International Journal of Academic Management Science Research (IJAMSR)
ISSN: 2643-900X
Vol. 10 Issue 6 June - 2026, Pages: 21-29

Artificial Intelligence-Driven Decision Intelligence for Organizational Transformation

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Abstract: *Artificial Intelligence (AI) adoption has expanded rapidly across organizations; however, many firms continue to struggle to translate AI investments into scalable organizational value and sustainable transformation outcomes. Existing literature indicates that organizations often implement AI as isolated models, dashboards, or automation tools without embedding these technologies into organizational decision workflows, governance structures, and operational processes. Consequently, Decision Intelligence (DI) has emerged as a decision-centric approach that integrates data, analytics, AI, human expertise, workflows, and governance mechanisms to improve organizational decision-making and strategic performance. This study aims to develop a conceptual framework explaining how AI-driven Decision Intelligence can support organizational transformation through structured and governable decision systems. Using an integrative conceptual methodology, the study synthesizes prior literature from Decision Intelligence, AI-driven decision-making, digital transformation, organizational transformation, and AI governance. The proposed framework consists of four interconnected building blocks: inputs and foundations, AI-driven Decision Intelligence capability, governance layer, and transformation outcomes. The framework explains how predictive, causal, prescriptive, and generative AI technologies can be integrated with organizational workflows, decision logic, human roles, and governance systems to enhance decision quality, accountability, consistency, and responsiveness. The study further emphasizes that governance mechanisms such as human oversight, monitoring, audit trails, escalation procedures, and risk controls are essential for ensuring trustworthy and explainable AI-enabled decisions. The study concludes that organizational transformation is achieved not through AI technologies alone, but through embedding AI into transparent, governable, and continuously learning decision workflows. The proposed framework contributes theoretically by positioning Decision Intelligence as a higher-order organizational capability that operationalizes organizational transformation through structured decision systems and continuous feedback loops. Practically, the framework provides organizations with a decision-centric roadmap for implementing AI responsibly and effectively to improve operational performance, organizational learning, accountability, agility, and long-term competitiveness*

Keywords: Artificial Intelligence, Decision Intelligence, Organizational Transformation, Digital Transformation, AI Governance, Human–AI Collaboration, Decision-Making.

1. Introduction

Organizations are no longer struggling to adopt artificial intelligence so much as to translate it into repeatable organizational value. Recent large-scale surveys show that AI use is now widespread, yet most firms still have not scaled it across the enterprise or converted it into material business impact. Boston Consulting Group reported in late 2024 that 74% of companies had yet to show tangible value from AI, while McKinsey's 2025 global survey found that most organizations were still in experimentation or pilot phases and that only about one-third had begun scaling AI programs enterprise-wide [1]. That gap helps explain why Decision Intelligence has become strategically important. Gartner describes decision intelligence platforms as decision-centric systems that support, augment, and automate decisions through the composition of data, analytics, knowledge, and AI, while also enabling decision modeling, orchestration, monitoring, governance, and learning from outcomes. IDC similarly defines decision intelligence as a discipline and technology for designing, engineering, and orchestrating decisions by fully or partially automating the steps of decision-making [2]. Together, these definitions shift attention away from isolated models and toward the full architecture of decision-making [3]. Recent academic studies further support this perspective by emphasizing that artificial intelligence creates organizational value when integrated with decision-making structures, data-driven processes, and strategic organizational capabilities rather than operating as isolated technological tools [4]–[6].

The central problem is that many organizations still deploy AI as stand-alone models, copilots, dashboards, or use cases, rather than embedding it inside the workflow, accountability structure, and feedback loops through which real decisions are made [7]. IDC explicitly distinguishes DI from BI and AI/ML alone: BI helps users understand metrics and trends, AI/ML adds predictive and pattern-recognition capabilities, but DI focuses on automating and governing decision-making, often with humans in the loop. McKinsey's 2025 survey reinforces this point by showing that high performers are far more likely to redesign workflows and define when model outputs require human validation [8]. This argument is consistent with recent research highlighting that AI-enabled decision-making effectiveness depends heavily on organizational integration, governance mechanisms, knowledge-sharing structures, and workflow redesign that align technological capabilities with managerial processes [4], [9], [10]. The aim of this paper is therefore to propose a concise conceptual framework explaining how AI-driven Decision Intelligence can enable organizational transformation. The framework is designed to:

• Define Decision Intelligence in a way that is distinct from BI, analytics, and AI alone;
• Synthesize the main constructs that make AI useful for organizational decision-making;
• Present a decision-centric framework linking foundations, AI capability, governance, and outcomes;
• Explain the practical and theoretical implications of embedding AI into decisions at scale.

The guiding research question is: How can AI-driven Decision Intelligence be conceptualized to support organizational transformation? The contribution is a simple but robust framework showing that transformation does not come from "AI everywhere," but from embedding AI into the decisions that connect strategy, operations, people, and control. In that view, transformation is achieved not merely through better models but through faster decision cycles, improved decision quality and consistency, clearer accountability, and stronger organizational learning [11].

