (UTAUT)	1
Multiple key theories (RBV, STS, CT, ROT, KBV, TAM)	21
Other / Unspecified	23
Total	**N = 58**

Source: Author

3.2 Thematic findings aligned to review questions

This section presents the core findings of the review, structured around the three guiding research questions. The previous sections mapped publication patterns, sectoral trends, and theoretical positioning. This section now focuses on what the selected studies reveal in response to each review question, with findings presented in grouped dimensions that reflect dominant patterns across the literature (Table 5).

The structure of this section follows the approach used by Lee et al. (2023), who examined AI implementation from a general business perspective and organised their findings by research question. Their systematic approach was adopted here because it supports transparency, ensures breadth of coverage, and allows the findings to remain grounded in the review questions and coded data. Notably, Lee et al. (2023) called for further investigation into AI implementation from an Operations Management perspective, this review responds to that call by focusing specifically on how AI disrupts, reshapes, and introduces tensions within operational models. The findings presented here serve as the empirical foundation for the interpretive synthesis that follows in Chapter 4.

Table 5. Themes across all review questions

RQ	Dimension	Theme	Summary of Findings	# Studies
RQ1	Disruption of Traditional Operational Models and Emergent Theories	Decision-making authority; Value reconstruction; AI-driven operational theories	AI disrupts traditional operational models by restructuring decision authority, reframing organisational value around adaptability and resilience, and driving the evolution of operational theories that explain firms' responses to uncertainty and change.	28
RQ2	Human Participation in Value Creation and Operational Trade-Offs	Sociotechnical alignment; Trust and Resistance in AI Use; Human-centred integration	AI-driven value creation depends on sociotechnical alignment, where trust, human agency, and organisational readiness shape the extent to which AI is integrated as a complement, rather than a substitute, for human participation in operations	23
RQ3	Operational Realities and the Implementation Gap	Governance & Control	Persistent gaps between strategic ambition and operational reality, driven by weak infrastructure, resource constraints, and misaligned leadership, continue to undermine AI implementation, exposing tensions in governance, accountability, and organisational capacity.	15

Source: Author

3.2.1 Findings for RQ1: Disruption of Traditional Operational Models and Emergent Theories

To address RQ1, 28 out of the 58 reviewed articles were found to examine how AI disrupts established operational models or expands theoretical frameworks in operations management. Through content analysis, these articles were examined for recurring patterns of disruption, encompassing shifts in decision-making structures, the reconfiguration of organisational capabilities, and the reinterpretation of operational logic.

3.2.1.1 Theme 1: Decision-making authority

The most prominent disruption emerging from the literature review involves the fundamental restructuring of decision-making authority and processes through AI integration (Wang et al., 2025). Analysis reveals that 28 of the 58 examined studies document AI systems as either supporting (Hendriksen, 2023) or autonomously executing operational decisions (Ayala et al., 2025), with particular prevalence in predictive maintenance (Hadid et al., 2024), risk management (Olan et al., 2024), and demand forecasting applications (Chowdhury et al., 2025). Notably, Artificial Intelligence-Driven Decision Support Systems (ADSS) have become instrumental in enhancing operational responsiveness and supply chain resilience under conditions of uncertainty (Roux et al., 2023).

AI-based decision support systems employ diverse methodological approaches, with literature documenting distinct applications of algorithmic techniques: artificial neural networks optimise predictive tasks (Hao & Demir, 2024), fuzzy logic systems enhance forecasting accuracy (Belhadi et al., 2024), genetic programming improves sales optimisation (Wong et al., 2024), and hybrid models integrate multiple approaches (Cannas et al., 2024). Sectoral implementations range from autonomous systems to augmented decision-support tools that preserve human judgment (Cannas et al., 2024; Helo & Hao, 2022). Effective implementation requires robust knowledge exchange mechanisms, particularly in high-risk sectors like healthcare supply chains (Abadie et al., 2023) and financial services (Olan et al., 2024). This creates unique operational dynamics where AI both redistributes control and establishes critical human-technical interdependencies (Belhadi et al., 2024).

3.2.1.2 Theme 2: Value reconstruction

Another dimension that can be seen in the literature involves a shift in how operational value is defined in AI-integrated environments. Rather than prioritising efficiency alone, many studies describe AI as enabling resilience, sustainability, and adaptive capacity, particularly in volatile or resource-constrained settings. Beyond task automation, AI is used to support dynamic decision-making, continuous learning, and organisational reconfiguration during disruption. Rodríguez-Espíndola et al. (2022) find that organisations with a resilience mindset are more likely to adopt technologies such as AI and blockchain, using them to strengthen adaptability and long-term risk management. Similarly, Roux et al. (2023) show how public innovation infrastructures have been reengineered to integrate digital technologies through employee-centred, collaborative practices. Wang et al. (2025) link AI to improvements in corporate environmental performance (CEP), especially where stakeholder governance is aligned. However, tensions remain, particularly where algorithm aversion limits adoption, or where poorly diagnosed AI solutions lead to value destruction (Al-Surmi et al., 2022). These findings point to a broader, context-sensitive reconstruction of value in AI-enabled operations, shaped by sectoral conditions and organisational priorities.

3.2.1.3 Theme 3: AI-driven operational theories

Building on the Resource-Based View (RBV), the Dynamic Capabilities View (DCV) has become a predominant lens for examining how firms respond to technological change, particularly through adaptive reconfiguration (Rahman et al., 2023). Extant research applies DCV to frame AI's role in this process, while Information Processing Theory (IPT) is used to explain how AI reshapes organisational decision-making. Across both perspectives, AI is consistently portrayed as a structural transformer of organisational responses to uncertainty, rather than merely a tool for efficiency.

