From Compliance to Strategic Intelligence: How AI Maturity, Automation Readiness, and Digital Trust in AI Shape Decision Intelligence and Sustainable Business Performance

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The rapid advancement of Artificial Intelligence (AI) and intelligent automation is reshaping organizational finance functions from traditional compliance-focused operations into strategic intelligence-driven business partners. While organizations across finance, fintech, consulting, technology, manufacturing, and professional service sectors are increasingly investing in AI-enabled systems, significant differences remain in their ability to translate these investments into sustainable business value. Few studies have simultaneously examined AI maturity, automation readiness, and digital trust as joint antecedents of decision intelligence within finance transformation contexts — a gap particularly pronounced in emerging economy settings where organizational readiness and trust barriers remain underexplored.

This study is situated within the emerging discourse on Trustworthy AI, emphasizing responsible deployment, human-AI collaboration, and explainability as prerequisites for sustainable organizational value. Rather than treating AI merely as an adoption variable, this paper foregrounds digital trust and AI maturity as governance-linked capabilities that determine whether AI-driven finance transformation is both effective and ethically grounded.

Drawing upon Resource-Based View and Dynamic Capability perspectives, the study proposes an integrated model examining how AI Maturity, Automation Readiness, and Digital Trust in AI contribute to Decision Intelligence — defined as the organization's capability to transform data, analytics, and AI-generated insights into effective strategic decisions — and subsequently to Strategic Finance Capability and Sustainable Business Performance. The study focuses on finance and business professionals across Indian industries including fintech, consulting, manufacturing, and professional services.

A mixed-methods design is adopted, combining semi-structured interviews with CFOs, finance managers, chartered accountants, and fintech professionals, alongside a structured questionnaire analyzed through Structural Equation Modeling (SEM). The study proposes that AI maturity, automation readiness, and digital trust positively influence decision intelligence, which strengthens strategic finance capability and enhances sustainable business performance — encompassing financial outcomes, operational resilience, and long-term value creation. The study further introduces the Finance Intelligence Transformation Framework (FITF), mapping the progression from compliance-driven operations to strategic intelligence-led value creation.

Keywords: Artificial Intelligence, AI Maturity, Automation Readiness, Digital Trust in AI, Decision Intelligence, Strategic Finance Capability, Sustainable Business Performance, Finance Transformation, Trustworthy AI, Responsible AI.

1. Introduction

Artificial Intelligence (AI) has stopped being a back-office curiosity. Over the past few years it has moved to the centre of how firms read their environment, allocate resources and decide what to do next. Across industrial, analytical and decision-heavy work, AI now carries real transformative potential, and it is steadily reshaping both jobs and the basis on which firms compete (Dwivedi et al., 2021). Nowhere is the change clearer than in the finance function. Work that once defined finance, such as reconciliation, reporting and control, is being automated, and finance teams are increasingly judged on the forward-looking analysis and decision support they provide instead.

Spending on AI, though, does not convert into value on its own. The early record of enterprise AI is uneven. A large share of organisations never move past isolated pilots that promise much and deliver little, while a smaller group manages to turn AI into a capability that scales and shows up in performance (Davenport & Ronanki, 2018). What separates the two groups is rarely the technology, which is broadly available, but the organisational scaffolding around it: the maturity of the data, the readiness of the processes, the quality of governance and, not least, whether people trust the output enough to act on it. The distance between owning AI and being able to use it well is the problem this paper takes up.

We develop the argument for India, where finance and business teams in fintech, consulting, manufacturing and professional services are taking up AI quickly even as readiness and trust remain patchy and lightly studied. The question we pursue is whether AI maturity, automation readiness and digital trust together shape an organisation's decision intelligence, and whether that decision intelligence then feeds strategic finance capability and, through it, sustainable business performance. The paper is conceptual. It builds an integrated, theory-led model with testable hypotheses, and sets out the research design needed to put that model to the test in later work.