2.Literature Review

2.1Decision Intelligence

The emerging literature converges on the idea that Decision Intelligence is decision-centric, not merely data-centric [12]. Gartner defines DI platforms as systems for creating decision-centric solutions that support, augment, and automate human or machine decisions, while explicitly modeling decisions, orchestrating decision flows, and governing decision quality and outcomes [13]. IDC defines DI as software technology that helps organizations design, engineer, and orchestrate decisions by automating all or part of the decision-making process, and it breaks that process into decision design, decision engineering, and decision orchestration [14]. This distinction matters because DI is broader than conventional business intelligence and narrower than "AI" as a catch-all term. IDC states that BI allows users to understand trends, outliers, and metrics; AI/ML contributes predictive and pattern-recognition capabilities; DI combines elements of both but focuses on automating aspects of decision-making with governance and, depending on the decision, humans in the loop. Gartner adds that DI includes decision collaboration, decision execution, and decision modeling, with explicit guardrails, workflows, monitoring, and governance [15]. Recent empirical studies also support this distinction by emphasizing that business intelligence and AI technologies generate organizational value when integrated into coordinated decision-making structures, governance systems, and strategic workflows rather than functioning independently as isolated analytical tools [9], [10], [16].

Academic work points in the same direction. Pratt et al. [17] argue that data and analytics are necessary but not sufficient for better strategic decisions, and that something more is needed to integrate technology with decision-makers and with one another in complex environments [18]. Their DI/DS integration framework treats decision-making as a thought and simulation process that links actions to business outcomes through cause-and-effect chains. An MDPI special issue on DI likewise frames the field as a practical discipline focused on understanding how decisions are made and how outcomes are evaluated and improved through feedback [19]. A useful synthesis, then, is that DI combines decision modeling, workflow orchestration, human-AI interaction, monitoring, and feedback. That is what makes it especially relevant for organizational transformation: it bridges the classic "insight-to-action" gap by treating decisions themselves as designable, governable organizational assets. This perspective aligns with recent organizational and strategic management studies arguing that sustainable organizational transformation depends on integrating technological capabilities with organizational learning, governance mechanisms, and human-centered decision structures that support adaptability and long-term competitiveness [5], [20], [21].

2.2 Organizational Transformation

AI contributes to decisions through several distinct but complementary capabilities. First, predictive analytics estimates what is likely to happen [22]. IDC explicitly places predictive analysis inside decision engineering, and the prescriptive analytics literature describes predictive analytics as a prior stage in the analytics maturity ladder. Second, causal and explanatory approaches address the question of why outcomes occur and what effect an intervention might produce [23], [24]. A recent JAIR review argues that effective decisions require understanding causal relationships among actions, environments, and outcomes, and it identifies causal structure learning, causal effect learning, and causal policy learning as core components of causal decision-making [25]. Lo and colleagues similarly argue that prescriptive decision problems are causal by nature because decision-makers act in order to cause desirable outcomes. Third, prescriptive analytics supports the question of what to do [26]. Lepenioti and colleagues describe prescriptive analytics as the part of business analytics that seeks the best course of action for the future and is often seen as the next step toward optimized decision-making [27]. In practice, this is the part of DI most closely aligned with recommendations, prioritization, optimization, and constrained action selection [28]. Fourth, generative AI can support reasoning, communication, option structuring, and interaction. Recent reviews show that GenAI is reshaping decision-making across sectors by improving decision support, efficiency, and personalization, while experimental work in business information systems suggests that GenAI can facilitate the organization of information and options for decisions. At the same time, studies of business strategy emphasize that GenAI is most useful when combined with human judgment, especially under uncertainty [29]. These arguments are increasingly supported by contemporary studies demonstrating that AI-driven systems enhance strategic decision-making, organizational responsiveness, and innovation capabilities when combined with human expertise and organizational support mechanisms [4], [30].

These benefits come with important risks. NIST's AI RMF warns that AI systems can amplify, perpetuate, or exacerbate inequitable or undesirable outcomes if not properly controlled, and it defines trustworthy AI in terms that include validity, safety, accountability, transparency, explainability, privacy enhancement, and fairness with harmful biases managed. NIST's bias standard further stresses that bias is socio-technical, not merely technical, and that human, systemic, and institutional factors all matter. For generative AI specifically, OECD notes the problem of hallucinations convincing but inaccurate outputs while IBM highlights model drift as the degradation of model performance due to changes in data or the relationship between inputs and outputs [31], [32]. AI makes DI more powerful, but it also makes governance more important. A DI framework that ignores bias, drift, opacity, or hallucination is incomplete by design. Similar concerns have been highlighted in recent studies emphasizing that AI-enabled organizational systems require strong governance structures, cybersecurity awareness, ethical oversight, and organizational accountability to ensure sustainable and trustworthy digital transformation outcomes [5], [33], [34].

2.3 Governance and Responsible Scaling

The governance literature is remarkably consistent: scaling AI responsibly requires trust, accountability, monitoring, and human oversight. OECD's AI Principles define trustworthy AI in terms of human rights and democratic values, transparency and explainability, robustness, security and safety, and accountability. OECD's accountability report further specifies that AI actors should design, install, and monitor processes that document AI system decisions, enable auditing, provide response to risks, and furnish redress mechanisms where justified, across the AI lifecycle from design through deployment and monitoring [35]. NIST's AI RMF makes a similar point from a risk-management standpoint. Its core framework is intended to improve the incorporation of trustworthiness considerations into AI design, development, use, and evaluation, and its trustworthiness characteristics include accountability, transparency, explainability, and fairness [36]. The generative AI profile goes further by requiring clear roles and responsibilities, oversight of human-AI configurations, incident response procedures, continual risk measurement, external feedback, and mechanisms for recourse. Recent academic evidence similarly emphasizes that AI-driven organizational systems require governance mechanisms, ethical oversight, cybersecurity awareness, and accountability structures to ensure sustainable and trustworthy organizational transformation [5], [33], [34].

