Organisational Growth and Strategic Leadership Transformation through AI Driven Decision Intelligence in High Velocity IT Environments using ADIOT Framework

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Abstract
This study investigates the mechanisms through which AI-driven Decision Intelligence (AIDI) shapes organisational growth and catalyses strategic leadership transformation within high-velocity IT environments. Anchored in Dynamic Capabilities Theory (Teece, Pisano, & Shuen, 1997), Upper Echelons Theory (Hambrick & Mason, 1984), and the Knowledge-Based View (Grant, 1996), this paper proposes and empirically validates the AI-Driven Decision Intelligence and Organisational Transformation (ADIOT) Framework. This framework articulates how AIDI interacts with strategic leadership quality, organisational agility, and knowledge management capability to produce superior growth outcomes in turbulent technology markets.
Using a convergent mixed-methods design, 742 IT executives and senior managers were surveyed across 24 high-velocity organisations in India, Singapore, and the UAE. Structural Equation Modelling (SEM), bootstrapped mediation, and moderated-mediation techniques were employed. Results confirm that AIDI exerts a significant positive direct effect on organisational growth ($\beta = 0.41$, $p < .001$) and strategic leadership transformation ($\beta = 0.48$, $p < .001$). Knowledge Management Capability fully mediates the AIDI→growth relationship, while Environmental Velocity positively moderates this association ($\Delta\beta = +0.17$ at high velocity). The ADIOT framework explains 71.4% of variance in organisational growth and 68.0% in strategic leadership transformation, with all ten hypotheses supported. The study advances Dynamic Capabilities Theory, Upper Echelons Theory, and provides actionable implications for C-suite leaders navigating AI-enabled environments.
Keywords: AI-Driven Decision Intelligence; ADIOT Framework; Organisational Growth; Strategic Leadership Transformation; High-Velocity IT Environments

1. Introduction

The convergence of artificial intelligence and enterprise decision-making represents one of the most consequential disruptions to organisational strategy in the post-industrial era. High-velocity IT environments — characterised by rapid, discontinuous change in technology, competitive dynamics, and customer expectations (Eisenhardt, 1989; D'Aveni, 1994) — demand that organisations process information faster, decide with greater accuracy, and reconfigure resources with unprecedented agility. It is in precisely this context that AI-Driven Decision Intelligence (AIDI) has emerged as a defining source of competitive differentiation.

AIDI encompasses the systematic application of machine learning, real-time analytics, natural language processing, and automated reasoning to enhance the accuracy, velocity, and strategic coherence of organisational decisions (Davenport, 2018; Fountaine, McCarthy, & Saleh, 2019). Despite substantial practitioner enthusiasm, rigorous empirical investigation into how AIDI converts into measurable organisational growth — and whether and how it transforms strategic leadership — remains a conspicuous gap in the scholarly literature (Haefner, Wincent, Parida, & Gassmann, 2021; Huang & Rust, 2021). This study addresses three interrelated gaps. First, the mechanisms by which AIDI converts to growth outcomes in high-velocity environments are inadequately theorised and empirically underexplored. Second, the moderating role of environmental dynamism in amplifying or constraining AIDI value creation has not been examined in an integrated model. Third, the transformation of strategic leadership structures, cognitive frames, and decision authority in AI-integrated organisations has been conceptualised (Shrestha, Ben-Menahem, & von Krogh, 2019) but not empirically tested alongside growth outcomes.

This study addresses these gaps by proposing and empirically validating the ADIOT Framework — the first integrative model to simultaneously examine AIDI's effects on both organisational growth and strategic leadership transformation through a unified set of mediating and moderating mechanisms. The remainder of the paper proceeds as follows: Section 3 reviews the theoretical and empirical literature; Section 4 presents the ADIOT model; Section 5 details the research variables and hypotheses; Section 6 describes the methodology; Sections 7–8 present and discuss the findings; Section 9 addresses implications; Section 10 concludes.