Recent studies like Le and Behl (2024) bridge DCV and IPT to analyse AI's simultaneous enhancement of organisational capabilities and decision structures, advancing beyond singular theoretical frames toward integrated models that account for AI's systemic operational influence. Similarly, Similarly, Zhang et al. (2023) introduce AI-infused operations capability (AIOP) as a mediator. Their findings show that IT capability has diminishing returns without complementary AIOP, refining understanding of AI's value as contingent on capability thresholds and operational contexts. Studies in the manufacturing sector applying Organisational Information Processing Theory (OIPT) distinguish between AI's varied impacts, highlighting its value as contingent on alignment with information processing needs under uncertainty and affirming OIPT's relevance for explaining AI-enabled decision-making through enhanced information flow and system responsiveness (Yu et al., 2024).

Rodríguez-Espíndola et al. (2022) note that technology adoption studies frequently employ frameworks such as TAM, UTAUT, and TOE to explain behavioural intentions behind digital technology adoption, with comparative studies showing how factors like performance expectancy and social influence vary by context (Dora et al., 2022). While these models effectively capture user-centric drivers, Dora et al. (2022) extend this stream by integrating the Technology-Organisation-Environment (TOE) and Human-Organisation-Technology (HOT) perspectives to examine critical success factors (CSFs) for AI adoption in food supply chains, where customer demands, sustainability mandates, and competitive pressures necessitate attention to both technical implementation and socio-organisational adaptation.

3.2.2 Findings for RQ2: Human Participation in Value Creation and Operational Trade-Offs

To address RQ2, 23 of the 58 reviewed articles investigate how human participation influences value creation in AI-driven operations, including the inherent trade-offs of this interaction. Through content analysis, recurring themes emerged around human-AI complementarity in task execution, the evolving nature of workforce roles, dynamics of trust and resistance, and frameworks for human-cantered integration.

3.2.2.1 Theme 1: Sociotechnical alignment

The literature highlights that successful AI adoption in SMEs depends not only on access to digital platforms but on the strategic alignment of human capabilities (Yao et al., 2025), leadership (Dey et al., 2024), and organisational learning (Dubey et al., 2022), particularly as AI technologies are often viewed as complex unless embedded in familiar domains like e-commerce or customer management. Drawing on frameworks such as resource orchestration theory (ROT) and the knowledge-based view (KBV), studies show that leadership behaviours, employee competencies, and organisational culture collectively shape AI readiness (Abadie et al., 2023; Dey et al., 2024). Human engagement spans multiple roles, from users to innovators, depending on the depth of operational and technological expertise available (Wei & Pardo, 2022). This evidence demonstrates that human-AI complementarity is not automatic (Dey et al., 2024), but cultivated through deliberate capability-building and contextual adaptation (S. Sahoo et al., 2024). As such, effective integration requires both robust infrastructure and a supportive ecosystem that fosters continuous learning and targeted skill development (Rana et al., 2022).

The literature demonstrates that in high-uncertainty environments such as humanitarian supply chains, studies highlight how AI-powered decision support systems enhance operational agility, visibility, and responsiveness by processing large-scale, complex data inputs (Hasija & Esper, 2022). These tools are particularly valued for their ability to deliver real-time insights and support adaptive decision-making under pressure (Dey et al., 2024). However, effective delegation to AI systems is shaped by organisational context, resource availability, and human capacity (Cadden et al., 2022). In disaster relief, for instance, while some managers view AI-driven analytics as transformative, others remain sceptical of their reliability and relevance in volatile settings (Dubey et al., 2022).

Similarly, SMEs often struggle to leverage AI due to limited resources, knowledge gaps, and competing survival priorities, factors that constrain their ability to delegate operational tasks to automated systems (Dey et al., 2024). In highly competitive markets, the impact of AI on performance appears weaker, suggesting that technological orientation alone does not guarantee efficiency gains (Yao et al., 2025). Studies also note that automation may alter job structures, with implications for employee engagement and satisfaction in increasingly gigified work environments (Braganza et al., 2022). These findings indicate that the value of AI in decision-making is contingent not only on system capabilities but on governance, organisational culture, and the preservation of human judgment within automated processes (Rana et al., 2022).

The literature highlights the evolving distribution of decision authority between humans and AI systems, with AI increasingly driving operational outcomes through autonomous, data-driven functions (Cadden et al., 2022). However, this shift does not eliminate the need for reciprocal human engagement. Studies show that SMEs often co-adapt with platform providers, contributing operational knowledge to shape AI applications. Wei and Pardo (2022) illustrate how such co-innovation blends human expertise with AI infrastructure to generate value. Hendriksen (2023) adds that even when AI selects actions autonomously, human actors retain override authority to align decisions with broader workflows. However, Rana et al. (2022) caution that when systems lack transparency or fail to match employee capabilities, they can trigger dissatisfaction and reduce firm performance. These findings demonstrate that successful AI delegation depends as much on trust, training, and context as on technical capability (Rana et al., 2022).

3.2.2.2 Theme 2: Trust and Resistance in AI Use

Trust is foundational for AI uptake in supply chains, requiring strong supplier-customer relationships for ethical data sharing and learning. Humanitarian contexts face greater trust challenges due to short-term operations and diverse actors disrupting coordination (Dubey et al., 2022). Organisational AI acceptance depends on employees' ability to understand and use systems effectively (Dey et al., 2024). Where AI tools are difficult to interpret or misaligned with roles, concerns arise over fairness, accuracy, and job security (Rana et al., 2022). Organisations address this through initiatives clarifying AI functionality while ensuring ethical use and role stability. Trust-building demands clear communication, training, and leadership support for responsible implementation (Wei & Pardo, 2022).