2. Problem Statement

Research on AI in organisations explains adoption far better than it explains value, so it remains unclear whether AI actually improves the quality of finance decisions and the outcomes that follow, particularly in emerging economies such as India. This study addresses that gap by modelling AI maturity, automation readiness and digital trust as joint drivers of decision intelligence, strategic finance capability and sustainable business performance in the Indian finance context.

3. Research Objectives

1. To examine the role of AI maturity in the transformation of the organisational finance function.
2. To analyse the influence of automation readiness on decision intelligence.
3. To investigate the effect of digital trust in AI on organisational decision-making capability.
4. To examine the relationship between decision intelligence and strategic finance capability.
5. To assess how strategic finance capability contributes to sustainable business performance.

6. To develop the Finance Intelligence Transformation Framework (FITF) for AI-enabled finance transformation.
7. To propose an integrated conceptual model and research design for future empirical validation in Indian organisations.

4. Theoretical Background

Two strands of strategy theory anchor the study. The Resource-Based View (RBV) argues that durable competitive advantage comes from resources that are valuable, rare, hard to imitate and difficult to substitute, together with the firm's ability to organise and exploit them (Barney, 1991). RBV offers a tidy explanation for an awkward fact. Two firms can buy the same AI tools and end up in very different places, because the tools are common while the proprietary data, the integrated processes, the people and the governance that surround them are not.

The Dynamic Capabilities perspective carries this reasoning into fast-moving technological settings. It treats capability as the firm's ability to sense opportunities, seize them and reconfigure its resource base as the environment shifts (Teece, Pisano, & Shuen, 1997). We read AI maturity, automation readiness and digital trust in that light, as higher-order capabilities rather than as pieces of technology. The reading has empirical backing, since AI capability has been conceptualised and measured as a distinct organisational resource that lifts creativity and firm performance (Mikalef & Gupta, 2021), which supports treating AI maturity as a capability rather than a tick-box for adoption.

Read together, the two theories give the paper its central claim. AI pays off not at the moment it is installed but when an organisation has built the capability to fold it into decisions and trusts it enough to follow its advice. Decision intelligence is where we locate that conversion from capability into outcome.

5. Literature Review

The review follows the six constructs in the proposed model. For each, we summarise the relevant ABDC-listed evidence and draw out a hypothesis. Table 1 sets out the working definitions used throughout.

Table 1. Working definitions of the study constructs

Construct	Working Definition For The Study
AI Maturity	The extent to which an organisation has developed the data infrastructure, governance, leadership commitment, talent and strategic alignment needed to deploy and scale AI across the finance function.
Automation Readiness	Organisational preparedness to adopt intelligent automation and redesign finance processes, spanning technology, workforce capability, process standardisation and change management.
Digital Trust in AI	Confidence of finance professionals in the reliability, transparency, fairness, accountability and explainability of AI systems used for decision support.
Decision Intelligence	The organisation's capability to convert data, analytics and AI-generated insight into effective strategic decisions.
Strategic Finance Capability	The ability of the finance function to use financial and non-financial information for planning, forecasting, risk management and business partnering.

Sustainable Business Performance	Economic, operational and governance outcomes that together support long-term value creation and resilience.

5.1 Artificial Intelligence Maturity

AI maturity describes how far an organisation has built the infrastructure, governance, leadership, talent and strategic alignment that AI requires, and it reaches well beyond the act of adoption to take in data governance, process integration and a culture of continuous learning. Collins, Dennehy, Conboy, and Mikalef (2021), in a systematic review of artificial intelligence in information systems research, conclude that organisational value rests on capability rather than on the acquisition of tools, and they identify capability building as a priority for future work. Berente, Gu, Recker, and Santhanam (2021) argue that managing AI is a distinct problem in its own right, because the autonomy, learning behaviour and inscrutability of AI oblige firms to govern it deliberately as they scale from isolated experiments to enterprise-wide use. Davenport and Ronanki (2018), reviewing early enterprise deployments, observe that the firms which capture value are those that move beyond pilots towards integrated, organisation-wide capability.

