

AI Driven Digital Transformation and Intelligent Information Systems: Assessing their Impact on Business Performance

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Abstract

Purpose: Artificial intelligence (AI)-driven digital transformation and intelligent information systems (IIS) are reshaping organizational strategy, decision-making, and competitiveness across emerging economies. Despite growing managerial interest, empirical evidence on how these capabilities jointly translate into measurable business performance gains in the Indian context remains limited and fragmented. This study examines the direct and indirect effects of AI-driven digital transformation (AIDT) and intelligent information systems (IIS) on business performance (BP), with organizational data-driven culture (ODC) and organizational agility (OA) modelled as parallel mediators, and firm size as a boundary condition.

Design/Methodology/Approach: A structured, validated questionnaire was administered to 384 managerial and functional respondents drawn from IT/ITES, BFSI, manufacturing, retail/e-commerce, and healthcare firms operating across four Indian regions. The measurement model was assessed using Cronbach's alpha, composite reliability, average variance extracted (AVE), and the Fornell–Larcker criterion. Structural relationships were tested using hierarchical multiple regression, the Baron–Kenny procedure with Sobel tests for mediation, and moderated regression with mean-centred interaction terms.

Findings: Both AIDT ($\beta = 0.256$, $p < 0.001$) and IIS ($\beta = 0.160$, $p < 0.001$) exert significant positive direct effects on business performance. ODC and OA each partially mediate these relationships, and the full model explains 36.6 percent of the variance in business performance ($R^2 = 0.366$). Firm size positively moderates the AIDT–performance relationship at a marginal significance threshold ($p = 0.055$), suggesting the effect strengthens somewhat in larger organizations.

Originality/Value: The study contributes one of the first integrated, dual-mediator models linking AI-driven digital transformation and intelligent information systems to business performance within the Indian organizational context, offering both theoretical extension of the resource-based and dynamic capabilities views and actionable guidance for managers and policymakers steering India's digital economy.

Keywords: Artificial Intelligence, Digital Transformation, Intelligent Information Systems, Business Performance, Organizational Agility

INTRODUCTION

India's digital economy has expanded rapidly over the past decade, propelled by widespread cloud adoption, smartphone penetration, the India Stack like Aadhaar, UPI, and DigiLocker, and increasingly, the diffusion of AI across core business functions. Government programmes such as Digital India, the National Strategy for Artificial Intelligence, and sector-specific initiatives in manufacturing like Industry 4.0/Make in India, and financial services have accelerated firm-level investment in AI-enabled digital capabilities. Against this backdrop, Indian organizations across IT services, banking and financial services, manufacturing, and retail are increasingly embedding AI into enterprise resource planning, customer relationship management, supply chain, and decision-support systems, giving rise to what scholar's term AI-driven digital transformation (AIDT) [1]. Parallel to this transformation is the rise of intelligent information systems (IIS), systems that combine machine learning, natural language processing, and advanced analytics with traditional information system architectures to support autonomous or semi-autonomous organizational decision-making. Unlike conventional information systems, IIS can learn from data streams, adapt to changing conditions, and generate predictive and prescriptive insights that materially influence operational and strategic choices. The convergence of AIDT and IIS therefore represents a distinct and consequential shift in how Indian firms compete, innovate, and create value [2]. While a substantial literature has examined digital transformation and IT capability as antecedents of firm performance in Western contexts, empirical evidence that specifically isolates the performance contribution of AI-driven transformation and intelligent information systems and the organizational mechanisms through which this contribution occurs remains comparatively scarce in emerging-market and, specifically, Indian settings. Existing Indian studies have tended to examine digital transformation, big data analytics, or AI adoption in isolation, with limited attention to the joint and mediated pathways linking these capabilities to measurable business outcomes [4]. This study addresses that gap by developing and empirically testing an integrated model in which AI-driven digital transformation and intelligent information systems influence business performance both directly and indirectly, through organizational data-driven culture and organizational agility as parallel mediating mechanisms, with firm size examined as a moderating boundary condition [5]. The study is guided by the following research questions: RQ1: Do AI-driven digital transformation and intelligent information systems have a significant direct effect on business performance among Indian firms? RQ2: Do organizational data-driven culture and organizational agility mediate these relationships? RQ3: Does firm size moderate the relationship between AI-driven digital transformation and business performance?