Trust in AI depends not only on accuracy but on how clearly system logic is communicated. Studies show that intuitive visualisation and interface design help users understand and engage with AI outputs (Hasija & Esper, 2022). Trust in AI is also constrained by limited awareness of its capabilities. Wei and Pardo (2022) show that some users disengage not out of fear, but because they lack the knowledge to see what AI could offer beyond familiar functions. When organisations focus narrowly on internal data and routine tasks, interpretability gaps deepen, not because systems are complex, but because users don't have full knowledge of system capabilities.

AI adoption can surface moral tensions when employees are caught between meeting short-term performance targets and supporting longer-term transformation goals. Abadie et al. (2023) observe that in efforts to implement omnichannel strategies, misaligned priorities and fragmented team cultures often generate ethical strain, as employees deprioritise collaboration and customer experience in favour of immediate operational demands. These tensions are compounded when accountability is unclear. Hasija and Esper (2022) note that responsibility for AI-related failures is often deflected (toward either business leaders who approved the systems or the developers who built them) highlighting ongoing concerns about trust, responsibility, and organisational risk.

3.2.2.3 Theme 3: Human-centred integration

In the literature, Hasija and Esper (2022) speak to human-centred integration extensively, highlighting that trust in AI systems depends not only on initial deployment but on their ongoing evaluation and improvement. Many organisations struggle to build trust in the first place, yet sustaining it requires a cultural mindset that prioritises continuous monitoring, model updates, and collaborative problem-solving. This reinforces the view that AI integration is not a one-time event but an evolving process shaped by human oversight and organisational commitment.

Bag et al. (2023) provides practical application to Hasija and Esper (2022) by indicating that I-enabled collaborative platforms can strengthen absorptive capacity and improve healthcare supply chain performance, especially in resource-constrained settings. In countries like India and South Africa, where state of the art hospitals coexist with critical shortages of skilled medical personnel, AI has the potential to address systemic inequities. By enhancing access, streamlining processes, and supporting professional training, these technologies serve as strategic enablers (not replacements) for human expertise (Dubey et al., 2022).

While the resource-based view (RBV) has frequently been used to link AI capabilities with firm performance, Abadie et al. (2023) argue that it overlooks the role of human agency at the point of AI use. In contrast, socio-technical systems (STS) theory offers a more holistic perspective by foregrounding the interaction between people, technology, and organisational processes which is central to human-centred AI integration. This integration is not limited to internal systems. Lu et al. (2025), applying the Actor–Partner Interdependence Model (APIM), show that supply chain resilience is co-developed through mutual adaptation in buyer–supplier relationships. Their findings suggest that partners build resilience by jointly adapting technologies, leveraging trust, and navigating power asymmetries, positioning AI as a collaborative tool across inter-organisational networks, not just within firms.

3.2.3 Findings for RQ3: Operational Realities and the Implementation Gap

To address RQ3, 15 of the 58 reviewed articles explore the operational tensions that arise when implementing AI-driven systems across varied organisational contexts. These studies reveal that the gap between strategic intent and real-world integration is shaped not only by technical constraints but also by organisational readiness, leadership alignment, infrastructure limitations, and socio-cultural frictions.

3.2.3.1 Theme 1: Strategic-Operational misalignment

Dubey et al. (2020) show that the impact of entrepreneurial orientation and BDA-AI on operational performance weakens in highly dynamic environments, highlighting that benefits are often delayed or misunderstood. Their findings highlight that AI implementation is not linear but shaped by timing, environmental volatility, and organisational adaptability. Related studies on generative AI adoption similarly find that innovation gains are moderated by ethical dilemmas and environmental volatility, particularly in dynamic R&D settings (Lu et al., 2025). Successful implementation depends not only on technological capability but also on ethical alignment, employee preparedness, and integration with existing workflows (Fosso Wamba et al., 2023).

Beyond technical integration, ethical concerns significantly complicate the operationalisation of AI systems. Merhi and Harfouche (2024) highlight that even when AI operates autonomously, legal accountability remains with the organisation, reinforcing the need for responsible AI governance. This legal framing may influence implementation decisions, as firms must weigh not only technical feasibility but also regulatory and reputational risk. Persistent concerns around bias, fairness, and data privacy further complicate AI implementation, requiring continuous monitoring and ethical supervision throughout the diffusion process (Fosso Wamba et al., 2023; Singh et al., 2024). As Merhi and Harfouche (2024) note, organisations remain legally accountable for outcomes, making responsible AI governance essential to mitigating reputational, and decision-making risks. The literature notes that clear legal and regulatory frameworks are essential for successful AI implementation, especially in production systems where liability and unintended consequences must be carefully managed (Merhi & Harfouche, 2024). Without proactive engagement with these ethical and legal complexities, organisations risk stalled adoption and unsustainable innovation outcomes (Singh et al., 2024).

3.2.3.2 Theme 2: Data, Infrastructure, and Technology bottlenecks

Across the dataset, data quality emerges as a critical constraint. Merhi and Harfouche (2024) rank data accuracy and complexity among the top enablers of successful AI adoption, warning that poor inputs undermine decision integrity and may lead to serious consequences. Fosso Wamba (2023) similarly points to ongoing challenges around data access in supply chain contexts, while Wei and Pardo (2022) highlight that SMEs' ability to leverage AI depends on evolving data infrastructure, knowledge depth, and platform readiness. Together, these studies confirm that without high-quality, accessible, and well-integrated data systems, AI implementation efforts remain fragile and limited in impact.