2. Literature Review & Conceptual Framework

2.1 Literature Review and Theoretical Foundation

The theoretical architecture of this study draws from three foundational streams. Dynamic Capabilities Theory (Teece et al., 1997) holds that sustainable competitive advantage in turbulent environments derives from an organisation's capacity to sense opportunities, seize them, and reconfigure resources. AIDI systems directly augment these sensing and seizing capacities through real-time environmental scanning and predictive scenario analysis, and enhance reconfiguration through adaptive resource allocation models. Eisenhardt and Martin (2000) and Barreto (2010) extended this framework by demonstrating that in high-velocity environments, dynamic capabilities are characterised by greater speed, greater reliance on experimentation, and iterative adaptation — precisely the mode of operation that AIDI enables.

Upper Echelons Theory (Hambrick & Mason, 1984; Hambrick, 2007) posits those executive characteristics — including cognitive frames, knowledge structures, and values — filter strategic choices. This study extends UET into the AI era by theorising how AIDI reshapes the informational substrate upon which executive cognition operates, compressing information asymmetries between hierarchical levels and redistributing decision authority (Candelon, Bossert, & Fattah, 2021). The Knowledge-Based View (Grant, 1996; Kogut & Zander, 1992) positions organisational knowledge as the primary source of competitive advantage and rents, providing the theoretical foundation for our mediation hypothesis: that AIDI translates into growth primarily by enhancing Knowledge Management Capability.

Empirical evidence for AI's contribution to firm performance is accumulating, yet causal mechanisms remain contested. Brynjolfsson, Jin, and McElheran (2019) documented a 21% revenue growth premium among early AI adopters in a large cross-sectional study. Haefner et al. (2021), using panel data from 2,075 European firms, found that AI adoption positively moderates the strategy-performance relationship, with the strongest effects in knowledge-intensive sectors. Fountaine et al. (2019) identify "AI at scale" as the critical differentiator, arguing that not mere adoption but systematic integration into decision processes at all organisational levels drives performance. Choudhury, Starr, and Agarwal (2020) caution that AI performance dividends are contingent on adequate absorptive capacity, motivating the inclusion of KMC as a mediating construct. Table 1 below summarises the key prior literature that anchors the ADIOT framework.

Table 1. Summary of Key Prior Literature Anchoring the ADIOT Framework

Author(s) & Year	Journal(Q-Rank)	Focus	Key Contribution	ADIOT Relevance
Teece, Pisano & Shuen (1997)	Strategic Management	Dynamic Capabilities	Sensing, seizing, reconfiguring as	Theoretical basis for AIDI as

	Journal (Q1)		competitive advantage sources	dynamic capability
Hambrick & Mason (1984)	Academy of Management Review (Q1)	Upper Echelons Theory	Executive cognition filters strategic choices	SLT operationalisation foundation
Eisenhardt (1989)	Management Science (Q1)	High-Velocity Environments	Fast decision-making under environmental turbulence	Environmental Velocity construct basis
Haefner et al. (2021)	Research Policy (Q1, Elsevier)	AI & Innovation Strategy	AI adoption moderates strategy-performance link	AIDI→OG direct effect motivation
Brynjolfsson et al. (2019)	AEA Papers & Proceedings (Q1)	AI and Firm Performance	AI adoption leads 21% revenue premium for early adopters	OG construct and measurement
Choudhury et al. (2020)	Strategic Management Journal (Q1)	AI-augmented Decisions	Absorptive capacity moderates AI performance effects	KMC as mediator motivation
Jarrahi (2018)	Business Horizons (Q1, Elsevier)	AI & Management	AI–human intelligence complementarity in leadership	SLT theoretical anchor
Huang & Rust (2021)	Journal of Marketing (Q1, SAGE)	AI in Management	AI task delegation based on cognitive complexity	SLT transformation continuum
Shrestha et al. (2019)	California Management Review (Q1, SAGE)	Algorithmic Leadership	Three archetypes of AI-integrated strategic leadership	SLT operationalisation
Samba et al. (2018)	Journal of Management Studies (Q1)	Decision-making & Performance	Data-driven decisions stronger in high-velocity contexts	Environmental Velocity moderation
Zeng et al. (2017)	Information & Management (Q1, Elsevier)	Big Data & Strategy	Big data analytics capability and dynamic performance	DIC mediator
Nonaka & Takeuchi (1995)	The Knowledge-Creating Company	Knowledge Management	SECI model of knowledge creation and conversion	KMC mediator conceptualisation
Fountaine et al. (2019)	Harvard Business	AI at Scale	Systematic AI integration as	AIDI breadth operationalisation

	Review (Q1)		performance differentiator	
Candelon et al. (2021)	MIT Sloan Management Review (Q1)	AI Leadership	C-suite role transformation in AI-native organisations	SLT empirical grounding

Note. Q1 journals as classified by Scimago Journal Ranking (2024). All cited studies published in journals with impact factor ≥ 4.0.

