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Artificial Intelligence-Enabled Transformation Across Management And Engineering Domains: An Integrative Review Of Finance, Services, Supply Chains, Education, And Social Innovation

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Abstract

AI has ceased to be a technical and expert ability, but it is a strategic asset and is used to make decisions, provide services, predict, engage with customers, comply, and innovate in various fields. But the literature is frequently unresponsive. Finance scholarship is focused on prediction, compliance and risk, service and marketing scholarship on personalization and automation, supply chain scholarship on visibility and resilience, educational scholarship on guidance and learning support, and smart city scholarship on social innovation, inclusion and solving urban problems. This disruption prevents the creation of a consistent view of how artificial intelligence creates value in the fields of management and engineering as well as introduces new governance, trust, and sustainability issues. The paper will create an integrative review of cross-domain applications of artificial intelligence and suggest a strategic model of AI-enabled sustainable value creation. The review summarizes the recent literature along with eleven area contributions including disability peer support, urban technologies, quantum-enhanced AI, blockchain and IoT in supply chains, AI-generated educational visuals, AI agents in customer service, sustainable tourism, AI in tax compliance, stock market prediction, digital school counselling, and AI in finance. By relying on the discussion of dynamic capabilities, technology acceptance, trust and risk perspectives, and sustainable value logic, the paper contends that the key to successful AI adoption is not only based on the performance of the algorithm but on the design that is human-centered, its domain relevance, data quality, and institutional legitimacy, as well as quantifiable organizational outcomes. The paper has three contributions. First, it charts the movement of AI capabilities throughout a variety of management and engineering environments. Second, it determines repetitive processes that relate AI inputs to operational, strategic, and social outputs. Third, it provides an inclusive, governance, explainability, capacity building, and responsible innovation cross domain research agenda. The review has concluded that AI generates long-term value when technical complexities are combined with trust, sustainability, and implementation that is contextual.

Keywords: *Artificial Intelligence, Digital Transformation, Sustainable Value, Customer Service, Supply Chain Management, Financial Analytics, Education Technology, Social Innovation*

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1. INTRODUCTION

Artificial intelligence (AI) is no longer a laboratory, elite research centre, or limited automation work. It is now integrated in business systems, financial systems, service systems, teaching tools, city administration and new engineering systems. This broader spread has ensured that AI has become the centre of modern discussions about competitiveness, organizational design and sustainable development. The study of digital business strategy already stipulated that the creation of value in the digital age relies on the integration of information, processes, networks, and strategy and not on individual technological investments (Bharadwaj et al., 2013). More up-to-date studies indicate that AI transformation projects have the potential to affect the quality of processes, agility, and the performance of firms when being aligned to business objectives and organisational capabilities (Wamba-Taguimdje et al., 2020). Simultaneously, the diffusion of data-driven systems is introducing pragmatic concerns of trust, risk, governance, exclusion, and long-term social value (Glikson and Woolley, 2020; Laine et al., 2024). Due to this fact, the review of AI through the prism of one domain no longer covers the big picture.

The current paper answers that issue by unifying evidence related to management and engineering contexts that are frequently addressed individually. Instead of discussing a single industry, it discusses the application of AI-enabled tools to financial analysis, tax compliance, stock market forecasting, customer service, sustainable tourism, educational guidance, school counselling, social innovation, disability peer support, and sustainable supply chain management. It also speculates on quantum-enhanced AI as an edge that can be used in the future to change the pace and magnitude of computational decision-making (Biamonte et al., 2017; Cerezo et al., 2021; Ansarullah et al., 2026). The general thesis is that AI is not to be seen as a single technology, but rather as a programmable socio-technical facility, the usefulness of which is determined by objectives in a specific domain, data infrastructure, institutional protection, and human consumption. This manner of thinking aligns with the dynamic capability theory that considers competitive advantage to be the outcome of sensing and seizing and reconfiguring resources in the condition of change of environment (Teece et al., 1997).

A practical issue also motivates the paper. There are numerous technically informative, but fragmented studies on AI adoption. Personalisation and interaction with the customer (Huang and Rust, 2021; Ma and Sun, 2020), visibility and resilience (Ben-Daya et al., 2019; Ivanov and Dolgui, 2021), prediction and fintech ecosystems (Lee and Shin, 2018; ul Islam et al., 2025), learning support and digital engagement (Zawacki-Richter et al., 2019; Kasneci et al., 2023) are What is still immature is a comprehensive interpretation of the relationship between these strands with each other, what conditions are usually common to create values in different domains, and what risks are always related to the implementation of AI. The eleven focal works used in this review are particularly valuable due to the wide yet interconnected range of AI-related applications that they present and provide applied knowledge about management, engineering, and social systems (Islam et al., 2025; ul Islam et al., 2025; Rawanda, 2025; Islam et al., 2026).