Security and scalability concerns remain critical constraints, especially in large, distributed systems where AI's effectiveness depends on trusted, authorised data transactions (Gupta et al., 2023). To address these limitations, studies advocate for complementary infrastructure such as blockchain and enhanced network connectivity, with dynamic capabilities like real-time responsiveness and information integration emerging as essential to supply chain resilience in volatile environments (Le & Behl, 2024; Roux et al., 2023).

Tangible infrastructure, such as big data platforms, cloud-based services, and funding, is foundational to BDA-AI implementation, yet firms often depend on institutional pressures to configure these resources effectively (Bag et al., 2021). In contrast, ecosystem participation through structured models like hub-and-spoke governance or third-party platforms offers a viable path for resource-constrained firms to access AI capabilities without building internal systems from scratch (Wei & Pardo, 2022).

IT governance emerges as a foundational enabler across all phases of AI implementation, yet is often weakened by fragmented strategies, unclear alignment, and insufficient leadership oversight (Hao & Demir, 2024). In this regard, Fosso Wamba et al. (2023) posit a learning-oriented governance culture, supported by knowledge sharing, risk management protocols, and ethical guidelines, is essential for sustaining AI adoption and mitigating persistent challenges such as security, privacy, and standardisation.

3.2.3.3 Theme 3: Organisational and strategic barriers to AI implementation

AI implementation is frequently hindered by internal organisational dynamics, including leadership uncertainty, weak alignment, and low change readiness. Hao and Demir (2024) identify organisational strategy and leadership support as foundational pre-development enablers, yet many firms lack clear direction or internal coherence at this stage. When senior leadership fails to prioritise AI or communicate a unified vision, initiatives often stall or remain fragmented. As Merhi and Harfouche (2024) emphasise in the literature, top management support not only ensures resource allocation but also fosters trust and reduces employee resistance, its absence can hinder capital flows, undermine commitment, and erode momentum before implementation gains traction.

Financial and strategic tensions further undermine implementation, particularly in settings where resource constraints and ROI ambiguity are pronounced. Le and Behl (2024) argue that SME managers must reassess internal capabilities and identify external supports, yet short-term cost pressures often outweigh long-term planning. Fosso Wamba (2023) notes that implementation costs and staff resistance are key challenges, even when firms expect future gains in efficiency, development, and customer satisfaction. Dubey et al. (2020) emphasise that AI-enabled dynamic capabilities are essential not just for innovation, but for reducing market risk and generating value sufficient to justify high investment costs. While some case studies demonstrate compelling returns, such as reduced delays, enhanced efficiency, and environmental benefits (Shankar & Gupta, 2024), many organisations lack the capital or confidence to sustain the upfront risks, leaving implementation efforts vulnerable to disruption.

Collaborative gaps continue to undermine coordinated AI implementation. While ecosystem models like hub-and-spoke arrangements can support alignment (Wei & Pardo, 2022), many firms lack central leadership, stakeholder consensus, and integration across teams. These issues are most visible during deployment, where poor communication and training weaken system adaptability (Hao & Demir, 2024). Effective collaboration requires employees who understand strategic goals and operate within digitally integrated workflows (Abadie et al., 2023). Without this alignment, firms struggle to act on AI insights or adapt to regulatory demands (Shankar & Gupta, 2024).

Chapter 4: Synthesis of the literature review

4 Introduction

The purpose of this structured literature review was to critically examine how Artificial Intelligence (AI) is reshaping operational practice, theory, and implementation across organisational contexts. Rather than offering a purely descriptive account, the review aimed to surface underlying patterns, tensions, and shifts in how AI is understood, applied, and contested in the field of operations. Using a structured approach, the review was organised around three research questions focused on disruption, human participation, and implementation tensions. These guided a thematic synthesis of 58 studies, generating insight into both the technological and organisational dimensions of AI integration. This synthesis builds on the findings to offer a broader interpretation of the literature, drawing connections between themes, identifying recurring patterns and tensions, and considering how context and methodology shape what we know about AI in operations.

4.1 Disruption of Traditional Operational Models

A dominant pattern across the literature is the delegation of operational decision-making to AI systems, particularly in functions that involve forecasting, scheduling, risk management, and supply chain coordination. The most prominent disruption emerging from the review involves the fundamental restructuring of decision-making authority and processes through AI integration (Wang et al., 2025). Studies such as Hendriksen (2023) and Ayala et al. (2025) highlight that AI systems can take on a variety of roles depending on organisational needs, from supporting human decision-makers to operating autonomously in areas like predictive maintenance and supply chain scheduling. However, this flexibility does not imply a diminished role for human judgment. In many cases, AI systems enhance operational efficiency while still allowing humans to remain the final arbiters of key decisions. This pattern reflects a growing interest in hybrid decision models that preserve human oversight while leveraging AI's speed, accuracy, and scalability.

4.1.1 Decision-making authority

A dominant pattern across the literature is the delegation of operational decision-making to AI systems, particularly in functions that involve forecasting, scheduling, risk management, and supply chain coordination. The most prominent disruption emerging from the review involves the fundamental restructuring of decision-making authority and processes through AI integration (Wang et al., 2025). Studies such as Hendriksen (2023) and Ayala et al. (2025) highlight that AI systems can take on a variety of roles depending on organisational needs, from supporting human decision-makers to operating autonomously in areas like predictive maintenance and supply chain scheduling. However, this flexibility does not imply a diminished role for human judgment. In many cases, AI systems enhance operational efficiency while still allowing humans to remain the final arbiters of key decisions. This pattern reflects a growing interest in hybrid decision models that preserve human oversight while leveraging AI's speed, accuracy, and scalability.