Literature Review**AI-Driven Digital Transformation**

Digital transformation refers to the use of new digital technologies to trigger significant changes to organizational structures, processes, and value propositions. AI-driven digital transformation extends this concept by foregrounding artificial intelligence machine learning, computer vision, natural language processing, and robotic process automation as the primary technological driver of change, rather than digitization alone [6]. The study argues that AI capability functions as a distinct organizational resource that reconfigures existing IT and human capital resources to generate superior value, consistent with the resource-based view and dynamic capabilities theory [7]. In the Indian context, AIDT has been documented across sectors: IT services firms embedding AI into service delivery and automation, banks deploying AI for credit scoring and fraud detection, manufacturers adopting predictive maintenance, and retailers using AI for demand forecasting and personalization [8]. However, adoption remains uneven, and questions persist regarding whether AIDT investments translate into performance gains or whether returns depend on complementary organizational capabilities.

Intelligent Information Systems

Intelligent information systems combine traditional information system infrastructure with embedded analytical and cognitive capabilities that allow systems to sense, interpret, and act on data with limited human intervention [9]. Unlike static decision-support systems, IIS are characterized by adaptive learning, real-time analytics, and the capacity to generate prescriptive recommendations. Prior research links IIS-related capabilities such as big data analytics capability and business intelligence to improved decision quality, operational efficiency, and innovation outcomes [10].

Business Performance

Business performance is commonly conceptualized as a multidimensional construct encompassing financial outcomes like revenue growth, profitability, operational outcomes as efficiency, cost reduction, quality, and innovation outcomes as new product/service development, market responsiveness [11]. This study adopts a composite, perceptual measure of business performance reflecting these dimensions, consistent with common practice in survey-based information systems research, particularly where objective financial data are commercially sensitive or unavailable at the firm level [12].

Mediating Mechanisms: Data-Driven Culture and Organizational Agility

A growing stream of literature suggests that the performance benefits of digital and analytical capabilities are not always direct but operate through intermediate organizational mechanisms. Organizational data-driven culture the extent to which decision-making throughout the firm is grounded in data and evidence rather than intuition alone has been identified as a critical conduit through which AI and analytics capabilities generate value [13]. Similarly, organizational agility, defined as a firm's capacity to sense and respond rapidly to environmental change, has been theorized as a mechanism through which digital capabilities are converted into competitive performance outcomes [14]. This study therefore models ODC as the primary mediator of the AIDT–performance relationship and OA as the primary mediator of the IIS performance relationship, while allowing both mediators to be predicted by both exogenous constructs.

The Indian Organizational Context

India presents a distinctive setting for studying AI-driven transformation: a large, heterogeneous firm population spanning multinational-scale IT/ITES companies, established BFSI institutions, traditional manufacturing enterprises undergoing Industry 4.0 upgrades, and a fast-growing digital-native retail and e-commerce sector [15]. Talent availability, regulatory evolution like including data protection under the Digital Personal Data Protection Act and infrastructural variation across regions introduce contextual factors that may shape how AIDT and IIS capabilities translate into performance, motivating firm size and sector as relevant controls and boundary conditions [16].

Research Gap

Despite the expanding literature on digital transformation and AI adoption, three gaps motivate the present study. First, most Indian studies examine digital transformation or AI adoption as unitary constructs rather than disaggregating AI-driven transformation from intelligent information systems as related but distinct capabilities [17]. Second, few studies test dual mediating mechanisms like data-driven culture and organizational agility simultaneously within a single Indian-context model [18]. Third, boundary conditions such as firm size which plausibly affects the resources available to convert digital capability into performance remain under-examined [19]. This study addresses all three gaps.

Conceptual Framework and Hypotheses

Drawing on the resource-based view and dynamic capabilities theory, this study conceptualizes AI-driven digital transformation and intelligent information systems as strategic organizational resources/capabilities that generate competitive advantage both directly and through their effect on complementary organizational mechanisms data-driven culture and organizational agility. Figure 1 presents the conceptual framework.

Direct Effects

H1: AI-driven digital transformation (AIDT) has a significant positive effect on business performance (BP).