The empirical evidence supports reading maturity as a capability rather than an adoption indicator. Mikalef and Gupta (2021) develop and validate an AI-capability construct grounded in the resource-based view, and they find that it raises both organisational creativity and firm performance. Roberts and Candi (2024) extend this line of work, linking AI capability to innovation outcomes as firms mature in their use of the technology. In the finance function specifically, greater maturity underwrites the automation of routine processing, sharper forecasting and analytical insight delivered in real time, each of which supplies the raw material for better decisions.

H1: AI Maturity positively influences Decision Intelligence.

5.2 Automation Readiness

Automation readiness concerns an organisation's preparedness to adopt intelligent automation and to redesign its processes around it. It spans technological infrastructure, workforce capability, leadership support, process standardisation and the capacity to manage change. Makarius, Mukherjee, Fox, and Fox (2020) frame the integration of AI as a sociotechnical process, arguing that technical deployment must be matched by socialisation and a deliberate human-AI configuration if adoption is to succeed. Helo and Hao (2022), through an exploratory case study in operations and supply-chain management, find that the principal barriers to automation are organisational rather than technical, since implementation depends on data, skills and managerial commitment as much as on the technology itself.

Within the finance function, readiness is what permits the transition from manual transaction processing to automated workflows, real-time reporting and predictive analytics, and it frees professionals to concentrate on analytical and advisory work. Where readiness is weak, automation stalls and its analytical benefits are never realised. Readiness is therefore expected to strengthen the organisation's capacity to convert data into decisions.

H2: Automation Readiness positively influences Decision Intelligence.

5.3 Digital Trust in Artificial Intelligence

Digital trust is the confidence that finance professionals place in the reliability, transparency, fairness, accountability and explainability of AI systems, and it largely determines whether AI is used at all. Glikson and Woolley (2020), in a wide-ranging review of empirical research, show that the form an AI system takes and its level of machine intelligence both shape cognitive and emotional trust, and they identify tangibility, transparency and reliability as central antecedents. Trust is not uniformly scarce. Logg, Minson, and Moore (2019) report that, across a series of estimation tasks, people often prefer algorithmic advice to human advice, an effect they label algorithm appreciation, though they also find that this preference weakens among experts.

Inside professional finance, reliance is more guarded. Commerford, Dennis, Joe, and Ulla (2022) find that experienced auditors discount evidence more heavily when it is produced by an AI system than when equivalent evidence is produced by a human specialist, an algorithm-aversion effect that is most pronounced for complex estimates. Reliance can nonetheless be repaired through design. Commerford, Eilifsen, Hatfield, Holmstrom, and Kinserdal (2024) show that allowing auditors to provide input into an AI system increases their reliance on its output, and Jussupow, Benbasat, and Heinzl (2024) reconcile aversion and appreciation by classifying the decision configurations under which each tends to arise.

A further group of studies sets out the conditions under which trust forms. Weber, Carl, and Hinz (2024), reviewing applications of explainable AI in finance, identify explainability as a recurring precondition for trust in financial settings. Newman, Fast, and Harmon (2020) show that fairness concerns intensify when algorithms strip away contextual information, so that an algorithmic decision can be judged less fair even when statistical bias has been reduced. Lebovitz, Levina, and Lifshitz-Assaf (2021) caution that the expert ground truth used to train and evaluate AI is itself uncertain, which tempers how far professionals can reasonably trust an AI tool.

Evidence from financial services reinforces the centrality of trust. Hildebrand and Bergner (2021) demonstrate that conversational robo-advisors act as surrogates of trust, with the onboarding interaction shaping how clients perceive the firm and the financial decisions they make. Mostafa and Kasamani (2022) find that anthropomorphism and ease of use build initial trust in financial chatbots, which in turn drives adoption, while Uysal, Alavi, and Bezencon (2022) show that humanlike features raise trust and self-disclosure yet can also provoke discomfort. Belanche, Casalo, and Flavian (2019) report that customer attitudes and trust are decisive in the adoption of robo-advisors, and Munoko, Brown-Liburd, and Vasarhelyi (2020) add an ethical dimension, identifying bias and accountability as risks that, if left unaddressed, erode the very trust on which AI use depends. Taken together, this body of work positions digital trust as the condition under which AI insight is actually relied upon in decision-making.