These findings suggest that while AI systems can enhance efficiency, organisations cannot delegate decision authority without considering the risks and contextual trade-offs involved. AI-based decision support systems employ a wide range of methodological approaches, including neural networks, fuzzy logic, genetic programming, and hybrid models, each bringing distinct strengths to forecasting, optimisation, and process control (Cannas et al., 2024; Hao & Demir, 2024; L. W. Wong et al., 2024). These techniques give rise to unique operational dynamics, particularly in how decisions are timed, validated, and implemented across different sectors. Overreliance on AI may accelerate decision-making but at the cost of transparency and explainability, while full dependence on human input may introduce delays and bias, especially in time-sensitive environments (Belhadi et al., 2024; Wang et al., 2025). Importantly, experience-based judgment remains a valuable safeguard, particularly in high-risk or ambiguous contexts (Abadie et al., 2023). This suggests that the future of operational decision-making will depend less on choosing between AI and human judgment, and more on how organisations design sociotechnical systems that distribute authority in ways that are context-aware, adaptive, and accountable.

4.1.2 Value reconstruction

These patterns suggest that AI's operational value is especially pronounced in organisations that face structural vulnerabilities, whether due to supply chain complexity, regulatory constraints, resource scarcity, or environmental uncertainty (Cadden et al., 2022; Luo et al., 2024). Rather than reinforcing efficiency in already optimised systems, many studies show AI enabling stability, adaptive coordination, and long-term resilience in contexts where organisation had previously struggled to perform (Rodríguez-Espíndola et al., 2022). This challenges the assumption that only digitally advanced firms can benefit from AI and instead highlights its potential as a supportive tool, used to compensate for organisational or contextual fragility. The implications for Operations Management are meaningful: value is no longer solely measured in terms of throughput or cost reduction, but increasingly in an organisation's capacity to respond, recover, and adapt (Roux et al., 2023). As such, the integration of AI is less about optimising what exists, and more about reconfiguring what's possible.

At the same time, the literature makes it clear that AI's ability to create operational value is not guaranteed. When poorly scoped or implemented without regard for organisational fit, AI systems can undermine coordination, displace existing capabilities, or amplify risks rather than reduce them (Yu et al., 2024). The potential for value erosion is especially high when implementation is approached as a technical upgrade rather than a strategic, cross-functional process (Al-Surmi et al., 2022). Studies caution, organisations that become overly focused on AI's promised benefits may overlook the complexity of its integration, failing to account for how it interacts with existing workflows, roles, and cultural norms. These dynamics suggest that AI adoption is not plug-and-play. Their integration is a process that must be contextually grounded and carefully aligned with broader organisational systems and ecosystem relationships.

4.1.3 AI-driven operational theories

DCV emerged in response to limitations within the Resource-Based View, particularly its failure to account for the dynamic and often volatile conditions in which firms operate (Rana et al., 2021). Where RBV emphasises access to valuable, rare, and inimitable resources, DCV shifts the focus toward a firm's ability to reconfigure those resources in response to environmental change. When used alongside Information Processing Theory, which examines how organisations gather, interpret, and act on information, these frameworks together offer a more comprehensive view of how AI supports organisational adaptation (Benzidia et al., 2021). In data-rich but uncertain environments, the challenge is not only accessing information, but processing it effectively, something that can become increasingly costly and complex as environmental dynamism grows (Rodríguez-Espíndola et al., 2022). In this context, AI is positioned not just as a resource or tool, but as an enabler of dynamic capabilities that allow firms to sense, learn, and respond to emerging conditions more efficiently.

Zhang et al. (2023) and Yu et al. (2024) demonstrate that AI's value is not inherent to the technology itself, but depends on how effectively it is embedded within the organisation's unique operational and strategic context. Zhang et al. (2023) make this especially clear by arguing that AI-infused operations capability (AIOP) must be assessed in relation to a firm's own processes, structures, and strategic context. At the same time, Yu et al. (2024) caution that even well-aligned models may struggle to predict major market shifts or detect subtle changes in the environment, highlighting that AI is not a one-size-fits-all solution. Organisations must therefore critically evaluate how AI tools align with their specific information processing needs, risk profiles, and decision environments during implementation.

Rodríguez-Espíndola et al. (2022) note that technology adoption studies often rely on behavioural models such as TAM, UTAUT, and TOE, with Dora et al. (2022) showing how drivers like performance expectancy and social influence vary by context. Extending this work, Dora et al. integrate TOE and Human-Organisation-Technology (HOT) perspectives to highlight that in complex sectors like food supply chains, successful AI adoption depends not only on technical implementation but also on socio-organisational alignment.

Taken together, the literature shows that no single theoretical lens is sufficient to capture the full scope of AI's impact on operations. Scholars draw on diverse frameworks, including DCV, IPT, TOE, HOT, and behavioural models like TAM and UTAUT, to reflect the complex, layered nature of AI integration. This theoretical pluralism mirrors the multidimensional role AI plays in organisations: reshaping decision-making structures, enabling dynamic capabilities, influencing adoption behaviours, and altering human-technology interactions. The result is a growing body of research that seeks to explain AI not just as a technical solution, but as a transformative force operating across sectors, systems, and organisational levels. For Operations Management, this signals a need to continue building integrative models that can account for both the strategic and socio-technical realities of AI-driven change.

4.2 Human Participation and the Shaping of Operational Value

The second research question explored how human participation influences value creation in AI-driven operations, and what trade-offs emerge in the process. Across the literature, AI is not seen as replacing human actors but reshaping their roles. Value is increasingly produced through sociotechnical alignment, trust, and shared control between humans and AI systems. While hybrid models that combine human oversight with AI capabilities are gaining traction, tensions around trust, resistance, and integration remain key to how AI is adopted and how value is realised in practice.