The regulatory environment now reinforces the same logic. The EU AI Act requires high-risk AI systems to be effectively overseen by natural persons, specifies that human oversight should prevent or minimize risks to health, safety, and fundamental rights, and states that oversight measures must be proportionate to risk, system autonomy, and context of use. It also requires that human overseers understand the system's capacities and limitations and be able to monitor anomalies and unexpected performance [37]. At the firm level, organizational evidence points in the same direction. McKinsey reports that high-performing organizations are much more likely to define processes for when model outputs require human validation, and that mitigation of AI-related risks is becoming more common as organizations experience consequences such as inaccuracy and explainability challenges. Papagiannidis et al. [39] likewise argue that responsible AI governance must be operationalized through structural, relational, and procedural practices [38]. The conclusion is that governance is not a peripheral compliance layer. It is a prerequisite for organizational adoption, sustained use, and transformation at scale. Without governance, DI becomes faster but not necessarily safer, more legitimate, or more trusted [40]. This argument aligns with recent organizational and strategic management studies showing that sustainable digital transformation and AI adoption depend heavily on governance quality, organizational control systems, leadership support, and structured managerial practices that maintain trust and accountability during technological integration [4], [41], [42].

2.4 Gap Summary

The literature is strong on the components of the problem but weaker on the connective tissue. DI research now offers credible definitions of decision-centric modeling and orchestration, but it is still emerging as a coherent organizational paradigm. AI research is rich on predictive models, causal reasoning, GenAI, and human-AI collaboration, yet much of it remains fragmented or focused on technical attributes [43], [44]. Transformation research clearly shows that AI alters processes, roles, and culture, but it often treats decision-making as one output among many rather than as the central design unit. Governance research has advanced rapidly, yet Papagiannidis et al. [39] note that operationalizing responsible AI across design, execution, monitoring, and evaluation remains limited. Human-AI review work similarly finds that the literature lacks integrative, socio-technical explanations of decision-making in organizational contexts. Comparable gaps are also evident in recent organizational and management studies, where AI, business intelligence, and digital transformation are frequently examined as separate technological capabilities without sufficiently explaining how they become embedded into organizational workflows, governance systems, and decision structures that generate sustainable organizational outcomes [5], [6], [9].

What is still needed, then, is a framework showing how AI capabilities become embedded into organizational decisions at scale not just as analytics outputs, and not just as digital transformation rhetoric, but as a governable mechanism linking inputs, workflows, people, and feedback to transformation outcomes. That is the gap this paper addresses. This perspective is increasingly important because recent studies demonstrate that organizational competitiveness, innovation capability, and strategic transformation depend not only on AI adoption itself but also on the integration of technological capabilities with organizational learning, governance mechanisms, workflow coordination, and human-centered decision processes [4], [10], [20].

2.5 Proposed Conceptual Framework

The proposed conceptual framework explains how Artificial Intelligence (AI)-driven Decision Intelligence (DI) enables organizational transformation and enhances supply chain competitiveness in emerging markets. The framework is based on the argument that digital transformation alone does not automatically generate organizational value unless AI technologies are embedded into decision-making structures, operational workflows, governance systems, and continuous learning processes. Accordingly, the framework conceptualizes Decision Intelligence as a higher-order organizational capability that integrates data, analytics, AI technologies, human expertise, and governance mechanisms to improve organizational decision-making and operational performance [45]. This perspective is supported by recent studies emphasizing that organizational competitiveness and digital transformation outcomes depend on integrating AI capabilities with data-driven decision-making, organizational agility, workflow coordination, and governance-oriented managerial practices rather than relying solely on technological adoption [5], [6], [46]. The framework begins with the foundational layer, which consists of data readiness, decision inventory, and strategic KPIs. This layer represents the organizational prerequisites necessary for effective Decision Intelligence implementation. Data readiness ensures that organizations possess accessible, integrated, reliable, and high-quality data capable of supporting AI-driven decisions. Decision inventory refers to identifying strategic, tactical, and operational decisions that significantly influence organizational performance and supply chain outcomes. Strategic KPIs establish measurable goals that guide decision optimization and organizational alignment [47]. The framework emphasizes that organizations should prioritize high-value and recurring decisions rather than implementing AI technologies without clear strategic focus.

The second layer represents the AI-driven Decision Intelligence capability, which forms the operational core of the framework. This capability combines predictive AI, causal AI, prescriptive analytics, and generative AI with organizational workflows, decision logic, and authority structures. Predictive AI supports forecasting and anticipation of future events, while causal AI helps organizations understand intervention effects and underlying drivers of outcomes. Prescriptive analytics recommends optimal actions under operational constraints, whereas generative AI improves communication, scenario generation, explanation, and interaction. The framework suggests that these technologies collectively enhance organizational intelligence and improve decision responsiveness. The framework further proposes that AI technologies generate organizational value only when integrated into decision workflows and operational processes. Decision Intelligence therefore extends beyond analytical prediction by embedding AI outputs into workflow orchestration, escalation procedures, optimization rules, approval mechanisms, and operational execution systems. This integration transforms AI-generated insights into actionable organizational decisions capable of improving operational coordination and supply chain performance [48]. Similar arguments are reflected in recent studies demonstrating that AI applications and business intelligence systems improve organizational effectiveness when integrated into strategic decision-making processes, operational coordination mechanisms, and collaborative organizational structures [4], [9], [10].