H3: Digital Trust in AI positively influences Decision Intelligence.

5.4 Decision Intelligence

Decision intelligence is the organisation's capacity to convert data, analytics and AI-generated insight into decisions that work. It integrates predictive analytics, machine learning and human judgement, and it places its emphasis on action and execution rather than on the production of further information. Duan, Edwards, and Dwivedi (2019) frame the interaction and integration of AI with human decision makers as the core challenge for the field, and they offer a set of research propositions on how AI can support or replace human judgement in the era of big data. Huang and Rust (2018) develop a theory of how mechanical, thinking and feeling AI progressively take on decision and service tasks, and in later work Huang and Rust (2021) extend this account to the relational tasks through which AI shapes engagement.

Decision intelligence is the pivot of the proposed model, the route through which AI maturity, automation readiness and digital trust become organisational capability and, in time, outcomes. Sun, Zhang, Hu, and Van Mieghem (2022), in a large-scale field experiment in warehouse operations, show that the value of an algorithmic prescription depends on how the discretion of human workers to adjust it is managed. Tong, Jia, Luo, and Fang (2021) find that AI feedback raises employee performance when deployed but can reduce it once disclosed, which underlines the human element in any decision system. Rialti, Zollo, Ferraris, and Alon (2019) and Chatterjee, Chaudhuri, Gupta, Sivarajah, and Bag (2023) provide convergent evidence that big-data analytics capabilities improve decision processes, forecasting and firm performance. Stronger decision intelligence should therefore raise the strategic capability of the finance function.

5.5 Strategic Finance Capability

The finance function has shifted over the past decade, moving away from a narrow base of accounting, reporting, compliance and control and towards planning, performance management, forecasting and business partnering. Strategic finance capability denotes the function's ability to put financial and non-financial information to work in support of strategy, risk management and value creation.

Auditing offers a clear illustration of the mechanism. Fedyk, Hodson, Khimich, and Fedyk (2022) find that investment in AI human capital improves audit quality through better anomaly detection and risk assessment, with the development of skilled staff identified as the principal constraint. Emett, Kaplan, Mauldin, and Pickerd (2023) add an important caveat, showing that external reviewers can judge analytics-based procedures as lower in quality because the procedures appear less effortful, which signals that analytic capability must be accompanied by credibility if it is to be valued. Where decision intelligence is strong, the finance function can produce more accurate forecasts, deeper scenario analysis and smarter resource allocation, which is what strategic finance capability amounts to in practice.

H4: Decision Intelligence positively influences Strategic Finance Capability.

5.6 Sustainable Business Performance

Sustainable business performance reaches past short-term financial results to cover the economic, operational and governance dimensions that sustain value and resilience over time. Viewed through the resource-based view and the dynamic-capabilities perspective, a finance function that can plan, forecast and partner strategically is difficult for rivals to replicate and should, on that basis, improve sustainable performance.

Shan, Umar, and Mirza (2022) provide evidence in this direction, finding that AI applications such as automated advisory services are associated with measurable sustainability outcomes. We also expect decision intelligence to influence sustainable performance directly, by improving the speed and quality of decisions across the organisation rather than only within the finance function.

H5: Strategic Finance Capability positively influences Sustainable Business Performance.

H6: Decision Intelligence positively influences Sustainable Business Performance.