4.2.1 Sociotechnical alignment

The reviewed literature underscores that AI implementation cannot be treated as a purely technical upgrade. Rather, AI actively shapes, and is shaped by, human interaction, decision-making, and organisational routines (Wei & Pardo, 2022; Yao et al., 2025). As such, successful adoption depends on more than infrastructure; it requires leadership support, managerial buy-in, and a sustained focus on upskilling (Abadie et al., 2023; Dey et al., 2024; Rana et al., 2022). Complementarity between human and AI systems is not inherent (Dey et al., 2024), but emerges through deliberate investments in organisational learning and capability-building (M. Sahoo, 2019). Organisational maturity and human capacity further shape the extent to which AI can be effectively delegated, especially under uncertainty (Cadden et al., 2022). Crucially, managerial perspectives must also evolve, as trust and perceived reliability strongly influence the willingness to embed AI into operational processes (Dubey et al., 2022; Hasija & Esper, 2022).

SMEs face adoption challenges due to resource constraints, knowledge gaps, and competing priorities (Dey et al., 2024), but delegation to AI must be carefully managed. Strong governance structures and attention to organisational culture are essential to ensure AI enhances rather than disrupts operational integrity (Braganza et al., 2022; Rana et al., 2022). Even as AI systems take on more autonomous roles, value is co-produced through human-AI collaboration, where domain expertise shapes meaningful implementation (Hendriksen, 2023; Wei & Pardo, 2022). Without trust, transparency, and alignment with employee capabilities, automation risks undermining engagement and weakening performance outcomes (Rana et al., 2022).

Sociotechnical alignment requires organisations to move beyond technical readiness by actively investing in human capacity, change management, and governance structures. This includes upskilling employees, fostering collaborative implementation processes, and ensuring that AI systems are integrated within clear organisational policies and cultural norms. Without such alignment, even advanced AI solutions risk underperformance due to poor contextual fit and limited user engagement. As the literature shows, successful AI integration is not only a technical endeavour but a coordinated organisational process involving both social and structural adaptation (Dey et al., 2024; Rana et al., 2022; Wei & Pardo, 2022).

4.2.2 Trust and resistance in AI use

Trust is central to AI adoption, shaped by ethical data-sharing practices, employee understanding, and clear accountability structures (Dey et al., 2024; Dubey et al., 2022). Where AI systems are difficult to interpret or poorly aligned with roles, users raise concerns about fairness, job security, and accuracy, prompting organisations to invest in training, interface design, and transparent communication (Hasija & Esper, 2022; Rana et al., 2022; Wei & Pardo, 2022). Trust also falters when users lack awareness of AI's broader capabilities, leading to disengagement even when systems are technically sound (Wei & Pardo, 2022). Moral tensions emerge when short-term performance pressures undermine longer-term transformation goals, especially in fragmented cultures with unclear responsibility for AI outcomes (Abadie et al., 2023; Hasija & Esper, 2022).

Organisations must enhance transparency by clearly communicating how AI systems function and make decisions. Aligning AI tools with existing workflows and user roles increases interpretability and supports adoption, especially when paired with intuitive design and targeted training (Hasija & Esper, 2022; Wei & Pardo, 2022). Ethical concerns, particularly around fairness, job security, and accountability, must be proactively addressed to foster trust and prevent resistance (Abadie et al., 2023; Rana et al., 2022). Ultimately, fostering engagement requires not only technical integration but also deliberate organisational strategies that build confidence, clarify roles, and support shared responsibility for AI outcomes.

4.2.3 Human-centred integration

Trust in AI depends not only on initial deployment but on continuous evaluation, improvement, and organisational commitment to human-centred integration (Hasija & Esper, 2022). Sustaining trust requires a culture of oversight, collaborative problem-solving, and regular model refinement. In resource-constrained contexts, AI-enabled platforms enhance absorptive capacity and strengthen supply chains by supporting, not replacing, human expertise (Bag et al., 2023; Dubey et al., 2022). While the resource-based view often links AI to performance, scholars increasingly favour sociotechnical perspectives that emphasise human agency, interdependence, and co-adaptation across organisational and inter-organisational systems (Abadie et al., 2023; Lu et al., 2025).

Organisations that design AI as a decision-support tool, rather than an autonomous decision-maker, are better positioned to foster meaningful human-AI collaboration. This approach allows human judgment to remain central while leveraging AI's analytical strengths. Cross-functional oversight, where different departments engage in monitoring, feedback, and refinement, further strengthens integration by embedding AI within broader organisational processes. Such distributed responsibility enhances both transparency and trust, aligning AI use with real-world organisational dynamics and human values (Rana et al., 2022).

4.3 AI implementation challenges

The second research question explored how human participation influences value creation in AI-driven operations, and what trade-offs emerge in the process. Across the literature, AI is not seen as replacing human actors but reshaping their roles. Value is increasingly produced through sociotechnical alignment, trust, and shared control between humans and AI systems. While hybrid models that combine human oversight with AI capabilities are gaining traction, tensions around trust, resistance, and integration remain key to how AI is adopted and how value is realised in practice.

4.3.1 Strategic-Operational misalignment

AI adoption rarely follows a straightforward path. Environmental instability, ethical dilemmas, and varying levels of organisational preparedness often disrupt deployment. As Dubey et al. (Dubey et al., 2020) demonstrate, even promising tools like entrepreneurial orientation and BDA-AI see their performance benefits weaken in volatile settings, sometimes appearing later than expected or being misread entirely. This pattern is similar for generative AI as well: while it offers innovation potential, studies show its impact is frequently limited by ethical concerns and integration hurdles, particularly in complex fields like R&D (Fosso Wamba et al., 2023; Lu et al., 2025). Ultimately, successful implementation hinges not just on technical competency but on ethical coherence, workforce readiness, and seamless workflow integration.