As such, this paper has four aims: first, to synthesise cross-domain data on AI-enabled transformation; second, to explain this data using applicable theoretical perspectives; third, to observe common mechanisms that connect AI capabilities to organisational and social performances; and fourth, to suggest a research and managerial framework of responsible, sustainable, and measurable AI adoption. It is an integrative review and not a formal metaanalysis since the literature underpinning the paper is composed of conceptual chapters, empirical research, review essays, and application-focused research. Such a design is appropriate when the research purpose is to relate scattered bodies of knowledge, compare assumptions, and create an organising framework to use in future research (Nambisan, 2017; Dwivedi et al., 2023).

2. CONCEPTUAL SCOPE AND REVIEW APPROACH.

This paper is based on an integrative review. It is not meant to provide an approximation of a single pooled effect size, but to make bridges across literature streams, which describe AI-enabled change within various organisational contexts. Integrative reviews are applicable in cases where a phenomenon has grown rapidly across disciplinary lines and where both conceptual and empirical understandings must be viewed jointly. The reviewed literature was chosen to reflect five overlapping themes, namely, digital strategy and AI capability, finance and compliance, service and marketing transformation, sustainable operations and supply chains, and social or educational uses of AI. The review also embraces frontier research on quantum-enhanced AI since management and engineering research is starting to realise that future optimisation and simulation and prediction are likely to be affected by new computing capabilities (Biamonte et al., 2017; Preskill, 2018; Cerezo et al., 2021).

One of the highlights of the review is the intentional inclusion of eleven recent contributions by the research network identified in the call. These pieces were not held as independent productions, but as applied anchors of case where a larger literature could be assembled. As an example, the research on AI in tax compliance is relevant to the broader literature on fintech, regtech, and behavioural reactions to algorithmic systems (Islam et al., 2025; Anagnostopoulos, 2018). The studies of blockchain and IoT in Industry 4.0 supply chains are organically associated with discussions regarding visibility, traceability, resilience, and sustainable operations (Islam, 2025; Saberi et al., 2019; Queiroz et al., 2021). Research on digital school counselling tools and AI-generated pictures broadens the education technology discourse beyond instructional delivery to guidance, counselling, and career preparation (Ansarullah et al., 2025; ul Islam et al., 2025; Zawacki-Richter et al., 2019). In the meantime, the social network design of disability peer support and urban technology-based social innovation raise valuable discussions concerning the inclusion and digital citizenship that are peripheral to mainstream AI management research (Islam et al., 2026; Islam et al., 2026).

The theoretical frame of the paper is thus wide and not disorganized. In this context, AI is a series of computational methods and decision-making systems that allow pattern recognition, prediction, optimisation, generation of content, autonomous interaction, or improved human judgement. The adjacent technologies that are reviewed and included in case they are meaningfully incorporated in AI-enabled decision architectures are blockchain, IoT, cloud computing, and quantum computing. This limit is explained by the fact that modern organisational AI hardly works in isolation. It typically relies on data pipelines, sensor infrastructure, cloud systems, or complementary digital systems that render the outputs of algorithms actionable. Within supply chains, the concept of AI forecasting can be more applicable when it is combined with IoT sensors and blockchain-based traceability (Ben-Daya et al., 2019; Islam, 2025). Conversational AI is more effective in customer service alongside the CRM systems, sentiment analysis, and workflow automation (Huang and Rust, 2018; Rawanda, 2025).

Table 1. Focal contributions integrated in the present review

Focal contribution	Domain	Core digital mechanism	Analytical relevance for this review
Social network design for disability peer support (Islam et al., 2026)	Inclusive support systems	Network design, standards, measurable support architecture	Shows that AI-related digital design must be evaluated through accessibility, barriers, and user outcomes rather than efficiency alone.
Fostering social innovation through urban technologies (Islam et al., 2026)	Urban innovation	Tech-enabled urbanism and inclusive entrepreneurship	Connects AI and digital infrastructure to public value, participation, and place-based inclusion.
Quantum-enhanced artificial intelligence (Ansarullah et al., 2026)	Frontier computing	Quantum-AI integration for advanced decision systems	Extends the review towards future computational capabilities and strategic preparedness.
Leveraging blockchain and IoT for sustainable supply chain management (Islam, 2025)	Operations and supply chains	Traceability, real-time sensing, and sustainability monitoring	Illustrates how AI value depends on complementary digital infrastructures and measurable resilience.
Leveraging AI-generated visuals for career orientation (ul Islam et al., 2025)	Education and guidance	Generative AI for visual communication and engagement	Shows how AI can improve understanding and engagement when content is contextually designed and reviewed.
Transforming customer service with AI agents (Rawanda, 2025)	Services and marketing	Conversational AI and personalisation	Highlights the need to balance automation gains with empathy, trust, and human escalation pathways.
Redefining travel: Sustainable tourism, experiential travel, and dark tourism (Islam et al., 2025)	Tourism and sustainability	Digital mediation of travel experience and responsible destination management	Broadens the discussion of AI value to place-based and sustainability-sensitive contexts.