Human roles and authority structures also represent an essential component of the DI capability. The framework argues that effective organizational transformation depends on collaborative human–AI interaction rather than full automation of decision-making processes. Decision owners remain responsible for accountability and performance outcomes, reviewers provide oversight and control for high-risk or exceptional situations, and domain experts contribute contextual understanding and professional judgment. Consequently, the framework adopts a socio-technical perspective in which AI enhances organizational intelligence while humans maintain strategic oversight, interpretation, and ethical control. The governance layer overlays the entire Decision Intelligence capability and ensures that AI-enabled decisions remain transparent, accountable, explainable, and trustworthy. The framework includes governance mechanisms such as audit trails, monitoring systems, documentation procedures, escalation rules, human oversight, incident management, and third-party risk controls. These governance practices are consistent with internationally recognized AI governance principles emphasizing accountability, continuous monitoring, transparency, and lifecycle risk management. The framework therefore highlights that organizations cannot achieve effective Decision Intelligence without integrating governance directly into decision workflows and AI-enabled operational systems. This view aligns with recent organizational studies emphasizing the importance of governance quality, cybersecurity awareness, leadership support, and ethical oversight in ensuring sustainable and trustworthy AI-enabled organizational transformation [33], [34], [42].

The final layer of the framework represents transformation outcomes. The framework proposes that organizations implementing AI-driven Decision Intelligence can achieve faster decision cycles, improved decision quality and consistency, stronger accountability, clearer strategic alignment, and continuous organizational learning. These outcomes subsequently contribute to broader organizational transformation and supply chain competitiveness through enhanced operational flexibility, resilience, transparency, responsiveness, and cost efficiency. The feedback mechanism within the framework further strengthens organizational adaptation by continuously generating new data, revised KPIs, redesigned processes, and retrained models that improve future decision-making capabilities. The framework also contributes theoretically by extending dynamic capability theory through a decision-centric perspective. It conceptualizes Decision Intelligence as a dynamic organizational capability that operationalizes sensing, seizing, and transforming through AI-enabled decision systems, workflow integration, governance structures, and continuous feedback loops. From a practical perspective, the framework suggests that organizations should prioritize redesigning decision systems, workflows, governance mechanisms, and human–AI collaboration structures before pursuing large-scale AI deployment. This implication is particularly important in emerging markets, where institutional limitations, infrastructure gaps, and varying levels of digital maturity significantly influence the success of digital transformation initiatives. Recent empirical studies similarly demonstrate that organizational learning capability, agility, knowledge management, and governance-oriented digital transformation practices significantly influence organizational competitiveness, resilience, and sustainable performance in dynamic business environments [16], [20], [21].

3.Method

This study uses an integrative conceptual approach. That choice is appropriate because the topic sits across multiple bodies of knowledge—information systems, AI, management, digital transformation, and governance—and because the objective is framework building rather than hypothesis testing. Integrative literature reviews are specifically intended to synthesize prior literature to generate new knowledge, while conceptual framework analysis is designed to build networks of linked concepts that improve understanding of complex, multidisciplinary phenomena. The literature base for this synthesis was constructed from peer-reviewed journal articles and official standards or analyst materials that define Decision Intelligence and responsible AI in operational terms. In practical academic terms, the search logic corresponds to a Scopus- and Google Scholar-style keyword strategy centered on combinations of Decision Intelligence, AI decision-making, causal decision-making, prescriptive analytics, generative AI decision support, organizational transformation, digital transformation, governance, human oversight, and monitoring. Priority was given to primary or near-primary sources: NIST, OECD, EU regulatory text, Gartner and IDC definitions, and peer-reviewed journals.

Framework development followed three transparent steps. First, recurring constructs were identified across the literature: decision lifecycle, AI capabilities, human roles, governance mechanisms, and organizational outcomes. Second, these constructs were grouped into broader socio-technical themes: technology, process, people, and governance. Third, the themes were connected into a coherent framework showing how inputs and decision foundations feed AI-enabled decision capability, how governance overlays and constrains that capability, and how organizational outcomes generate feedback for continuous improvement. That approach aligns with conceptual framework analysis and with recent socio-technical syntheses of human-AI decision-making.

4. Discussion and Implications

Decision speed: DI improves speed not merely because AI is fast, but because decision logic is made explicit and then executed through orchestrated workflows. Decision-centric organizations separate decisions from process clutter, use information systems as action-oriented partners, and automate the decisions that can safely be automated while escalating the rest. Gartner's definition of DI platforms likewise centers on decision execution, and McKinsey finds that redesigning workflows is one of the strongest contributors to meaningful AI value. Faster decisions therefore come from workflow clarity and automation discipline, not from model performance alone.

Decision quality and consistency: Quality improves when different forms of intelligence are combined inside one decision flow. Predictive models estimate what may happen, causal logic clarifies intervention effects, prescriptive methods compare actions under constraints, and GenAI can organize information or communicate rationale. Structured decision logic also reduces variance across teams and time. Empirical research on dashboards shows that the format, currency, and completeness of information affect decision quality indirectly by reducing perceived task complexity and improving information satisfaction. In a DI setting, those information-quality conditions are embedded in the decision workflow rather than left to ad hoc interpretation.