The operational challenges are deepened by ethical and legal risks. Organisations retain full liability for AI-driven decisions, making robust governance frameworks and unambiguous accountability mechanisms essential (Merhi & Harfouche, 2024). Persistent issues like algorithmic bias, fairness, and data privacy demand ongoing vigilance and collaboration with regulators (Fosso Wamba et al., 2023; Singh et al., 2024). Firms that neglect these dimensions face stalled projects, reputational damage, and innovation efforts that fail to deliver lasting value.

4.3.2 Data, Infrastructure, and Technology bottlenecks

Security and scalability emerge as equally critical concerns, especially in decentralised systems where AI depends on protected data flows (Gupta et al., 2023). Recent studies highlight how supporting technologies (including blockchain, cloud computing, and real-time processing) can strengthen both responsiveness and system resilience (Le & Behl, 2024; Roux et al., 2023). For resource-limited organizations, ecosystem approaches like hub-and-spoke models or third-party platforms provide viable alternatives to building complete in-house solutions (Wei & Pardo, 2022).

These technical challenges reveal a deeper governance issue, organisations must focus on learning, and improving governance structures (Fosso Wamba et al., 2023; Hao & Demir, 2024).

4.3.3 Organisational and strategic barriers to AI implementation

AI implementation frequently falters due to internal challenges like misaligned leadership, vague strategy, and organisational inertia. While Hao and Demir (2024) emphasise leadership support and strategic clarity as key prerequisites, many companies lack these fundamentals. Without executive buy-in, projects face resource shortages, disjointed execution, and workforce pushback (Merhi & Harfouche, 2024).

Financial constraints and strategic uncertainty pose particular barriers for SMEs, where short-term costs overshadow long-term benefits. Despite AI's proven potential for efficiency gains and innovation (Dubey et al., 2020; Fosso Wamba et al., 2023), implementation often stalls due to funding gaps and risk avoidance, even with evidence of tangible returns (Le & Behl, 2024; Shankar & Gupta, 2024).

Collaborative failures further undermine efforts. Although ecosystem approaches like hub-and-spoke models show promise (Wei & Pardo, 2022), most implementations suffer from poor stakeholder coordination and digital silos (Abadie et al., 2023). These weaknesses emerge during deployment, where inadequate training and communication hinder adaptability and compliance (Hao & Demir, 2024; Shankar & Gupta, 2024).

To address implementation barriers, organisations must allocate resources strategically, streamline efforts across departments, and actively engage employees through clear communication and upskilling initiatives. Rather than attempting full-scale adoption from the outset, firms can prioritise phased implementation, focusing first on areas where AI can deliver immediate value within existing capabilities. This staged approach allows organisations to manage cost and complexity while building the internal readiness needed for broader transformation. Ultimately, sustained progress depends on aligning leadership, strategy, and capacity with realistic, context-aware deployment plans.

Chapter 5: Future research and conclusion

5 Introduction

This structured literature review has examined how AI technologies are reshaping operational models, redefining human participation, and exposing tensions between strategic ambition and implementation realities. While the reviewed literature offers valuable insights into these transformations, it also reveals persistent gaps and unresolved questions that warrant further scholarly attention. This section outlines targeted areas for future research derived directly from the review findings, ensuring conceptual continuity and relevance to both the academic field and practice of operations management.

5.1 Directions for Future Research

5.1.1 Disruption and theoretical development

The review identified that AI is often positioned as a disruptive force capable of reconfiguring operational logics, yet the associated theoretical development remains uneven. While frameworks such as dynamic capabilities, resource orchestration theory, and socio-technical systems theory have been applied, many studies stop short of engaging deeply with the theoretical implications of disruption.

Future research question 1:
How does the theorisation of AI's disruptive impact vary across sectors, operational maturities, and types of AI technologies (e.g., generative vs. predictive systems)?

This question invites comparative research to understand where and how theory development is emerging, and where it remains underdeveloped. It also highlights the need for context-sensitive frameworks that reflect the diverse realities of AI use across organisational types and environments.

5.1.2 Human participation and organisational trade-offs

The literature affirms that human-AI complementarity is not automatic and must be cultivated through deliberate capability-building, ethical integration, and organisational alignment. However, current research offers limited understanding of how human roles are evolving in AI-mediated decision spaces, especially beyond initial adoption phases.

Future research question 2:
What models of human-AI collaboration best support sustained engagement, ethical integration, and organisational learning across different operational contexts?

Future research question 3:
How do trade-offs between short-term performance and long-term transformation manifest in employee experiences, and what governance models can mitigate resistance or disengagement?

These questions address the conceptual and practical tensions exposed in the literature, particularly around role clarity, trust, and moral strain. They also acknowledge that AI's impact is not merely technical but deeply relational, requiring further study of participatory dynamics and organisational ethics.

5.1.3 Implementation challenges and contextual constraints

The third review question highlighted widespread misalignment between strategic intent and operational reality. Barriers such as resource scarcity, fragmented leadership, low data maturity, and ethical uncertainty frequently hinder implementation efforts, especially in SMEs and high-volatility environments.

Future research question 4:
How can firms prioritise AI implementation in stages to balance resource constraints, manage risk, and maximise early value capture?

Future research question 5:
How do different IT governance models influence the scalability, accountability, and ethical sustainability of AI deployments in operational systems?