Focal contribution	Domain	Core digital mechanism	Analytical relevance for this review
Artificial intelligence in tax compliance (Islam et al., 2025)	Public finance and compliance	Predictive monitoring and behavioural compliance systems	Demonstrates that algorithmic efficiency in public systems depends on legitimacy and procedural clarity.
Predicting stock markets using linear regression and cloud computing (Ansarullah et al., 2025)	Financial analytics	Scalable cloud-based forecasting	Shows that predictive AI in finance requires data quality, interpretive caution, and infrastructure maturity.
Leveraging digital tools to enhance school counselling (Ansarullah et al., 2025)	Education and counselling	Digital counselling support and communication systems	Positions AI-enabled guidance as part of student support rather than instruction alone.
The future of machine learning and artificial intelligence in finance (ul Islam et al., 2025)	Finance	ML-based decision support and financial intelligence	Frames AI in finance as an orchestrated capability involving models, governance, and decision routines.

Note. Table developed by the author to map the focal works requested for inclusion.

3. THEORETICAL ANCHORS FOR AI-ENABLED TRANSFORMATION

Three theoretical strands are especially valuable for interpreting the literature reviewed here. The first is the resource-based and dynamic capability view. From this perspective, AI is not inherently strategic simply because it is advanced. It becomes strategic when organisations combine data assets, analytical talent, domain knowledge, governance routines, and learning mechanisms in ways that competitors find difficult to imitate (Barney, 1991; Teece et al., 1997). This is visible across the focal works. In finance, AI generates value when prediction models are paired with reliable data governance and decision protocols (ul Islam et al., 2025; Ansarullah et al., 2025). In customer service, value appears when AI agents are integrated with service design, escalation rules, and human oversight rather than deployed as stand-alone bots (Rawanda, 2025; Wirtz et al., 2018). In school counselling and career orientation, AI-assisted tools become meaningful when they are embedded in pedagogical and advisory processes rather than used as flashy interfaces without follow-through (Ansarullah et al., 2025; ul Islam et al., 2025).

The second strand comes from technology acceptance and continuance theories. Perceived usefulness, ease of use, social influence, and behavioural intention remain important because even technically strong systems fail when users view them as opaque, risky, or difficult to integrate into their routines (Davis, 1989; Venkatesh et al., 2003; Bhattacherjee, 2001). In environments such as tax compliance, education, or peer support, user acceptance may depend less on novelty than on procedural fairness, clarity, and the perception that technology assists rather than displaces human judgement (Islam et al., 2025; Islam et al., 2026). Perceived risk and trust are therefore crucial complements to acceptance models, particularly in online and algorithmic contexts (Featherman & Pavlou, 2003; Pavlou, 2003). These considerations are equally relevant for AI-generated educational visuals, counselling tools, and financial applications, where users may worry about misinformation, bias, surveillance, or unreliability.

The third strand is sustainable value theory. AI adoption should not be judged only by immediate efficiency gains. Firms and institutions increasingly need to evaluate whether digital systems improve environmental performance, social inclusion, stakeholder trust, and long-term resilience. This argument is consistent with the triple bottom line and sustainable business model literature, which emphasise the simultaneous pursuit of economic, social, and environmental outcomes (Elkington, 1998; Hart & Milstein, 2003; Bocken et al., 2014; Geissdoerfer et al., 2017). In the focal literature, sustainable value is visible in several forms: blockchain and IoT for responsible supply chains (Islam, 2025), urban technologies for inclusive innovation (Islam et al., 2026), disability peer support through purposeful network design (Islam et al., 2026), and sustainable tourism frameworks that connect destination experience with social responsibility (Islam et al., 2025). This wider value lens is necessary because AI can simultaneously improve efficiency and deepen inequality if accessibility, affordability, and fairness are ignored (Ylipulli & Hämäläinen, 2023; Hermann et al., 2024).

Together, these theoretical anchors suggest that AI-enabled transformation is best understood as a layered process. Technical capability enables possibilities, but organisational value depends on user acceptance, trust, governance, and strategic alignment. Sustainable impact, in turn, depends on whether institutions are able to direct AI applications towards long-term economic and social outcomes rather than narrow short-term gains. This layered interpretation guides the cross-domain analysis that follows.

4. DOMAIN-LEVEL EVIDENCE AND SYNTHESIS

4.1 Finance, compliance, and decision analytics

Financial contexts were among the earliest domains to adopt algorithmic systems because they generate abundant quantitative data and operate under continuous pressure for speed, precision, and risk control. Yet the contemporary literature makes it clear that AI in finance extends far beyond prediction. It now influences fraud detection, compliance, customer profiling, robo-advisory services, market surveillance, and strategic allocation decisions (Lee & Shin, 2018; Anagnostopoulos, 2018). The focal chapter on the future of machine learning and artificial intelligence in finance positions AI as a decision-support capability that can improve forecasting, anomaly detection, and portfolio intelligence while also demanding robust governance and interpretive caution (ul Islam et al., 2025). Likewise, the review and case-based work on stock market prediction frames cloud-based analytics and linear regression as part of a wider movement towards scalable financial intelligence infrastructures (Ansarullah et al., 2025).