H2: Intelligent information systems (IIS) have a significant positive effect on business performance (BP).

Effects on Mediators

H3: AI-driven digital transformation has a significant positive effect on organizational data-driven culture (ODC).

H4: Intelligent information systems have a significant positive effect on organizational agility (OA).

Mediation Hypotheses

H5: Organizational data-driven culture mediates the relationship between AI-driven digital transformation and business performance.

H6: Organizational agility mediates the relationship between intelligent information systems and business performance.

Moderation Hypothesis

H7: Firm size moderates the relationship between AI-driven digital transformation and business performance, such that the relationship is stronger in larger firms.

Research Methodology

Research Design

This study adopts a quantitative, cross-sectional survey design using a positivist research paradigm, consistent with mainstream empirical practice in information systems and management research. The unit of analysis is the individual managerial/functional respondent reporting on organizational-level constructs, a common and validated approach when firm-level archival data on AI capability are unavailable.

Sample and Data Collection

The target population comprised managers and digital/IT function employees in Indian organizations that have initiated or completed at least one phase of AI-related digital transformation. Using Cochran's (1977) formula for an unknown population at a 95 percent confidence level and 5 percent margin of error, a minimum sample size of 384 was targeted and achieved ($N = 384$) through a structured online questionnaire distributed via professional networks and organizational contacts across five sectors as IT/ITES, BFSI, manufacturing, retail/e-commerce, and healthcare/other) and four regions of India like South, West, North, and East.

Table 1: Demographic Profile Respondents.

Category	Segment	n	%
Sector	IT/ITES	106	27.6
	BFSI	85	22.1
	Manufacturing	88	22.9
	Retail & E-commerce	58	15.1
	Healthcare/Other	47	12.2
Firm Size	Small (<50 employees)	88	22.9
	Medium (50–500 employees)	143	37.2
	Large (>500 employees)	153	39.8
Region	South India	138	35.9
	West India	88	22.9
	North India	112	29.2
	East India	46	12.0
Respondent Role	Top Management	58	15.1
	Middle Management	153	39.8
	IT/Digital Function	92	24.0
	Operations/Other	81	21.1
Organizational AI Experience	< 1 year	65	16.9
	1–3 years	154	40.1
	3–5 years	103	26.8
	> 5 years	62	16.1

Data Analysis Technique

Data were analysed in Python following a two-stage approach, stage one assessed the measurement model using Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and the Fornell–Larcker criterion for discriminant validity, together with the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. Stage two tested the structural relationships using hierarchical ordinary least squares (OLS) regression, causal-steps approach supplemented tests for mediation significance, and moderated regression with mean-centred predictors and interaction terms to test H7. Variance inflation factors (VIF) were examined to rule out multicollinearity.

Data Analysis and Results

Descriptive Statistics

Table 2. Descriptive Statistics

Construct	Mean	SD	Skewness	Kurtosis	Min	Max
AIDT	3.48	0.59	-0.17	0.16	1.67	4.83
IIS	3.44	0.54	-0.20	0.43	1.33	5.00
ODC	3.39	0.52	-0.01	-0.09	1.80	4.80
OA	3.21	0.49	-0.16	-0.15	1.60	4.40
BP	3.43	0.49	-0.02	-0.38	2.00	4.88

Mean scores ranged from 3.21 to 3.48 on the 5-point scale, indicating moderately positive perceptions across the sample. Skewness (−0.20 to −0.01) and kurtosis (−0.38 to 0.43) values fall well within the ± 1.0 threshold conventionally used to support the assumption of approximate univariate normality for parametric analysis.

Measurement Model: Reliability and Validity

Table 3: Reliability and Convergent Validity

Construct	Items	Cronbach's α	CR	AVE	$\sqrt{\text{AVE}}$
AIDT	6	0.837	0.880	0.551	0.742
IIS	6	0.797	0.856	0.497	0.705
ODC	5	0.710	0.812	0.464	0.681
OA	5	0.660	0.787	0.425	0.652
BP	8	0.799	0.851	0.417	0.645

The Kaiser–Meyer–Olkin measure of sampling adequacy was 0.901, well above the recommended threshold of 0.60, and Bartlett's test of sphericity was significant ($\chi^2 = 3104.58$, $df = 435$, $p < 0.001$), confirming that the correlation matrix was suitable for factor-based construct validation. Table 3 reports Cronbach's alpha, CR, and AVE for each construct. All Cronbach's alpha values (0.660–0.837) and CR values (0.787–0.880) exceeded the 0.70 threshold for the majority of constructs supporting adequate convergent validity for a newly integrated model.