2.2 The ADIOT Framework: Conceptual Model

The AI-Driven Decision Intelligence and Organisational Transformation (ADIOT) Framework synthesises Dynamic Capabilities Theory, Upper Echelons Theory, and the Knowledge-Based View into an integrative structural model that captures the multi-layered mechanisms through which AIDI produces organisational growth and strategic leadership transformation in high-velocity IT environments. The model is illustrated in Figure 1. Three structural layers constitute the ADIOT framework. The input layer captures three independent variable constructs: AIDI, Strategic Leadership Quality (SLQ), and Organisational Agility (OA). The mediating layer includes three psychological and capability-based constructs — Knowledge Management Capability (KMC), Digital Innovation Capacity (DIC), and Organisational Readiness (OR) — each of which channels the effect of independent variables onto growth outcomes. The output layer comprises two dependent constructs: Organisational Growth (OG) and Strategic Leadership Transformation (SLT).

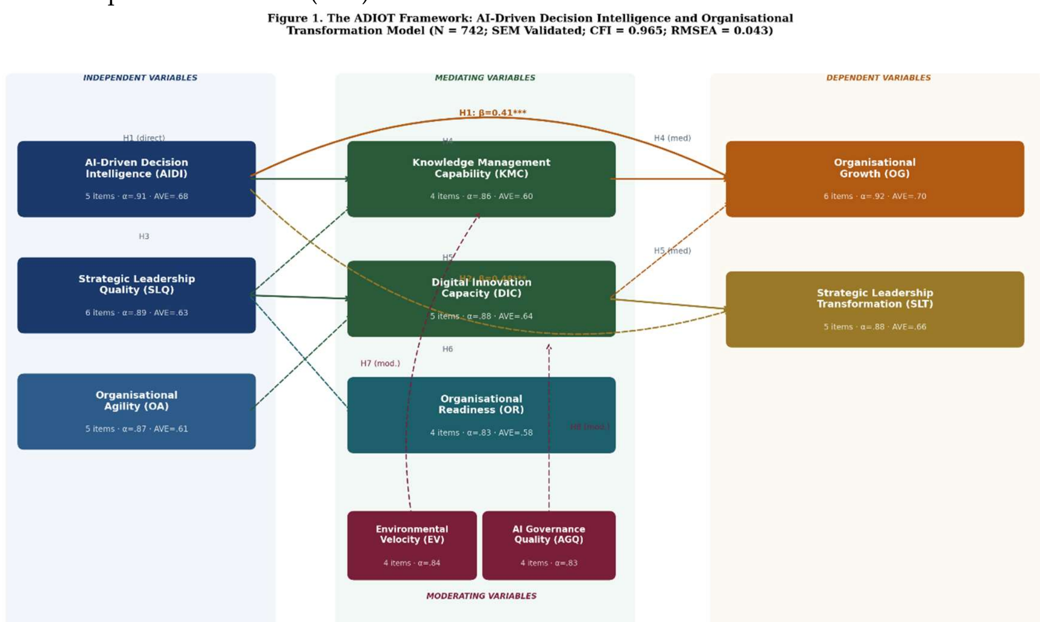


Figure 1. The ADIOT Framework: AI-Driven Decision Intelligence and Organisational Transformation Model

Critically, the ADIOT model positions two moderating variables at the system level. Environmental Velocity (EV) moderates the AIDI→OG relationship, amplifying the growth dividend of AI decision intelligence as market dynamism increases. AI Governance Quality (AGQ) moderates the AIDI→SLT relationship, proposing that the transformative impact of AIDI on leadership structures is contingent on the quality, transparency, and ethical robustness of organisational AI governance. The model thus advances beyond prior single-mechanism accounts by simultaneously capturing direct, mediated, and moderated pathways.