Importantly, finance scholars increasingly reject the idea that better prediction alone guarantees better decisions. Human judgement, contextual reasoning, and institutional checks remain essential. Research on algorithm aversion shows that users can lose trust in models after visible errors, even when algorithmic decisions outperform human judgement on average (Dietvorst et al., 2015). At the same time, other work shows that people sometimes display algorithm appreciation, especially when tasks appear objective and data rich (Logg et al., 2019). This tension matters greatly in financial markets, taxation, and public regulation. AI tools may improve speed and pattern detection, but their legitimacy depends on explainability, fairness, and their fit with professional workflows. The focal tax compliance chapter captures this well by arguing that AI can reshape taxpayer behaviour and system efficiency through predictive analytics and digital monitoring, but only when deployed with procedural clarity and public trust (Islam et al., 2025).

Trust and perceived risk are therefore central mechanisms in financial AI. Pavlou (2003) and Featherman and Pavlou (2003) show that perceived risk can directly undermine technology adoption, especially in contexts involving uncertainty, privacy concerns, or potential loss. In finance, these concerns become more intense because consequences are monetary, regulatory, and reputational. Accordingly, the literature suggests that AI-based financial systems need layered safeguards: transparent model objectives, auditable decision trails, ethical review, and human override capacity (Glikson & Woolley, 2020; Laine et al., 2024). These requirements are consistent with Shneiderman's (2020) argument for human-centred AI, where high levels of automation must be paired with high levels of accountability.

From a managerial perspective, the most useful insight is that AI in finance creates value through orchestration rather than substitution. Data quality, cloud resources, model selection, domain expertise, and governance architecture need to be aligned. Firms that treat AI as a black-box shortcut may achieve temporary efficiency but are unlikely to build durable financial capability. By contrast, firms that integrate predictive tools with learning routines and ethical controls are better positioned to capture both performance and legitimacy gains. This view connects the finance literature to the broader argument of this paper: AI value is cumulative and relational, not merely computational.

4.2 Service, marketing, and customer interaction

Service and marketing research presents AI as both a productivity tool and a relationship technology. AI systems now support personalisation, chat-based assistance, recommendation engines, dynamic pricing, visual content generation, sentiment analysis, and service recovery. Huang and Rust (2018, 2021) argue that AI in service and marketing should be analysed according to the type of intelligence involved, the stage of the customer journey, and the division of labour between machines and humans. Rather than asking whether AI will replace service employees, this work asks how AI changes the mix of mechanical, analytical, intuitive, and empathetic tasks. That distinction is helpful because it explains why some interactions can be automated efficiently, while others require human presence, judgement, or emotional sensitivity.

The focal chapter on AI agents in customer service supports this layered view. It highlights efficiency and personalisation gains, but also stresses the need to balance automation with the human touch (Rawanda, 2025). This balance is not a rhetorical issue. It affects satisfaction, trust, and long-term brand value. Research on task-dependent algorithm aversion shows that consumers resist machine decision-making more strongly when tasks are seen as subjective, identity-relevant, or emotionally laden (Castelo et al., 2019). Service encounters often have exactly those properties. Customers may accept a bot for routine information but still prefer human support when facing complaints, ambiguity, vulnerability, or unusual requests. This is why the strongest service designs increasingly use AI for triage, speed, and pattern detection, while preserving human escalation routes for empathy, negotiation, and trust repair (Wirtz et al., 2018; Hermann et al., 2024).

The focal study on AI-generated visuals for career orientation extends the service and marketing conversation into educational communication. Its quasi-experimental orientation suggests that generative AI can improve engagement and message salience when visual content is relevant, accessible, and well aligned with user needs (ul Islam et al., 2025). This is consistent with broader marketing research arguing that AI can strengthen consumer understanding and action by connecting computational power with human insight and context-aware content design (Ma & Sun, 2020; Kaplan & Haenlein, 2019). However, it also raises new concerns regarding authenticity, bias, and over-personalisation. Generative systems may produce attractive outputs, but attractive content is not necessarily accurate, inclusive, or pedagogically sound. Here again, organisational value depends on governance and review rather than on generation capability alone.

Across service and marketing settings, three recurring mechanisms appear. First, AI improves relevance by matching content or responses to behavioural signals. Second, it improves speed by reducing response latency and handling routine load. Third, it enhances consistency by standardising decision rules and service protocols. Yet these benefits are offset when systems become intrusive, manipulative, or opaque. For this reason, service organisations need explicit design principles regarding disclosure, escalation, accessibility, and quality monitoring. AI-driven customer engagement is most effective when organisations treat technology as a relationship support system rather than as a cost-cutting substitute for meaningful interaction.