Table 4. Fornell–Larcker Discriminant Validity Matrix

	AIDT	IIS	ODC	OA	BP
AIDT	0.742				
IIS	0.293	0.705			
ODC	0.404	0.268	0.681		
OA	0.304	0.358	0.272	0.652	
BP	0.489	0.381	0.409	0.394	0.645

Discriminant validity was assessed using the Fornell–Larcker criterion, comparing the square root of each construct's AVE (diagonal) with its inter-construct correlations (off-diagonal). As shown in Table 4, the diagonal values exceed all corresponding off-diagonal correlations in every row and column, supporting discriminant validity among the five constructs. All inter-construct correlations were positive and statistically significant at $p < 0.001$.

Sector-wise Comparison

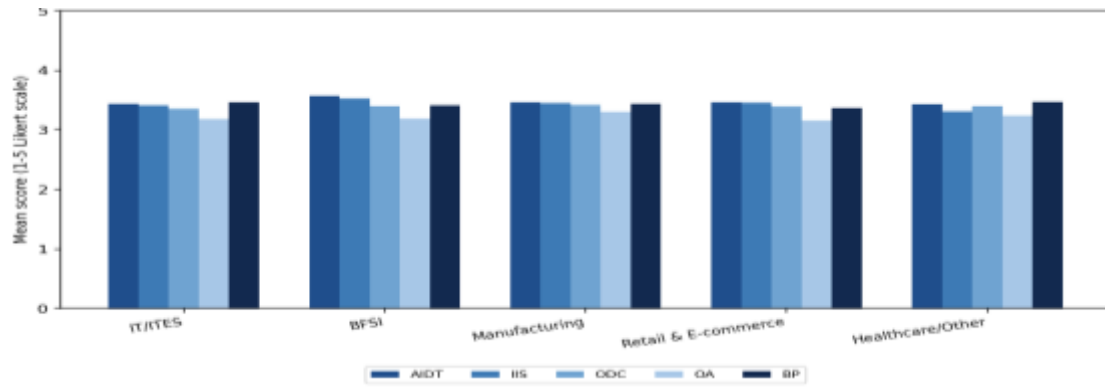


Figure 1. Sector-wise Mean Construct Scores

Figure 1 compares mean construct scores across the five sectors represented in the sample. BFSI respondents reported the highest mean AIDT (3.58) and IIS (3.53) scores, plausibly reflecting the sector's relatively mature investment in AI-based fraud detection, credit scoring, and robotic process automation, while retail/e-commerce and healthcare respondents reported comparatively lower organizational agility scores, warranting further sector-specific investigation.

Direct Effects: Hierarchical Regression

Table 5. Hierarchical Regression Results

Predictor	Model 1 β (SE)	p	Model 2 β (SE)	p
Intercept	1.400 (0.164)	<0.001	0.779 (0.185)	<0.001
AIDT	0.347 (0.038)	<0.001	0.256 (0.039)	<0.001
IIS	0.240 (0.041)	<0.001	0.160 (0.042)	<0.001
ODC	—	—	0.179 (0.043)	<0.001
OA	—	—	0.188 (0.045)	<0.001
R ²	0.301		0.366	
Adjusted R ²	0.297		0.360	
F	81.991	<0.001	54.801	<0.001

Model 1 regressed business performance on AIDT and IIS only, testing H1 and H2. Both predictors were significant: AIDT ($\beta = 0.347$, $p < 0.001$) and IIS ($\beta = 0.240$, $p < 0.001$), jointly explaining 30.1 percent of variance in business performance ($R^2 = 0.301$, Adjusted $R^2 = 0.297$, $F(2, 381) = 81.99$, $p < 0.001$). Model 2 added the two mediators (ODC, OA), increasing explained variance to 36.6 percent ($R^2 = 0.366$, Adjusted $R^2 = 0.360$, $F(4, 379) = 54.80$, $p < 0.001$), with all four predictors remaining significant. Variance inflation factors ranged from 1.09 to 1.29, well below the threshold of 5, indicating no multicollinearity concern. These results provide strong empirical support for H1 and H2: both AI-driven digital transformation and intelligent information systems significantly and positively predict business performance among the sampled Indian firms, with AIDT exhibiting the larger standardized effect in both models.