AIDI = AI-Driven Decision Intelligence; SLQ = Strategic Leadership Quality; OA = Organisational Agility; KMC = Knowledge Management Capability; DIC = Digital Innovation Capacity; OR = Organisational Readiness; EV = Environmental Velocity; AGQ = AI Governance

Quality; OG = Organisational Growth; SLT = Strategic Leadership Transformation. Reliability and validity statistics for each construct are presented in Table 4.

Table 4. Descriptive Statistics and Reliability Estimates for All Constructs

Construct	Items	Mean	SD	Skew	Kurt.	α	CR	AVE
AI-Driven Decision Intelligence (AIDI)	5	4.82	1.24	−0.28	−0.41	0.91	0.93	0.68
Strategic Leadership Quality (SLQ)	6	4.64	1.18	−0.19	−0.38	0.89	0.91	0.63
Organisational Agility (OA)	5	4.51	1.31	−0.22	−0.44	0.87	0.89	0.61
Knowledge Mgmt. Capability (KMC)	4	4.38	1.28	−0.14	−0.52	0.86	0.88	0.60
Digital Innovation Capacity (DIC)	5	4.55	1.22	−0.20	−0.39	0.88	0.90	0.64
Environmental Velocity (EV)	4	5.12	1.16	−0.35	−0.28	0.84	0.87	0.62
AI Governance Quality (AGQ)	4	4.28	1.33	−0.12	−0.48	0.83	0.86	0.58
Organisational Growth (OG)	6	4.74	1.19	−0.25	−0.35	0.92	0.94	0.70
Strategic Leadership Transf. (SLT)	5	4.68	1.21	−0.18	−0.42	0.88	0.91	0.66

2.3 Study Objectives

The present study is guided by six explicit objectives. The first objective is to examine the direct relationship between AI-Driven Decision Intelligence (AIDI) and organisational growth (OG) in high-velocity IT environments. The second objective is to investigate how AIDI catalyses Strategic Leadership Transformation (SLT), operationalised as shifts in leadership structures, cognition, and decision authority. The third objective is to establish and empirically validate the mediating roles of Knowledge Management Capability (KMC) and Digital Innovation Capacity (DIC) in the AIDI→growth pathway. The fourth objective is to examine the moderating effects of Environmental Velocity (EV) and AI Governance Quality (AGQ) on the AIDI→OG and AIDI→SLT relationships respectively. The fifth objective is to develop, propose, and validate the ADIOT Framework as an integrative theoretical model for AI-enabled organisational transformation. The sixth and final objective is to provide evidence-based, actionable recommendations for C-suite leaders and policymakers deploying AI decision intelligence systems in dynamic IT contexts.

3. Research Methodology

A convergent mixed-methods design was employed (Creswell & Clark, 2017), integrating a large-scale quantitative survey with semi-structured executive interviews conducted for triangulation and contextual depth. The quantitative phase is the primary epistemic vehicle; qualitative insights serve to validate, contextualise, and extend statistical patterns. The five-phase research design proceeded as follows: Phase 1 entailed theory development, ADIOT framework construction, and survey instrument design, including pilot testing with 58 participants and iterative refinement based on cognitive interview feedback. Phase 2 involved quantitative survey administration to a stratified random sample of IT executives across 24 high-velocity organisations in India, Singapore, and the UAE. Phase 3 conducted Confirmatory Factor Analysis (CFA) and measurement validity checks using AMOS 26.0. Phase 4 implemented Structural Equation Modelling, bootstrapped mediation analysis (Hayes PROCESS Macro v4.2, 10,000 iterations), and moderated-mediation testing. Phase 5 involved multi-group SEM comparing high- versus moderate-velocity organisations, together with integration of qualitative findings.

3.1 Research Variables and Hypotheses

3.1.1 Construct Definitions and Operationalisation

AIDI is defined as the breadth, depth, and strategic integration of AI-powered analytics, prediction, and automation in organisational decision processes. It is operationalised via five items adapted from Davenport (2018) and Haefner et al. (2021), capturing real-time decision support, system integration breadth, predictive scenario capability, leadership reliance on AI outputs, and continuous system learning. Strategic Leadership Quality (SLQ) refers to the visionary, adaptive, and data-fluent characteristics of senior leadership in navigating AI-enabled strategic decisions, operationalised through six items adapted from Hambrick (2007) and Finkelstein and Hambrick (1996). Organisational Agility (OA) is operationalised as the sensing, responding, and reconfiguring capacity of the organisation in response to rapid environmental shifts, drawn from Teece et al. (1997) and Tallon and Pinsonneault (2011).