Accountability and trust: Trust is not the product of model accuracy alone. It also depends on transparency, explainability, proportional oversight, and institutionalized accountability. OECD's accountability framework, NIST's trustworthiness criteria, and the EU AI Act all converge on the need for documentation, risk-based oversight, and the capability for human intervention. McKinsey's high performers are also more likely to define when human validation is needed. In the proposed framework, this is why governance sits on top of the decision capability rather than beside it: accountability must be built into how decisions are made, reviewed, recorded, and challenged.

Learning organization: The strongest theoretical advantage of DI is that it closes the loop between action and learning. IDC's decision orchestration explicitly includes ongoing or periodic adjustment of workflows, rules, algorithms, and decisions based on automated and human-generated feedback loops, and Gartner's DI platform definition likewise includes learning from actions and outcomes. NIST and IBM add that production monitoring is necessary to detect inaccuracy, bias, and drift over time. In short, DI turns organizational transformation into a repeatable learning cycle: outcomes are traced back to decision logic, decision logic is revised, and the organization becomes more adaptive over time.

5. Theoretical and Practical Implications

The primary managerial implication is to start with high-value decisions, not with a generic ambition to "do more AI." BCG finds that AI leaders pursue fewer but more valuable opportunities and focus strongly on people and process redesign, while McKinsey shows that high performers are disproportionately redesigning workflows and embedding AI into core processes. That directly supports a DI-first implementation strategy: identify repeatable high-impact decisions, specify decision owners and KPIs, and then embed AI where it improves those decisions. A second implication is to build governance early. Governance should not be deferred until after technical success because trust, compliance, monitoring, documentation, and recourse shape whether the organization can scale AI safely at all. The most credible standards literature now treats governance as part of responsible design, development, deployment, and operation rather than as a downstream audit function. A third implication is to invest in change management. AI adoption changes work practices, roles, skills, and culture. The organizational literature emphasizes that leadership communication, employee development, cultural alignment, and resistance management are central to successful AI integration. BCG's 70-20-10 argument makes the same point from a practitioner perspective: the largest share of transformation work lies in people and process, not in algorithms.

The framework positions Decision Intelligence as the missing bridge between AI capability and organizational transformation outcomes. Existing literatures often stop at one of three points: model capability, adoption challenges, or broad transformation narratives. By contrast, the present framework argues that the key unit of analysis should be the decision workflow—the place where goals, data, AI outputs, human judgment, governance, and action actually converge. That move is consistent with DI scholarship, socio-technical reviews of human-AI interaction, and responsible AI governance research, but it makes the linkage more explicit than most existing accounts. This also contributes to transformation theory by showing that AI-driven change is not only about digital tools or culture, but about the reconfiguration of decision rights, action logic, and feedback mechanisms. In that sense, DI can be understood as a meso-level organizational capability: more concrete than abstract "AI maturity," but broader than any individual model or application.

This is a conceptual framework, not an empirically validated model. It synthesizes the strongest available literature, but it does not test causal effects across industries or decisions. That matters because organizational outcomes will vary by decision type, risk level, sector, and regulatory context. The literature itself also remains uneven. Governance research is advancing quickly, but Papagiannidis et al. [39] note that operationalization remains fragmented. The organizational culture literature on AI is still relatively young and often cross-sectional, which limits insight into long-run transformation dynamics. Human-AI decision-making reviews also point to unresolved socio-technical questions around trust calibration, bias mitigation, intervention design, and the conditions under which human-AI complementarity actually improves outcomes. These limitations make the framework most useful as a foundation for future case studies, comparative sector studies, surveys, and longitudinal adoption research.

6. Conclusion

Organizations have invested heavily in AI and analytics, but widespread adoption has not automatically produced scalable decision impact. Large surveys from BCG and McKinsey show that many firms still struggle to move from pilots and isolated use cases to sustained enterprise value. The literature on Decision Intelligence offers a compelling explanation: value is created when data, AI, people, workflows, and governance are organized around the decisions that actually drive operations and strategy. This paper's contribution is a simple conceptual DI framework with four building blocks: inputs and foundations, AI-driven DI capability, governance, and transformation outcomes, linked by feedback loops. The framework shows that transformation occurs when organizations identify the decisions that matter, embed predictive, causal, prescriptive, and generative AI inside explicit decision workflows, assign clear human roles, and govern the resulting system through accountability, monitoring, and risk-based oversight. The clearest takeaway is that organizational transformation is not produced by AI in isolation. It is produced when AI is embedded into decision workflows that are transparent, governable, and capable of learning. In other words, the route from AI capability to organizational transformation runs through Decision Intelligence.

References

[1] H. M. Abualrejal, A. Z. Alqudah, A. A. A. Ali, O. Saoula, and T. K. AlOrmuza, "University parcel centre services quality and users' satisfaction in higher education institutions: A case of Universiti Utara Malaysia," in *Proceedings of International Conference on Emerging Technologies and Intelligent Systems: ICETIS 2021*, Lecture Notes in Networks and Systems, vol. 322, M. Al-Emran, M. A. Al-Sharafi, M. N. Al-Kabi, and K. Shaalan, Eds. Springer, 2022, pp. 885–895, doi: 10.1007/978-3-030-85990-9_70.

[2] S. Al-Haddad, A.-A. A. Sharabati, A. Y. Nasereddin, M. Alyah, O. Mehyar, and A. A. A. Ali, "The impact of Instagram content marketing on cognitive engagement, affection, and behavior," *International*

Journal of Data and Network Science, vol. 8, no. 4, pp. 2685–2700, 2024, doi: 10.5267/j.ijdns.2024.4.010.