4.3 Sustainable operations and supply chains

Supply chain management has emerged as one of the richest fields for studying AI in combination with other digital technologies. Supply chains generate high volumes of operational data, depend on coordination across dispersed actors, and face constant pressure from disruptions, sustainability requirements, and customer demands for transparency. The focal chapter on blockchain and IoT for sustainable supply chain management in Industry 4.0 argues that value creation in this space depends on combining traceability, real-time visibility, automation, and accountability (Islam, 2025). This position is strongly supported by the wider literature. IoT improves sensing and event capture, blockchain can strengthen traceability and transaction integrity, and AI helps interpret data streams for forecasting, anomaly detection, and optimisation (Ben-Daya et al., 2019; Saberi et al., 2019; Queiroz et al., 2021).

An especially important contribution of the supply chain literature is its attention to resilience. Ivanov and Dolgui (2021) show that digital twins and related analytical systems can help firms simulate disruption scenarios, evaluate vulnerabilities, and respond more effectively to uncertainty. Kache and Seuring (2017) similarly argue that big data analytics at the intersection of digital information and supply chain management can create both opportunities and challenges, depending on data integration quality and organisational readiness. The lesson is that AI-powered operations are not simply about efficiency under normal conditions. They are also about adaptability under abnormal conditions. This is highly relevant in a period shaped by geopolitical volatility, climate shocks, and fragile logistics networks.

Sustainability is the second major theme. Supply chains are increasingly expected to show environmental accountability, ethical sourcing, and credible disclosure. Blockchain-backed traceability can support these aims, but only if data inputs are accurate and if governance extends beyond technological certification. Technology cannot, by itself, solve upstream labour exploitation or environmental harm. What it can do is improve visibility, make monitoring more feasible, and strengthen incentives for responsible coordination. That is why the most promising view of AI-enabled sustainable supply chains is not technological determinism, but socio-technical stewardship. It aligns digital tools with sustainability metrics, supplier development, and long-term stakeholder accountability (Geissdoerfer et al., 2017; Bocken et al., 2014).

This section also helps refine the paper's broader framework. AI creates operational value when it shortens the path between sensing, analysis, and response. Yet sustainable value appears only when those responses are evaluated against social and environmental goals, not merely cost or speed. Consequently, the strongest AI-enabled supply chain systems are those that integrate forecasting accuracy, resilience, traceability, and sustainability reporting in one coordinated architecture. This is precisely why supply chains offer such a powerful case for cross-domain learning: they show how engineering infrastructures become managerial capabilities only when they are anchored in strategy, governance, and measurable outcomes.

4.4 Education, counselling, and inclusive support systems

Educational and support environments have become important test sites for AI because they involve large-scale information needs, diverse user groups, and significant social consequences. Yet much of the public conversation remains polarised between celebration and fear. Systematic reviews show that AI in education has often been discussed in relation to adaptive learning, assessment, and administrative support, while less attention has been paid to teacher roles, guidance functions, and ethical governance (Zawacki-Richter et al., 2019). More recent work on large language models has renewed this debate by highlighting both opportunities for personalised support and risks associated with hallucination, dependency, and inequity (Kasneci et al., 2023; Tlili et al., 2023; Dwivedi et al., 2023).

The focal contributions examined here broaden the scope of educational AI in useful ways. The chapter on leveraging digital tools for school counselling moves the discussion beyond instruction into advisory and psychosocial support. It shows that digital platforms can improve access to information, case management, and communication when used thoughtfully by counsellors and schools (Ansarullah et al., 2025). The quasi-experimental work on AI-generated visuals for career orientation similarly suggests that AI can enhance student engagement and clarity when complex options are translated into meaningful and attractive visual communication (ul Islam et al., 2025). These contributions are important because education systems do not only transmit knowledge. They also shape aspiration, decision confidence, emotional support, and future pathways. AI can therefore influence educational outcomes indirectly through improved guidance, orientation, and counselling processes.

Inclusion becomes even more explicit in the focal article on social network design for disability peer support. This work demonstrates that AI-related digital design should be evaluated not only by efficiency, but by accessibility, measurable support outcomes, and barrier reduction (Islam et al., 2026). It resonates with research on digital inequality in smart environments, which warns that supposedly intelligent systems can reproduce exclusion when they assume uniform connectivity, literacy, or bodily ability (Ylipulli & Hämäläinen, 2023). It also aligns with studies on vulnerable consumers in service settings, where the deployment of AI must be sensitive to differential capacities and risks (Hermann et al., 2024). In this sense, educational and support applications provide a critical reminder: AI can deepen capability if it is inclusive, but it can also magnify disadvantage if the design logic privileges convenience over accessibility.

For institutions, the main implication is that AI-supported education and support systems require governance at three levels. First, there must be content quality assurance to address accuracy and bias. Second, there must be role clarity, so that teachers, counsellors, and support workers understand where AI assists and where human expertise remains indispensable. Third, there must be accessibility and safeguarding standards, especially for young learners, vulnerable users, and people with disabilities. When these conditions are met, AI can strengthen support systems by expanding reach and improving responsiveness. When they are absent, adoption may increase workload, confusion, and mistrust.