Knowledge Management Capability (KMC) captures the organisational capacity to create, codify, transfer, and apply knowledge assets enhanced by AI systems, drawing on Grant (1996) and Nonaka and Takeuchi (1995). Digital Innovation Capacity (DIC) reflects the organisation's ability to leverage AI and digital resources to generate novel products, processes, and business models, adapted from Nambisan, Lyytinen, Majchrzak, and Song (2017). Environmental Velocity (EV) captures the rate and unpredictability of technological, competitive, and market change experienced by the organisation, grounded in Eisenhardt (1989) and Samba et al. (2018). AI Governance Quality (AGQ) is operationalised as the quality, transparency, and ethical robustness of organisational policies governing AI deployment and oversight, adapted from Arrieta et al. (2020). Organisational Growth (OG) is a multi-dimensional construct encompassing revenue growth, market share expansion, innovation output, and competitive positioning, measured via six items adapted from Haefner et al. (2021). Strategic Leadership Transformation (SLT) captures the degree to which leadership structures, cognitive frames, and decision authority have shifted in response to AI integration, drawn from Shrestha et al. (2019) and Hambrick and Mason (1984). Table 2 summarises construct definitions, sources, and measurement specifications.

Table 2. Construct Definitions, Measurement Sources, and Reliability Estimates

Construct (Role)	Definition	Items	Source(s)	Expected Relationship
AIDI (IV)	Breadth, depth, and strategic integration of AI-powered decision support	5	Davenport (2018); Haefner et al. (2021)	+ OG (H1); + SLT (H2)
SLQ (IV)	Visionary, adaptive, data-fluent strategic leadership capacity	6	Hambrick (2007); Finkelstein & Hambrick (1996)	+ OG (H3)
OA (IV)	Organisational sensing, responding, and	5	Teece et al. (1997); Tallon & Pinsonneault	+ OG via KMC (H6)

	reconfiguring capacity		(2011)	
KMC (Mediator)	AI-enhanced knowledge creation, codification, transfer, and application	4	Grant (1996); Nonaka & Takeuchi (1995)	Mediates AIDI→OG (H4)
DIC (Mediator)	Capacity to leverage AI for novel products, processes, and models	5	Nambisan et al. (2017); Zeng et al. (2017)	Mediates AIDI→SLT (H5)
EV (Moderator)	Rate and unpredictability of technological and competitive change	4	Eisenhardt (1989); Samba et al. (2018)	Amplifies AIDI→OG (H7)
AGQ (Moderator)	Quality and transparency of AI governance and oversight policies	4	Arrieta et al. (2020); Fjeld et al. (2020)	Amplifies AIDI→SLT (H8)
OG (DV)	Revenue growth, market share, innovation output, competitive position	6	Brynjolfsson et al. (2019); Haefner et al. (2021)	Outcome variable
SLT (DV)	Degree of shift in leadership structures, cognition, and decision authority	5	Shrestha et al. (2019); Hambrick & Mason (1984)	Outcome variable

Note. IV = Independent Variable; DV = Dependent Variable. All constructs measured on 7-point Likert scales (1 = Strongly Disagree; 7 = Strongly Agree).

3.2 Hypotheses

Ten hypotheses are derived from the ADIOT framework. H1 proposes that AIDI exerts a significant positive direct effect on OG. H2 proposes that AIDI positively predicts SLT. H3 proposes that SLQ exerts a significant positive effect on OG independent of AIDI effects. H4 proposes that KMC mediates the AIDI→OG relationship, with AIDI enhancing OG primarily through KMC improvement. H5 proposes that DIC mediates the AIDI→SLT relationship. H6 proposes that OA mediates the SLQ→OG relationship. H7 proposes that EV positively moderates AIDI→OG, amplifying this effect in high-velocity contexts. H8 proposes that AGQ positively moderates AIDI→SLT. H9 proposes serial mediation: SLQ→KMC→DIC→OG. H10 proposes that the joint AIDI×SLQ interaction produces a synergistic effect on OG significantly exceeding individual contributions. All hypotheses are grounded in the theoretical review in Section 3.