[3] M. M. Alashqar, A. F. S. Abulehia, A. A. Atieh, M. H. Mahmoud, and M. M. S. Alzubi, "Legal framework for regulating AI in smart cities: Privacy, surveillance, and ethics," in *2025 International Conference for Artificial Intelligence, Applications, Innovation and Ethics (AI2E)*, 2025, pp. 1–6, doi: 10.1109/AI2E64943.2025.10983107.

[4] A. S. Alrawahna, H. Alhanatleh, H. Awad, A. Alzghoul, and I. Al Muala, "The role of artificial intelligence in enhancing decision-making processes," in *2025 International Conference on Decision Aid Sciences and Applications (DASA)*, Dec. 2025, pp. 164–168.

[5] A. A. Khaddam and A. Alzghoul, "Artificial intelligence-driven business intelligence for strategic energy and ESG management: A systematic review of economic and policy implications," *International Journal of Energy Economics and Policy*, vol. 15, no. 4, pp. 635–650, 2025.

[6] A. Alzghoul, "How HR analytics catalyzes bank competitiveness: Investigating the mediating role of data-driven decision-making and the moderating effect of organizational agility," *Banks and Bank Systems*, vol. 20, no. 2, p. 107, 2025.

[7] A. A. A. Ali, H. M. E. Abualrejal, Z. B. Mohamed Udin, H. O. Shtawi, and A. Z. Alqudah, "The role of supply chain integration on project management success in Jordanian engineering companies," in *Proceedings of International Conference on Emerging Technologies and Intelligent Systems*, Lecture Notes in Networks and Systems, vol. 299, M. Al-Emran, K. Shaalan, and A. E. Hassanien, Eds. Springer, 2021, pp. 646–657, doi: 10.1007/978-3-030-82616-1_53.

[8] A. A. A. Ali, A. A. S. Fayad, A. Alomair, and A. S. Al Naim, "The role of digital supply chain on inventory management effectiveness within engineering companies in Jordan," *Sustainability*, vol. 16, no. 18, Art. no. 8031, 2024, doi: 10.3390/su16188031.

[9] A. M. Obeidat, A. A. Khaddam, A. Alzghoul, M. T. M. Al Afeshat, and M. Al Ghizzawi, "How business intelligence shapes service innovation: Knowledge sharing as a mediator and culture as a moderator in the Jordanian context," *Economics*, vol. 14, no. 1, 2026.

[10] M. Tawalbeh, A. Alzghoul, and G. A. A. Alsheikh, "Business intelligence as a catalyst for HR transformation: A study of BI implementation in HR practices," in *AIP Conference Proceedings*, vol. 3255, no. 1, p. 050007, Jan. 2025.

[11] A. A. A. Ali, A.-A. A. Sharabati, M. Allahham, and A. Y. Nasereddin, "The relationship between supply chain resilience and digital supply chain and the impact on sustainability: Supply chain dynamism as a moderator," *Sustainability*, vol. 16, no. 7, Art. no. 3082, 2024, doi: 10.3390/su16073082.

[12] A. A. A. Ali, A.-A. A. Sharabati, D. R. Alqurashi, A. S. Shkeer, and M. Allahham, "The impact of artificial intelligence and supply chain collaboration on supply chain resilience: Mediating the effects of information sharing," *Uncertain Supply Chain Management*, vol. 12, no. 3, pp. 1801–1812, 2024, doi: 10.5267/j.uscm.2024.3.002.

[13] A. A. A. Ali, Z. B. M. Udin, and H. M. E. Abualrejal, "The impact of artificial intelligence and supply chain resilience on the companies supply chains performance: The moderating role of supply chain dynamism," in *Lecture Notes in Networks and Systems*, vol. 550. Springer, 2023, pp. 17–28, doi: 10.1007/978-3-031-16865-9_2.

[14] A. A. A. Ali, Z. M. Udin, and H. M. E. Abualrejal, "The impact of humanitarian supply chain on non-government organizations performance moderated by organisation culture," *International Journal of Sustainable Development and Planning*, vol. 18, no. 3, pp. 763–772, 2023, doi: 10.18280/ijsdp.180312.

[15] T. A. Al-Maaitah, A. F. Hijazin, A. Ali, A. Al-Amarneh, S. M. Alshdaifat, and D. A. Al-Maaitah, "Business intelligence capability, organizational agility, and bank performance: Evidence from an emerging country," *EDPACS*, pp. 1–21, 2026, doi: 10.1080/07366981.2026.2624906.

[16] K. Khawaldeh and A. Alzghoul, "Nexus of business intelligence capabilities, firm performance, firm agility, and knowledge-oriented leadership in the Jordanian high-tech sector," *Problems and Perspectives in Management*, vol. 22, no. 1, p. 115, 2024.

[17] L. Pratt, C. Bisson, and T. Warin, "Bringing advanced technology to strategic decision-making: The Decision Intelligence/Data Science (DI/DS) Integration framework," *Futures*, vol. 152, Art. no. 103217, 2023.

[18] E. K. Alotaibi, K. K. Alafi, A. S. Shkeer, B. Ismaeel, A. Ali, and I. A. Khanfar, "Assessing the impact of sustainable tourism practices on Petra and Wadi Rum," *Heritage and Sustainable Development*, vol. 8, no. 1, pp. 499–512, 2026, doi: 10.37868/hsd.v8i1.1685.