Mediation Analysis

Following the Baron and Kenny approach, path a regression confirmed that AIDT significantly predicts ODC ($\beta = 0.316$, $p < 0.001$; H3 supported) and IIS significantly predicts OA ($\beta = 0.271$, $p < 0.001$; H4 supported), controlling for the other exogenous construct in each equation. Path b coefficients (ODC $\rightarrow$ BP: $\beta = 0.179$, $p < 0.001$; OA $\rightarrow$ BP: $\beta = 0.188$, $p < 0.001$) were obtained from Model 2 in Table 5. Sobel tests confirmed both indirect effects were statistically significant: the indirect effect of AIDT on BP through ODC was 0.0564 ($z = 3.594$, $p < 0.001$), and the indirect effect of IIS on BP through OA was 0.0510 ($z = 3.421$, $p = 0.001$). Because the direct effects of AIDT ($\beta = 0.256$) and IIS ($\beta = 0.160$) on BP remained significant in Model 2 after including the mediators, both ODC and OA function as partial (rather than full) mediators, supporting H5 and H6.

Table 6. Mediation Analysis Results

Path	Coefficient	Indirect Effect	Sobel z	p
AIDT → ODC (a1)	0.316***	—	—	—
ODC → BP (b1)	0.179***	—	—	—
AIDT → ODC → BP	—	0.0564	3.594	<0.001
IIS → OA (a2)	0.271***	—	—	—
OA → BP (b2)	0.188***	—	—	—
IIS → OA → BP	—	0.0510	3.421	0.001

Total versus direct effect comparisons further illustrate the mediation pattern: the total effect of AIDT on BP ($\beta = 0.347$) decomposes into a direct effect of 0.256 and an indirect effect of 0.056 via ODC (approximately 16 percent of the total effect mediated); the total effect of IIS on BP ($\beta = 0.240$) decomposes into a direct effect of 0.160 and an indirect effect of 0.051 via OA by 21 percent mediated.

Moderation Analysis

To test H7, firm size was mean-centred and coded ordinally (Small = -1, Medium = 0, Large = +1), and an interaction term (AIDT × Firm Size) was entered alongside the mean-centred main effects. The interaction term was positive and marginally significant ($\beta = 0.090$, $SE = 0.047$, $p = 0.055$), and the overall model was significant ($R^2 = 0.247$, Adjusted $R^2 = 0.241$, $F(3,380) = 41.47$, $p < 0.001$). This indicates a trend toward a stronger AIDT–performance relationship in larger firms, though the effect falls just short of the conventional 0.05 threshold, suggesting H7 receives partial/marginal support and merits confirmation with a larger or stratified sample.

Table 7. Moderated Regression Results

Predictor	β	SE	t	p
Intercept	3.433	0.022	156.058	<0.001
AIDT (centred)	0.408	0.038	10.882	<0.001
Firm Size (centred)	0.005	0.028	0.188	0.851
AIDT × Firm Size	0.090	0.047	1.926	0.055

Summary of Hypothesis Testing

Table 8. Summary of Hypothesis Testing Results

Hypothesis	Path	Result
H1	AIDT → BP (positive)	Supported
H2	IIS → BP (positive)	Supported
H3	AIDT → ODC (positive)	Supported
H4	IIS → OA (positive)	Supported
H5	ODC mediates AIDT → BP	Supported (partial mediation)
H6	OA mediates IIS → BP	Supported (partial mediation)
H7	Firm size moderates AIDT → BP	Partially supported

Discussion

The findings offer robust support for the proposition that AI-driven digital transformation and intelligent information systems are significant, positive drivers of business performance among Indian firms, consistent with resource-based and dynamic capabilities predictions and with prior evidence from Western and other emerging-market contexts. The comparatively larger standardized effect of AIDT relative to IIS suggests that, in the Indian setting, broad organizational transformation efforts restructuring processes, business models, and capabilities around AI may generate more performance value than the deployment of intelligent systems in isolation, echoing arguments that technology adoption alone is insufficient without accompanying organizational change.