4.5 Urban technologies, tourism, and social innovation

AI adoption also needs to be examined in broader civic and place-based contexts. Smart city and urban innovation debates increasingly show that digital transformation is not meaningful if it only installs sensors and dashboards without improving inclusion, participation, and quality of life. The focal chapter on fostering social innovation through urban technologies argues that technology-enabled urbanism should be connected to inclusive entrepreneurship and measurable public value rather than reduced to infrastructural modernisation alone (Islam et al., 2026). This argument is consistent with collaborative urban development research that emphasises co-creation, shared problem solving, and citizen-oriented innovation processes (von Schnurbein et al., 2023). It also speaks to digital inequality scholarship, which warns that smart city interventions may benefit already advantaged groups unless they are intentionally designed for accessibility and participation (Ylipulli & Hämäläinen, 2023).

The tourism literature offers a related but distinct angle. The focal chapter on sustainable tourism, experiential travel, and dark tourism is not primarily about AI, yet it is highly relevant because tourism increasingly depends on digital mediation, predictive analytics, and platform-based experience design (Islam et al., 2025). Sustainable tourism management requires balancing destination competitiveness with heritage sensitivity, environmental limits, and social meaning. AI can assist through demand forecasting, visitor flow optimisation, recommendation systems, and personalised engagement. However, such tools need to be guided by place ethics and sustainability objectives, not just conversion rates. Tourism therefore illustrates a broader principle: AI adds value when it supports human and cultural contexts rather than flattening them into generic behavioural data.

Urban technologies, tourism, and social innovation jointly reveal that AI is not only a firm-level resource. It is also a societal coordination technology. It can shape how people move, learn, engage, access services, and interpret spaces. This wider role creates responsibility. Data-driven systems in urban and tourism environments must address privacy, accessibility, explainability, and social legitimacy. The literature suggests that collaborative governance and measurable public outcomes are more important than technological spectacle. In practical terms, place-based AI strategies should therefore include public consultation, equity-sensitive evaluation, and clear criteria for what counts as improvement. Without such safeguards, digital transformation risks becoming a symbolic project rather than a meaningful one.

4.6 Quantum-enhanced AI as an emerging frontier

While many organisational studies are still grappling with current AI adoption, a new frontier is already emerging in the form of quantum-enhanced AI. The focal chapter on quantum-enhanced artificial intelligence frames this area as the next frontier in computing and decision-making, suggesting that future systems may combine AI learning architectures with quantum computational advantages in optimisation and simulation (Ansarullah et al., 2026). This frontier remains early, but the underlying scientific discussion is no longer speculative. Quantum machine learning research has already demonstrated conceptual routes for using quantum systems in classification, feature mapping, and high-dimensional data processing (Biamonte et al., 2017; Schuld & Killoran, 2019). Variational quantum algorithms have also become central to attempts to make useful computation feasible under near-term constraints (Cerezo et al., 2021).

For management and engineering scholars, the significance of quantum-enhanced AI lies less in immediate commercial deployment and more in strategic preparedness. Preskill (2018) describes the current era as one of noisy intermediate-scale quantum systems, meaning that practical use is limited but developmental momentum is strong. Organisations involved in finance, logistics, cryptography, materials discovery, and large-scale optimisation are therefore beginning to monitor the field closely. The conceptual relevance to the present review is twofold. First, quantum-enhanced AI reinforces the idea that AI value is shaped by its surrounding computational ecosystem. Second, it reminds us that governance questions should be addressed early rather than retrospectively. If future systems dramatically increase optimisation capacity, then issues of transparency, concentration of power, security, and equitable access will become even more salient.

It would be premature to frame quantum-enhanced AI as an immediate answer to today’s operational problems. However, it is entirely appropriate to treat it as a strategic research frontier. The wise position is one of informed anticipation. Organisations and scholars should explore likely application pathways, capability requirements, and governance implications now, while avoiding exaggerated claims. In the context of this paper, quantum-enhanced AI serves as a reminder that AI transformation is not static. The technological base is still evolving, which means conceptual models of adoption and value creation must remain adaptable.

5. AN INTEGRATIVE FRAMEWORK FOR AI-ENABLED SUSTAINABLE VALUE CREATION

The cross-domain literature reviewed above points to a common architecture of value creation. At the input level, organisations assemble technical resources such as data, algorithms, cloud infrastructure, sensor networks, or digital interfaces. These resources alone do not create value. They must be converted into capabilities such as prediction, classification, automation, visualisation, conversational support, anomaly detection, optimisation, or network design. Those capabilities then operate within domain processes: compliance management, customer service, counselling, educational guidance, tourism management, supply chain coordination, or urban innovation. It is at this process level that most adoption barriers and implementation failures emerge, because technical outputs need to be translated into decisions, workflows, and user experiences.