6. Research Gap

Read as a whole, the literature leaves four connected gaps. The first is a tilt towards adoption. The work explains whether AI is taken up far better than it explains whether AI improves the quality of decisions and the outcomes that follow. Integrated adoption models exist for India (Chatterjee, Rana, Dwivedi, & Baabdullah, 2021), and the adoption of AI in banking and payments has been studied in emerging markets and in India in particular (Rahman, Ming, Baigh, & Sarker, 2023; Srivastava, Mohta, & Shunmugasundaram, 2024), but these accounts stop at intention or uptake and rarely reach realised value.

The remaining gaps build on the first. AI maturity, automation readiness and digital trust are usually examined separately, which leaves their joint contribution to decision intelligence unclear. Digital trust is generally framed as a personal reaction to a system rather than as an organisational condition that governs whether AI insight is relied on at all (Glikson & Woolley, 2020; Commerford et al., 2022). And the empirical base is thin where it matters most, since workforce and capability evidence is mostly conceptual or drawn from non-Indian samples (Chowdhury, Budhwar, & Wood, 2024), while primary evidence on whether AI improves finance decision quality in India is scarce. The model proposed here addresses all four, tying the three capabilities to decision intelligence, strategic finance capability and sustainable business performance, and framing the whole for the Indian finance function.

7. Conceptual Model and Hypotheses Development

The model places AI maturity, automation readiness and digital trust as joint antecedents of decision intelligence. Decision intelligence then strengthens strategic finance capability, and both decision intelligence and strategic finance capability feed sustainable business performance. We treat decision intelligence and strategic finance capability as sequential mediators, which produces two further hypotheses. Figure 1 sets out the model and Table 2 lists the hypotheses.

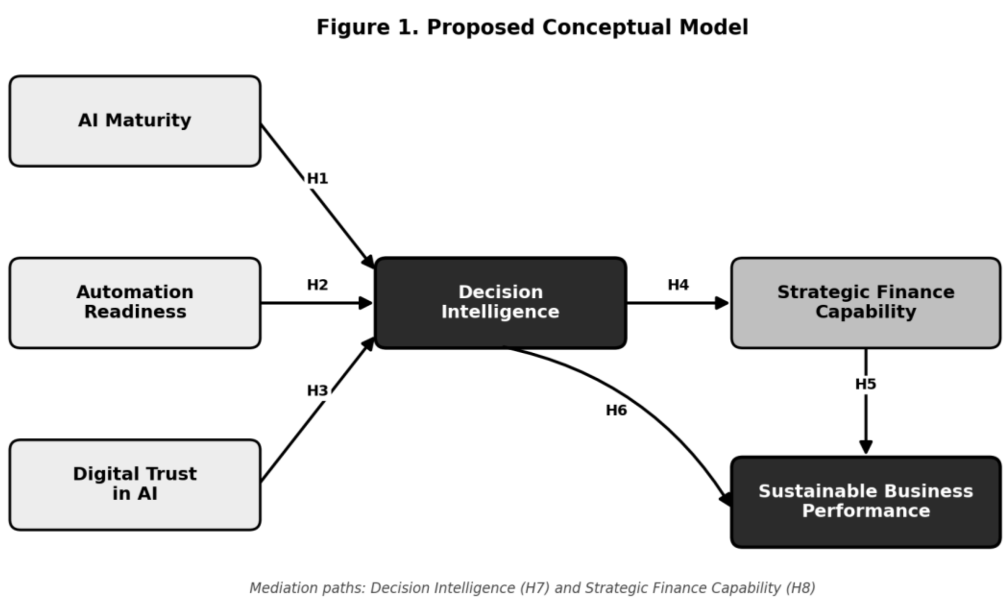

Figure 1. Proposed conceptual model linking AI capabilities, decision intelligence, strategic finance capability and sustainable business performance.

The mediation logic restates the theoretical argument in path form. Capabilities create value only once they are turned into decisions and, by way of the finance function, into outcomes. We expect decision intelligence to carry the effect of the three antecedents through to performance, and strategic finance capability to carry the effect of decision intelligence through to performance.

H7: Decision Intelligence mediates the effects of AI Maturity, Automation Readiness and Digital Trust on Sustainable Business Performance.