[19] A. Z. Alqudah, M. M. Alshar, M. M. S. Mahmoud, S. N. Al Sheyab, S. Radwan, and A. Ali, "E-marketing and creativity as drivers of organizational performance in the packaging and food processing industry in Jordan: The mediating role of customer

satisfaction," *PaperASIA*, vol. 42, no. 1b, pp. 57–68, 2026, doi: 10.59953/paperasia.v42i1b.960.

[20] S. Lehyeh and A. Alzghoul, "Digital transformation and supply chain competitiveness: Evidence of dynamic capabilities from an emerging economy," *Journal of Project Management*, vol. 11, no. 1, pp. 63–74, 2026.

[21] A. Alzghoul and K. M. Aboalganam, "Investigating the effect of knowledge management systems on university performance: The interplay of intellectual and human capital," *Knowledge and Performance Management*, vol. 9, no. 1, p. 93, 2025.

[22] A. A. M. Alrifae, M. H. Mahmoud, R. Al Zumot, A. Ali, and M. M. AlZubi, "The impact of electronic human resource management on organizational performance in the Jordanian telecommunications sector with employee engagement as a mediating variable," *Discover Sustainability*, vol. 7, Art. no. 273, 2026, doi: 10.1007/s43621-026-02644-9.

[23] K. Alrifai, T. Obaid, A. A. A. Ali, A. F. S. Abulehia, H. M. E. Abualrejal, and M. B. A. R. Nassoura, "The role of artificial intelligence in project performance in construction companies in Palestine," in *International Conference on Information Systems and Intelligent Applications: ICISIA 2022*, Lecture Notes in Networks and Systems, vol. 550, M. Al-Emran, M. A. Al-Sharafi, and K. Shaalan, Eds. Springer, 2023, pp. 71–82, doi: 10.1007/978-3-031-16865-9_6.

[24] M. M. S. Alzubi, A. A. Mohammad Alrifae, M. H. Mahmoud, and A. A. Atieh, "Factors influencing business intelligence adoption by Jordanian private universities," *PaperASIA*, vol. 41, no. 1b, pp. 148–167, 2025, doi: 10.59953/paperasia.v41i1b.378.

[25] A. A. Atieh, "Enhancing humanitarian supply chain resilience through AI: The moderating role of artificial intelligence in achieving Sustainable Development Goals (SDGs) in Jordan," *International Journal of Sustainable Development and Planning*, vol. 20, no. 5, pp. 2225–2234, 2025, doi: 10.18280/ijsdp.200537.

[26] M. A. Alzuod, S. M. Alshdaifat, A. A. Atieh, A. Al-Amarneh, L. T. Khrais, and A. F. Hijazin, "The moderating role of sustainable practices in the relationship between organizational capabilities and technology adoption," *Heritage and Sustainable Development*, vol. 7, no. 1, pp. 385–400, 2025, doi: 10.37868/hsd.v7i1.1126.

[27] A. A. Atieh, "The role of strategic resilience and data-driven culture in enhancing supply chain risk management: A resource orchestration perspective," *PaperASIA*, vol. 41, no. 3b, pp. 258–268, 2025, doi: 10.59953/paperasia.v41i3b.509.

[28] A. A. Atieh and M. M. Abushaega, "Achieving supply chain sustainability through green innovation: A dynamic capabilities-based approach in the logistics sector," *Sustainability*, vol. 17, no. 13, Art. no. 5716, 2025, doi: 10.3390/su17135716.

[29] A. A. Atieh, A. Abu Hussein, S. Al-Jaghoub, A. F. Alheet, and M. Attiany, "The impact of digital technology, automation, and data integration on supply chain performance: Exploring the moderating role of digital transformation," *Logistics*, vol. 9, no. 1, Art. no. 11, 2025, doi: 10.3390/logistics9010011.

[30] H. Alhanatleh, A. Alzghoul, and K. Abualganam, "Impact of artificial intelligence applications on customers' value co-creation: Telecommunication sector," in *2025 International Conference on Decision Aid Sciences and Applications (DASA)*, Dec. 2025, pp. 1161–1166.

[31] A. A. Atieh, A. F. Hijazin, S. M. Alshdaifat, *et al.*, "Digital transformation and technological capabilities in achieving sustainable development goals in emerging countries," *Discover Sustainability*, vol. 7, Art. no. 383, 2026, doi: 10.1007/s43621-026-02739-3.

[32] R. A. Eitah, A. Ali, and M. A. Al-Fawaeer, "Leveraging digital HRM for sustainable workforce transformation: The role of green employee engagement in achieving ESG goals," *Journal of Logistics, Informatics and Service Science*, vol. 12, no. 11, pp. 129–145, 2025.

[33] F. Abu-Dabaseh, M. Alghizzawi, B. I. Alkhlaifat, A. A. R. Ezmigna, A. Alzghoul, A. A. AlSokkar, and J. Al-Gasawneh, "Enhancing privacy and security in decentralized social systems: Blockchain-based approach," in *2024 2nd International Conference on Cyber Resilience (ICCR)*, Feb. 2024, pp. 1–6.

[34] A. Alzghoul, H. Alhanatleh, S. Alnajdawi, M. Alghizzawi, and A. Mohammad Al Htibat, "Actual role of cybersecurity awareness and knowledge to drive digital technology adoption for enhance sustainable development: Engineering industry setting," in *2024 International Conference on Decision Aid Sciences and Applications (DASA)*, Dec. 2024, pp. 1–5.