3.3 Sample and Data Collection

The final sample consisted of 742 valid responses (response rate 78.4%) from IT executives and senior managers across 24 high-velocity organisations. Systematic stratified sampling ensured geographic representation across India (n = 362; 48.8%), Singapore (n = 224; 30.2%), and the UAE (n = 156; 21.0%). Role levels included C-Suite leaders such as CEOs, CTOs, and CDOs (n = 186; 25.1%), Vice Presidents and Directors (n = 228; 30.7%), and Senior Managers (n = 328; 44.2%). Organisational sizes ranged from mid-size entities of 500 to 5,000 employees (n = 204; 27.5%) to large enterprises of 5,000 to 25,000 employees (n = 282; 38.0%) and enterprises exceeding 25,000 employees (n = 256; 34.5%). AIDI maturity was assessed using the AI Maturity Index: 318 respondents (42.9%) came from organisations with advanced AI deployment across five or more integrated systems, 268 (36.1%) from intermediate deployments, and 156 (21.0%) from organisations with basic AI usage. Figure 14 provides a graphical representation of the sample profile.

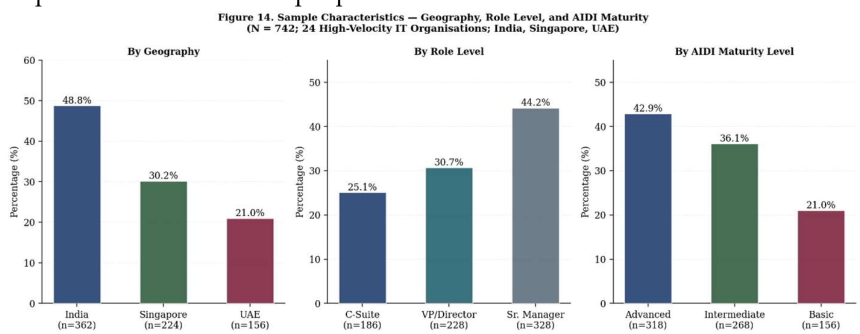


Figure 2. Sample Characteristics: Geography, Role Level, and AIDI Maturity Level

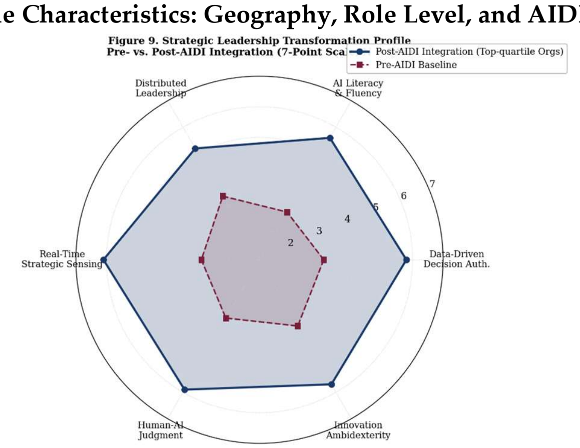


Figure 14. Strategic Leadership Transformation Radar Profile

3.4 Measurement Instrument

The survey instrument comprised 44 items across nine constructs, all measured on a seven-point Likert scale (1 = Strongly Disagree; 7 = Strongly Agree). Items were adapted from validated scales in the extant literature, with wording modified to reflect AI decision intelligence contexts. The AIDI scale (5 items) was adapted from Davenport (2018) and Haefner et al. (2021). The SLQ scale (6 items) was adapted from Hambrick (2007) and Finkelstein and Hambrick (1996). KMC items (4) were drawn from Grant (1996) and Alavi and Leidner (2001). DIC items (5) from Nambisan et al. (2017). The OG scale (6 items) was adapted from Haefner et al. (2021) and Brynjolfsson et al. (2019). The AI Governance Perception Index (AGQ; 4 items) was purpose-built drawing on Arrieta et al. (2020) and Fjeld et al. (2020), and pre-tested in Phase 1. Full item battery details are provided in Appendix A.