H8: Strategic Finance Capability mediates the effect of Decision Intelligence on Sustainable Business Performance.

Table 2. Summary of hypotheses

Code	Hypothesised Relationship
H1	AI Maturity positively influences Decision Intelligence.
H2	Automation Readiness positively influences Decision Intelligence.
H3	Digital Trust in AI positively influences Decision Intelligence.
H4	Decision Intelligence positively influences Strategic Finance Capability.
H5	Strategic Finance Capability positively influences Sustainable Business Performance.
H6	Decision Intelligence positively influences Sustainable Business Performance.
H7	Decision Intelligence mediates the effects of AI Maturity, Automation Readiness and Digital Trust on Sustainable Business Performance.
H8	Strategic Finance Capability mediates the effect of Decision Intelligence on Sustainable Business Performance.

8. Proposed Research Methodology

Being a conceptual paper, the study reports no primary data. What it offers instead is the design through which the model can be tested later, so that the framework is workable rather than merely argued.

8.1 Research design

We propose a sequential mixed-methods design. A qualitative first phase, built on semi-structured interviews with chief financial officers, finance managers, chartered accountants and fintech professionals, would localise the constructs to India and sharpen the measurement items. A quantitative second phase would then use a structured questionnaire and test the model with structural equation modelling. Partial least squares is the appropriate estimator here, given the complexity of the model and its orientation towards prediction and theory building.

8.2 Population and sampling

The population of interest is finance and business professionals in Indian organisations across fintech, consulting, manufacturing and professional services. A purposive frame can be assembled through professional bodies and industry networks, including chapters of the Institute of Chartered Accountants of India and finance communities, with snowball referrals to extend reach. Following common guidance for structural equation modelling, the target is at least ten observations per estimated path, which for this model means roughly two hundred and fifty usable responses as a floor.

8.3 Measurement

Each construct would be measured reflectively, on multi-item seven-point scales adapted from validated instruments and localised during the qualitative phase. AI maturity would draw on the AI-capability literature (Mikalef & Gupta, 2021), digital trust on established trust scales (Glikson & Woolley, 2020), and decision intelligence and performance on big-data analytics capability and performance measures (Rialti et al., 2019). Content validity would be secured through expert review and a pilot before the main collection.

8.4 Validity, reliability and bias

Reliability would be checked through Cronbach's alpha and composite reliability, convergent validity through average variance extracted, and discriminant validity through the heterotrait-monotrait ratio. Because the design is self-reported and cross-sectional, common method bias would be held down by procedural means, such as anonymity and item separation, and then tested statistically. Where it can be obtained, a single objective indicator from public disclosures would be folded in to ease the reliance on one source. Done this way, the instrument becomes a citable, reusable measure of AI capability and trust in the Indian finance workforce.

9. Finance Intelligence Transformation Framework (FITF)

The Finance Intelligence Transformation Framework traces how a finance function travels from compliance-bound operations to strategic, intelligence-led value creation, pulling the model's constructs into a single maturity pathway. A function starts in compliance-oriented work, develops automation readiness, builds AI maturity, then establishes digital trust and responsible-AI practice, and through these reaches decision intelligence. Decision intelligence opens the way to strategic finance capability, which in turn supports sustainable business performance. Figure 2 presents the framework.