These questions respond directly to the literature's emphasis on implementation complexity and the need for nuanced, context-sensitive strategies. They invite comparative research across sectors, regions, and organisational forms to explore how firms can build capacity, reduce friction, and scale responsibly.

6 Contribution of the review

6.1 Academic contribution

This review contributes to operations management scholarship by synthesising how AI disrupts not only technical processes but also decision structures, governance models, and organisational norms. It advances understanding of human-AI complementarity by foregrounding trust, ethical alignment, and the trade-offs between short-term gains and long-term transformation. The study also exposes a persistent implementation gap, highlighting how contextual factors (such as leadership, infrastructure, and organisational readiness) mediate the effectiveness of AI strategies. In doing so, it responds directly to Lee et al.'s (2023) call for more operations management-focused research on AI, offering a grounded and discipline-specific lens on emerging implementation challenges.

6.2 Practical contribution

This review offers operational leaders, strategists, and technology implementers a more realistic and actionable understanding of AI integration within organisations. Its contributions centre on surfacing patterns, risks, and opportunities that can inform better planning, investment, and change management strategies (Rana et al., 2022).

6.2.1 Clarifying what AI disrupts

The review shows that AI doesn't just automate processes; it disrupts how decisions are made, who has authority, and how value is created. For managers, this means planning for shifts in workflows, control structures, and accountability, not just performance optimisation (Rahman et al., 2023).

6.2.2 Emphasising human roles in sustained AI use

Successful AI use depends on trust, skills, and clear human roles. This review highlights the need to invest in upskilling, build employee confidence, and engage teams early in the implementation process to reduce resistance and improve long-term system effectiveness (Fosso Wamba et al., 2023).

6.2.3 Helping organisations navigate the implementation gap

Many AI projects stall because strategy and operations are misaligned. The review identifies common points of failure (such as weak leadership support, poor data infrastructure, and unclear rollout priorities) and encourages firms to take a staged, resource-aware approach tailored to their context (Lee et al., 2023).

7 Conclusion

This review contributes to the growing field of AI-driven operations by synthesising empirical and conceptual research across three central themes: disruption of traditional models, the evolving role of human participation, and the operational realities of implementation. It highlights that while AI holds transformative potential, its integration into operational systems is neither automatic nor neutral. Rather, it is shaped by organisational values, strategic choices, technical constraints, and human responses.

By surfacing gaps in theoretical engagement, participation models, and implementation strategy, the review provides a foundation for future research that is both practically relevant and academically rigorous. The proposed research questions aim to deepen understanding of how AI can be implemented in ways that are not only efficient and scalable, but also ethically grounded, human-centred, and contextually responsive.

To that end, future inquiry should resist universalist narratives of AI as a purely disruptive force and instead engage with the complex, evolving relationship between technology and organisation, one marked as much by trade-offs and adaptation as by innovation and optimisation..

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Appendices

Appendix A: Atlas.ti document report

AI-Driven Operations

Documents

Report created by Mandisa N on 30 Jun 2025

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1 Influences of artificial intelligence and blockchain technology on financial resilience of supply chains.pdf

PDF Document

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2 Small and medium-sized enterprises as technology innovation intermediaries in sustainable business ecosystem- interplay between AI adoption, low carbon.pdf

PDF Document

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3 In artificial intelligence (AI) we trust- A qualitative investigation of AI technology acceptance.pdf

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Appendix B: Atlas.ti Intentional AI Codebook

Atlas.ti Codebook

Code	Comment
AI-Driven Disruption & Theoretical Contribution – Operational Model Disruption	Explicit discussion of how AI has altered traditional processes, structures, or systems in operations
AI-Driven Disruption & Theoretical Contribution – Emergent Theoretical Insight	Introduction or refinement of conceptual frameworks, models, or propositions driven by AI-related change
AI-Driven Disruption & Theoretical Contribution – Operational Value Reconfiguration	AI-led changes in how value is structured, delivered, or reinterpreted within operations
AI-Driven Disruption & Theoretical Contribution – Autonomy in Decision-Making	Increased machine-led decision authority or restructuring of decision hierarchies
AI-Driven Disruption & Theoretical Contribution – Service Design Transformation	AI-triggered innovation in how services are structured, customized, or delivered
Human Participation & Trade-Offs in Value Creation – Human-AI Value Co-Creation	How human actions shape or influence the value delivered by AI systems in operations
Human Participation & Trade-Offs in Value Creation – Interpretability & Understanding	The extent to which humans can understand and meaningfully interpret AI outputs
Human Participation & Trade-Offs in Value Creation – Trust & Reliance Dynamics	The presence or absence of trust in AI-generated decisions or recommendations
Human Participation & Trade-Offs in Value Creation – Skill Adaptation & Learning	Human learning, upskilling, or resistance in adapting to AI-augmented roles
Human Participation & Trade-Offs in Value Creation – Delegation Trade-offs	Consequences (positive or negative) of handing over tasks or decisions to AI
Human Participation & Trade-Offs in Value Creation – Moral or Practical Dilemmas	Situational tensions or conflicts faced by humans during AI integration
Implementation Tensions – Leadership Resistance	Delay, skepticism, or misalignment from leadership toward AI initiatives
Implementation Tensions – Data Infrastructure Challenges	Limitations in data quality, access, or readiness that constrain implementation
Implementation Tensions – Cost & ROI Concerns	Uncertainty about financial returns, cost-benefit justification, or sustainability
Implementation Tensions – Change Management Gaps	Lack of structured planning, communication, or user engagement during implementation
Implementation Tensions – Ethical, Legal, or Policy Barriers	Conflicts with norms, regulations, or transparency expectations