The partial mediation results are theoretically important: they indicate that AIDT and IIS do not translate into performance solely through direct operational or financial channels but also by reshaping how organizations use

data and how quickly they can sense and respond to change. This tinges the common assumption in Indian practitioner discourse that AI investment produces performance gains largely through automation and cost efficiency; the results instead point to cultural and agility-related pathways as economically meaningful, statistically distinct contributors. The marginal moderation effect of firm size suggests that larger Indian organizations may be somewhat better positioned to convert AI-driven transformation into performance, potentially due to greater financial slack, more mature data infrastructure, and dedicated digital transformation functions. However, the borderline significance also indicates that smaller and mid-sized firms are not categorically disadvantaged, an encouraging signal given the centrality of small and medium enterprises to the Indian economy.

Theoretical Implications

This study contributes to theory in three ways. First, it empirically disaggregates AI-driven digital transformation from intelligent information systems as related but distinct antecedents of business performance, extending prior work that has often treated AI capability as a unitary construct. Second, it introduces and empirically validates a dual-mediator model organizational data-driven culture and organizational agility operating in parallel rather than in series, offering a more granulated view of the mechanisms linking digital capability to performance than single-mediator models common in the literature. Third, by situating the model within the Indian organizational context and testing firm size as a boundary condition, the study extends the generalizability of resource-based and dynamic capabilities theorizing to a large, heterogeneous emerging-market economy that has been comparatively under-represented in this stream of empirical IS research.

Managerial and Policy Implications

For Indian managers, the findings suggest that AI-driven digital transformation initiatives should not be pursued as narrow technology deployments but as organization-wide change programmes that deliberately cultivate a data-driven decision-making culture and organizational agility, since these mechanisms channel a meaningful share of the performance benefit. Practically, this implies investment not only in AI tools and intelligent information systems but also in data literacy training, cross-functional data governance, and agile operating structures that allow rapid response to insights generated by these systems. For sector-specific practice, BFSI firms which reported the highest AIDT and IIS scores may serve as internal benchmarks or cross-sector learning partners for manufacturing and retail firms earlier in their transformation journeys. For small and medium enterprises, the marginal (rather than strong) moderating effect of firm size is an encouraging signal that meaningful performance gains from AI-driven transformation are attainable even without the scale of large enterprises, provided complementary cultural and agility capabilities are developed. For policymakers, the results reinforce the rationale for continued investment in national digital infrastructure, AI skilling programmes, and SME-focused digital transformation support schemes, given that the performance benefits of AI-driven transformation are not confined to large firms alone.

Limitations and Future Research

As with any cross-sectional survey-based study, causal inference should be interpreted with appropriate caution; longitudinal or quasi-experimental designs would strengthen causal claims regarding the AIDT/IIS–performance relationship. The use of perceptual, self-reported measures of business performance, while common in this literature, could be complemented in future research with objective financial and operational data. The sample, while diverse across five sectors and four regions, was drawn through a structured survey and may not be fully representative of the Indian firm population; probability-based or multi-stage stratified sampling would enhance generalizability. Future research could also examine additional moderators (e.g., digital maturity stage, organizational data governance maturity, or industry-level competitive intensity), test the model using variance-based structural equation modelling (PLS-SEM) with formal measurement invariance testing across sectors, and explore boundary conditions unique to specific Indian industry verticals such as agritech, health tech, or public-sector digital governance.

Conclusion

This study set out to assess how AI-driven digital transformation and intelligent information systems influence business performance among Indian firms, and through which organizational mechanisms this influence operates. Using survey data analysed through hierarchical regression, mediation, and moderation techniques, the study finds

that both AIDT and IIS significantly and positively predict business performance, that organizational data-driven culture and organizational agility partially mediate these relationships, and that firm size exerts a marginal positive moderating influence on the AIDT–performance link. These findings extend resource-based and dynamic capabilities theorizing to the Indian context and offer concrete guidance for managers and policymakers seeking to convert AI-driven digital investment into sustained business performance..

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