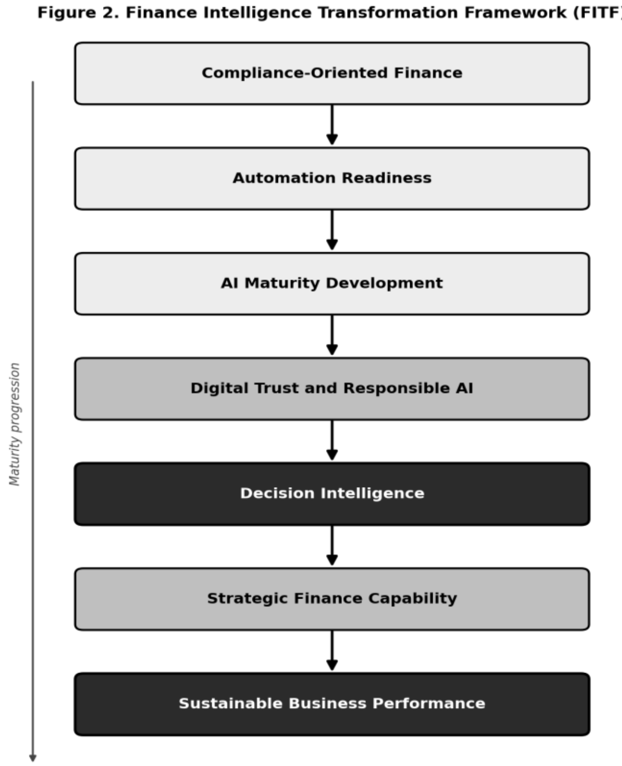

Figure 2. The Finance Intelligence Transformation Framework (FITF).

We intend the framework as a diagnostic and planning aid rather than a description after the fact. It lets an organisation place itself on the pathway and pick out the capability that is holding it back, instead of treating AI investment as one undifferentiated choice.

10. Expected Contributions

We expect three contributions. Theoretically, the paper shifts attention from AI adoption to decision value, and it gathers AI maturity, automation readiness and digital trust into one capability model rooted in RBV and dynamic capabilities. Methodologically, it proposes a validated, India-specific instrument for AI maturity, readiness and trust in the finance workforce that other researchers can reuse. Practically, it puts forward the Finance Intelligence Transformation Framework as a route map for the move from compliance-driven to intelligence-led finance, of use to firms, professional bodies and regulators alike.

11. Managerial Implications

The model carries a plain message for managers. Money spent on AI tools should be matched by money spent on the capabilities around them. Leaders are better off prioritising data governance, process readiness, workforce skills and the trust environment than treating procurement as the finish line. Since trust governs reliance, finance leaders should make AI output explainable and bring professionals into the design and review of AI systems, because that kind of participation is what lifts reliance on AI evidence (Commerford et al., 2024). The finance function itself should then be moved off transactional reporting and towards decision support and business partnering.

12. Policy Implications

For policymakers and regulators, the study argues for frameworks that back responsible AI, covering transparency, accountability and the fair use of data. Governance of this kind strengthens trust, and far from slowing adoption it tends to enable it, because reliance on AI insight rests on confidence that the insight is fair and reliable. Support for skills development, and clear standards on explainability, would help organisations turn AI investment into decision value while keeping stakeholders protected.

13. Limitations and Future Research Directions

- The study is conceptual. The proposed relationships are theoretically argued and require empirical validation.
- No primary survey or interview data are reported at this stage; the design in Section 8 is intended to guide future collection.
- Industry-specific differences across fintech, consulting, manufacturing and professional services are not yet examined and may moderate the relationships.
- The framework is developed within the Indian context, so generalisation to other economies should be tested rather than assumed.

Future work should take the model to data and test it with structural equation modelling, look at digital trust as a moderating condition as well as an antecedent, run multi-group analysis across industries, and bring in objective performance indicators from public disclosures to sit alongside the survey measures.

14. Conclusion

AI is remaking the finance function, turning it from a compliance-bound operation into a strategic, intelligence-led partner to the business. The argument of this paper is straightforward. The technology spend, on its own, does not create value. AI maturity, automation readiness and digital trust are the organisational capabilities that decide whether AI becomes decision intelligence, and through decision intelligence becomes strategic finance capability and sustainable business performance. The conceptual model and the Finance Intelligence Transformation Framework give that conversion a theory-led, testable shape, set in the Indian context. By putting decision value ahead of adoption, and trust ahead of mere access, the paper offers both a foundation for empirical research and a practical map for finance functions that want to use AI responsibly and well.

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