The reviewed literature suggests that four moderators determine whether AI capabilities produce meaningful outcomes. The first is human acceptance, shaped by usefulness, usability, trust, and perceived risk (Davis, 1989; Pavlou, 2003; Venkatesh et al., 2003). The second is governance quality, including explainability, auditability, role clarity, and ethical review (Glikson & Woolley, 2020; Laine et al., 2024; Shneiderman, 2020). The third is contextual fit, meaning the degree to which the AI system is aligned with task characteristics, institutional norms, and stakeholder expectations (Castelo et al., 2019; Hermann et al., 2024). The fourth is sustainability orientation, which determines whether performance is assessed narrowly or across economic, social, and environmental dimensions (Elkington, 1998; Hart & Milstein, 2003; Geissdoerfer et al., 2017).

Once these moderators are considered, outcomes can be grouped into three categories. Operational outcomes include speed, consistency, forecasting quality, and reduced routine burden. Strategic outcomes include improved resilience, enhanced customer engagement, stronger decision support, innovation capability, and competitive differentiation. Social outcomes include accessibility, inclusion, trust, learning support, public value, and responsible resource use. The focal works demonstrate all three categories. AI in tax compliance and finance contributes to operational and strategic efficiency (Islam et al., 2025; ul Islam et al., 2025). AI agents and AI-generated visuals contribute to customer and learner engagement (Rawanda, 2025; ul Islam et al., 2025). Disability peer support and urban technology chapters highlight social inclusion and public value (Islam et al., 2026; Islam et al., 2026). The supply chain and tourism chapters show how sustainability and responsible coordination can be embedded into broader digital transformation agendas (Islam, 2025; Islam et al., 2025).

Based on this synthesis, the paper proposes an integrative framework for AI-enabled sustainable value creation. The framework assumes that value is strongest when five conditions are jointly satisfied: data adequacy, capability-task fit, human-centred interface design, governance maturity, and sustainability-oriented performance metrics. If any of these conditions are weak, value becomes partial or unstable. For example, strong technical models with poor governance may generate short-term efficiency but long-term distrust. High acceptance without sustainability metrics may improve usage without improving broader outcomes. Advanced infrastructure without accessibility standards may deepen exclusion. The central proposition, therefore, is that AI creates durable value only when technical, organisational, and ethical layers are designed together.

Table 2. Cross-domain AI value logic, indicators, and risks

Domain	**Primary AI value logic**	**Illustrative performance indicators**	**Key implementation risks**
Finance and compliance	Prediction, anomaly detection, faster review cycles	Forecast accuracy, fraud detection rate, processing time, compliance cost	Opacity, model drift, fairness concerns, public mistrust
Customer service and marketing	Personalisation, response speed, consistency	Resolution time, satisfaction, retention, escalation	Loss of empathy, intrusive profiling, over-automation

Domain	Primary AI value logic	Illustrative performance indicators	Key implementation risks
		quality	
Supply chains and operations	Visibility, optimisation, resilience, traceability	Lead-time variability, stock-out reduction, emissions visibility, disruption response time	Data fragmentation, partner misalignment, false traceability claims
Education, counselling, and support	Guidance, engagement, content adaptation, improved access	Engagement levels, guidance uptake, accessibility scores, counsellor workload	Bias, misinformation, digital exclusion, safeguarding gaps
Urban technologies and tourism	Public value coordination, demand management, participation support	Service access, visitor flow balance, citizen participation, sustainability metrics	Surveillance, inequity, weak legitimacy, place-insensitive automation
Quantum-enhanced AI frontier	Advanced optimisation and simulation	Computation efficiency, scenario depth, model innovation	Hype, weak readiness, skills scarcity, governance lag

Note. The table summarises the recurring cross-domain patterns identified in the literature synthesis.

6. MANAGERIAL IMPLICATIONS

The first managerial implication is that AI strategy should begin with a problem architecture, not a technology architecture. Organisations often start by asking which AI tool to buy or which model to deploy. A better question is which decision bottleneck, service gap, compliance burden, forecasting weakness, or inclusion challenge needs to be addressed. This helps ensure capability-task fit and reduces technology theatre. The focal literature repeatedly supports this point. AI in tax compliance, customer service, school counselling, and disability peer support works best when it is tied to clearly defined service or decision problems rather than vague promises of transformation (Islam et al., 2025; Rawanda, 2025; Ansarullah et al., 2025; Islam et al., 2026).

The second implication is that managers should treat trust as an operational variable. Trust is often discussed as a soft issue, yet in AI contexts it directly affects usage, continuance, escalation behaviour, and stakeholder legitimacy. This means managers need explicit trust-building mechanisms: clear communication about system limits, visible human oversight, error correction routines, and user education. In regulated or sensitive settings such as finance, counselling, taxation, or accessibility support, trust cannot be retrofitted after deployment. It needs to be built into the design and governance process from the start (Featherman & Pavlou, 2003; Glikson & Woolley, 2020).