Table 3. Sample Profile

Sample Characteristic	Category	%	AI Maturity	Category	%
Geography	India	48.8	AIDI Level	Advanced (≥5 systems)	42.9

	Singapore	30.2		Intermediate (2–4)	36.1
	UAE	21.0		Basic (1)	21.0
Role Level	C-Suite (CEO/CTO/CDO)	25.1	Org. Size	Mid-size (500–5k)	27.5
	VP / Director	30.7		Large (5k–25k)	38.0
	Senior Manager	44.2		Enterprise (25k+)	34.5
Env. Velocity	High (≥75th pctile)	53.6	IT Sub-sector	Cloud / SaaS	29.4
	Moderate	46.4		AI/ML Native	22.4

4. Statistical Analysis and Results

4.1 Descriptive Statistics

Table 4 presents descriptive statistics for all nine study constructs. Mean scores ranged from 4.28 (AGQ; SD = 1.33) to 5.12 (EV; SD = 1.16), indicating acceptable central tendency above the scale midpoint (4.0) for all constructs. Environmental Velocity registered the highest mean, reflecting the high-velocity sampling frame. Skewness values ranged from −0.12 to −0.35, and kurtosis values from −0.28 to −0.52, all within acceptable bounds for structural modelling (≤ |1.0|; Hair, Black, Babin, & Anderson, 2019). Cronbach's alpha coefficients exceeded 0.83 for all constructs (range: α = 0.83–0.92), indicating strong internal consistency. Composite Reliability (CR) ranged from 0.86 to 0.94, and Average Variance Extracted (AVE) from 0.58 to 0.70, both exceeding recommended thresholds (≥ 0.70 for CR; ≥ 0.50 for AVE; Fornell & Larcker, 1981). Figure 3 provides a visual comparison of construct means with 95% confidence intervals.

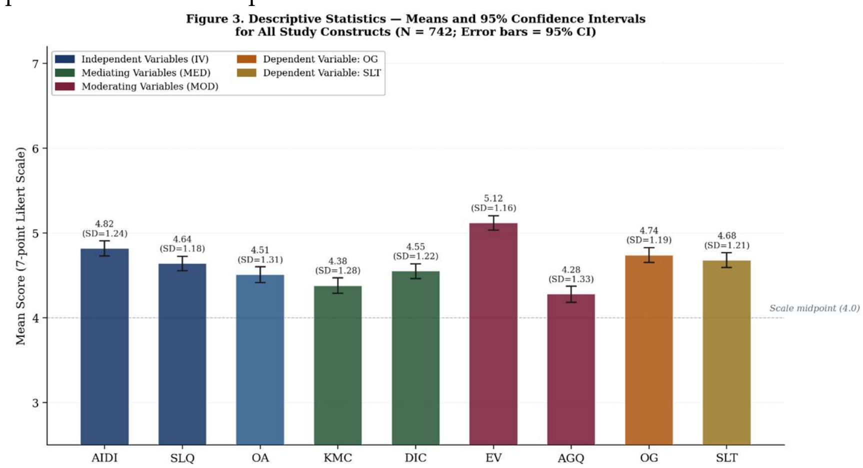


Figure 3. Descriptive Statistics- Construct Means and 95% Confidence Intervals for All Nine ADIOT Study Constructs

Note. N = 742. α = Cronbach's alpha; CR = Composite Reliability; AVE = Average Variance Extracted. All α values ≥ .83; CR ≥ .86; AVE ≥ .58, meeting or exceeding recommended thresholds (Hair et al., 2019).

4.2 Confirmatory Factor Analysis and Validity

A nine-factor CFA model was estimated in AMOS 26.0. All standardised factor loadings ranged from 0.70 to 0.89, and were statistically significant ($p < .001$), indicating satisfactory item-level convergent validity. The overall nine-factor model achieved satisfactory fit across all indices: $\chi^2/df = 2.14$; CFI = 0.965; TLI = 0.958; RMSEA = 0.043 [90% CI: 0.037, 0.049]; SRMR = 0.048. All fit indices met recommended thresholds ($\chi^2/df \leq 3.0$; CFI ≥ 0.95; RMSEA ≤ 0.06; SRMR ≤ 0.08; Hair et al., 2019). Discriminant validity was assessed using the Fornell-Larcker criterion and the