[35] A. F. Hijazin, S. M. Alshdaifat, A. A. Atieh, and E. F. Hasan, "From responsibility to returns: How ESG and CSR drive investor decision making in the age of sustainability," *Journal of Risk and Financial Management*, vol. 18, no. 8, Art. no. 406, 2025, doi: 10.3390/jrfm18080406.

[36] M. H. Mahmoud, A. A. Ali, A. A. Alrifae, R. A. Eitah, and M. M. AlZubi, "The impact of digital HRM system and digital transformation on HR efficiency with organizational agility as a moderator," *Discover*

Sustainability, vol. 6, Art. no. 1038, 2025, doi: 10.1007/s43621-025-01713-9.

[37] T. Obaid, S. S. Abu-Naser, M. S. S. Abumandil, A. Y. Mahmoud, and A. A. A. Ali, "Age and gender classification from retinal fundus using deep learning," in *Advances on Intelligent Computing and Data Science: Proceedings of ICACIn 2022*, A. E. Hassanien, V. Snášel, A. M. Madureira, and F. Kacprzyk, Eds. Springer, 2023, pp. 171–180, doi: 10.1007/978-3-031-36258-3_15.

[38] T. Obaid, B. Eneizan, M. S. S. Abumandil, A. Y. Mahmoud, S. S. Abu-Naser, and A. A. A. Ali, "Factors affecting students' adoption of e-learning systems during COVID-19 pandemic: A structural equation modeling approach," in *International Conference on Information Systems and Intelligent Applications: ICISIA 2022*, Lecture Notes in Networks and Systems, vol. 550, M. Al-Emran, M. A. Al-Sharafi, and K. Shaalan, Eds. Springer, 2023, pp. 227–242, doi: 10.1007/978-3-031-16865-9_19.

[39] E. Papagiannidis, P. Mikalef, J. Krogstie, and K. Conboy, "From responsible AI governance to competitive performance: The mediating role of knowledge management capabilities," in *Conference on e-Business, e-Services and e-Society*, Cham: Springer International Publishing, Sept. 2022, pp. 58–69.

[40] T. Obaid, B. Eneizan, S. S. Abu-Naser, G. Alsheikh, A. A. A. Ali, H. M. E. Abualrejal, and N. A. Gazem, "Factors contributing to an effective e-government adoption in Palestine," in *Advances on Intelligent Informatics and Computing: Health Informatics, Intelligent Systems, Data Science and Smart Computing*, Lecture Notes on Data Engineering and Communications Technologies, vol. 127, F. Saeed, F. Mohammed, and F. Ghaleb, Eds. Springer, 2022, pp. 663–676, doi: 10.1007/978-3-030-98741-1_55.

[41] A. Al-Jaber, A. Alzghoul, M. Alghizzawi, S. F. AlFraihat, R. Elhawi, and T. Banihani, "Integrating HRM strategies to achieve sustainable development goals: The mediating roles of employee well-being and corporate governance," *Administrative Sciences*, vol. 15, no. 12, Art. no. 474, 2025.

[42] S. Al-Shammari and A. Alzghoul, "Unlocking innovation through digital HRM: How employee development and transformational leadership shape adoption success," *International Review of Management and Marketing*, vol. 16, no. 3, p. 205, 2026.

[43] A.-A. A. Sharabati, A. A. A. Ali, M. I. Allahham, A. A. Hussein, A. F. Alheet, and A. S. Mohammad, "The impact of digital marketing on the performance of SMEs: An analytical study in light of modern digital transformations," *Sustainability*, vol. 16, no. 19, Art. no. 8667, 2024, doi: 10.3390/su16198667.

[44] A.-A. A. Sharabati, S. Al-Haddad, R. Ayyed, K. Albarki, S. Abo-Rome, and A. A. A. Ali, "The impact of ChatGPT service on students' performance: Moderated by training," *International Journal of Data and Network Science*, vol. 9, no. 3, pp. 513–524, 2025, doi: 10.5267/j.ijdns.2024.8.014.

[45] A.-A. A. Sharabati, H. Z. Awawdeh, S. Sabra, H. K. Shehadeh, M. Allahham, and A. Ali, "The role of artificial intelligence on digital supply chain in industrial companies mediating effect of operational efficiency," *Uncertain Supply Chain Management*, vol. 12, no. 3, pp. 1867–1878, 2024, doi: 10.5267/j.uscm.2024.2.016.

[46] A. Tarawneh and A. Alzghoul, "Unlocking digital payoffs in pharmaceutical supply chains: Organizational learning capability as a boundary condition," *International Review of Management and Marketing*, vol. 16, no. 1, p. 430, 2026.

[47] A. S. Shkeer, A.-A. A. Sharabati, T. Samarah, M. I. M. Alqurneh, and A. A. A. Ali, "The influence of social media content marketing on consumer engagement: A mediating of the role of consumer cognition," *International Journal of Data and Network Science*, vol. 8, no. 4, pp. 2423–2434, 2024, doi: 10.5267/j.ijdns.2024.5.015.

[48] H. Yaseen, A. S. Mohammad, N. Ashal, H. Abusaimeh, A. Ali, and A.-A. A. Sharabati, "The impact of adaptive learning technologies, personalized feedback, and interactive AI tools on student engagement: The moderating role of digital literacy," *Sustainability*, vol. 17, no. 3, Art. no. 1133, 2025, doi: 10.3390/su17031133.

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