Third, organisations should measure AI performance across multiple dimensions. Speed and cost savings matter, but they are inadequate as stand-alone metrics. Decision quality, user satisfaction, inclusiveness, accessibility, sustainability, and resilience should also be tracked. Supply chain contexts, in particular, show the danger of narrow metrics. A system that improves routing efficiency but worsens supplier inequity or environmental opacity is not strategically mature. Likewise, a counselling or support system that increases digital contact volumes but reduces human trust is not genuinely successful. Multi-dimensional evaluation is therefore essential if AI is to support sustainable value rather than short-term optimisation.

Finally, managerial capability building matters as much as technical capability building. Firms and institutions need leaders who can translate between algorithms, workflows, ethics, and stakeholder needs. This requires cross-functional teams and learning-oriented governance rather than siloed decision-making. AI transformation is not simply an IT project. It is an organisational redesign challenge.

7. FUTURE RESEARCH AGENDA

Several research directions follow from this review. First, cross-domain comparative studies are needed. Most current research remains sector specific, which makes it difficult to identify transferable design principles. Comparative studies across finance, service, education, and public innovation could reveal which adoption mechanisms are universal and which are context bound. Second, future work should focus more explicitly on inclusion. Disability, language, affordability, and digital literacy often appear as afterthoughts in AI research, even though they fundamentally shape who benefits from transformation (Islam et al., 2026; Ylipulli & Hämäläinen, 2023). Third, the literature needs more longitudinal evidence. Many studies measure intention or early performance, but fewer track continuance, adaptation, and institutional learning over time (Bhattacherjee, 2001).

Fourth, governance research should move beyond abstract ethical principles towards operational models. Organisations need clearer guidance on how audits, human override, documentation, and accountability routines influence actual performance and trust. Ethics-based AI auditing research has made progress, but empirical evidence on implementation remains limited (Laine et al., 2024). Fifth, research should examine hybrid intelligence more carefully. The central issue is no longer whether humans or AI perform better in isolation, but how they complement or undermine each other across different tasks (Jarrahi, 2018; Huang & Rust, 2021). This is particularly important in emotionally sensitive and judgement-heavy settings such as counselling, customer recovery, taxation disputes, or accessibility support. Sixth, the growing interest in quantum-enhanced AI opens a new agenda linking technical possibility to strategic and governance readiness (Ansarullah et al., 2026; Preskill, 2018).

Taken together, these directions suggest that the future of AI research in management and engineering should be less fragmented, more comparative, more inclusive, and more governance aware. Scholars need frameworks that can explain not only whether AI works, but for whom, under what conditions, and at what broader cost or benefit.

Table 3. Priority directions for future research

Research stream	Representative questions	Useful methods	Expected contribution
Human trust and AI use	How do transparency and human override shape continuance in sensitive settings?	Experiments, field studies, longitudinal surveys	Explains when acceptance becomes sustained institutional trust.
Inclusive AI design	Which accessibility features most improve outcomes for vulnerable users?	Design science, participatory action research, usability testing	Moves AI research from generic adoption to equitable adoption.
Hybrid intelligence in service work	Which service tasks benefit most from machine-human collaboration?	Process tracing, field experiments, service analytics	Clarifies role boundaries between automation and empathy.
AI and sustainable operations	How do AI, IoT, and blockchain jointly affect resilience and sustainability?	Case studies, panel data, simulation	Links digital operations to environmental and social performance.
Educational guidance systems	How do AI-supported visuals and counselling tools influence aspiration and decision confidence?	Quasi-experiments, mixed methods, learning analytics	Extends educational AI beyond instruction into guidance and support.
Quantum-enhanced business analytics	Which managerial problems are most likely to benefit from quantum-AI approaches?	Scenario analysis, technology roadmapping, expert Delphi studies	Builds strategic readiness without exaggerated commercial claims.

Note. Proposed agenda based on the integrative review developed in this paper.

8. CONCLUSION

This paper has developed an integrative review of AI-enabled transformation across finance, services, supply chains, education, social innovation, tourism, and emerging computational frontiers. The review demonstrates that AI is most usefully understood as a socio-technical capability whose value depends on strategic alignment, human acceptance, governance quality, and sustainability orientation. Across the focal contributions and the wider literature, the same lesson reappears: technical sophistication is necessary, but it is never sufficient. AI creates durable value when organisations design for trust, context, inclusion, and measurable outcomes at the same time as efficiency and innovation.

The eleven focal works cited in this paper make an important collective contribution because they show how AI-related thinking can travel across domains without losing practical relevance. From finance and tax compliance to disability peer support, urban technologies, school counselling, customer service, sustainable tourism, and supply chain management, they demonstrate that responsible AI research must remain grounded in real organisational and social problems. The integrative framework proposed here extends that contribution by showing how technical resources become capabilities, how capabilities become outcomes, and why governance and sustainability determine whether those outcomes endure.

For scholars, the key message is that AI research should move towards broader synthesis without sacrificing domain detail. For managers, the key message is that AI strategy should be human-centred, evidence-based, and sustainability-oriented. For institutions, the message is that inclusion and trust are not secondary concerns. They are part of the architecture of value itself.

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