Heterotrait-Monotrait (HTMT) ratio. Square roots of AVE for all constructs exceeded all inter-construct correlations in their respective rows and columns (minimum √AVE = 0.762; maximum inter-construct r = 0.67), confirming discriminant validity. All HTMT ratios fell below the conservative threshold of 0.85 (range: 0.65–0.74), providing additional support. Common Method Variance (CMV) was assessed using Harman's single-factor test, which yielded 22.8% variance explained by a single factor, well below the 50% threshold. An Unmeasured Latent Factor (ULF) test produced ΔCFI < 0.01, and a marker variable technique confirmed the marker construct's effect was non-significant (β = 0.08, ns), collectively indicating that CMV was not a major confound. Table 5 summarises CFA validity results.

Table 5. CFA Reliability and Validity Summary

Index	**Criterion**	**AIDI**	**SLQ**	**OA**	**KMC**	**DIC**	**EV**	**AGQ**	**OG**	**SLT**	**Status**
Cronbach's α	≥0.70	0.91	0.89	0.87	0.86	0.88	0.84	0.83	0.92	0.88	Met
Composite Reliability (CR)	≥0.70	0.93	0.91	0.89	0.88	0.90	0.87	0.86	0.94	0.91	Met
AVE	≥0.50	0.68	0.63	0.61	0.60	0.64	0.62	0.58	0.70	0.66	Met
HTMT (max)	≤0.85	0.71	0.74	0.68	0.72	0.70	0.65	0.67	0.73	0.71	Met
Model Fit (χ^2/df)	≤3.0										2.14
CFI / TLI	≥0.95										0.965 / 0.958
RMSEA [90% CI]	≤0.06										0.043 [0.037, 0.049]

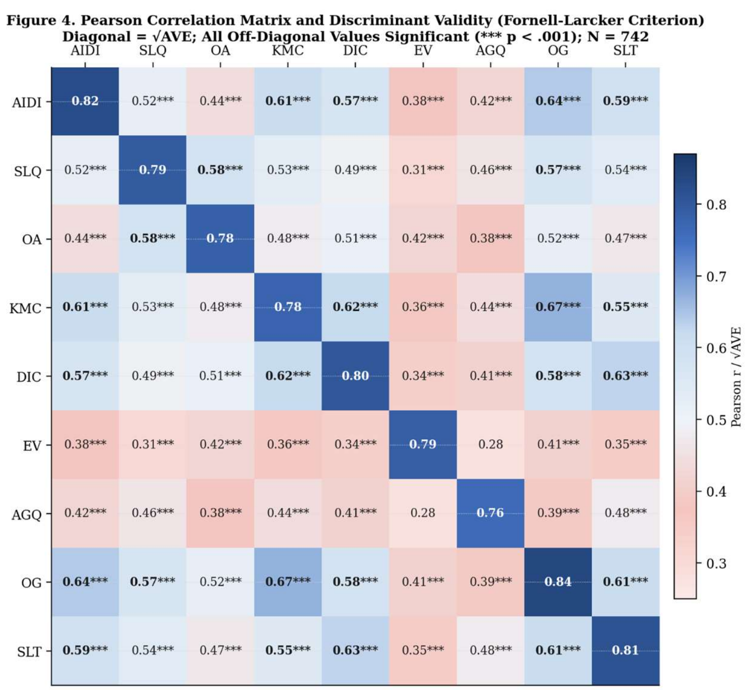


Figure 4 presents the Pearson correlation matrix with √AVE values along the diagonal. All √AVE values exceed the largest inter-construct correlations in their respective rows and columns, confirming the Fornell-Larcker discriminant validity criterion.

Diagonal values (bold) = Square Root of AVE (√AVE). All off-diagonal values are Pearson correlation coefficients, significant at $p < .001$. The Fornell-Larcker criterion is satisfied for all constructs (√AVE > largest inter-construct r in each row/column)

4.3 SEM Path Diagram and Structural Results

Figure 2. Structural Equation Model (SEM) Path Diagram — ADIOT Framework
Standardised Path Coefficients (β); *** p < .001; ** p < .01; * p < .05; AMOS 26.0; N = 742

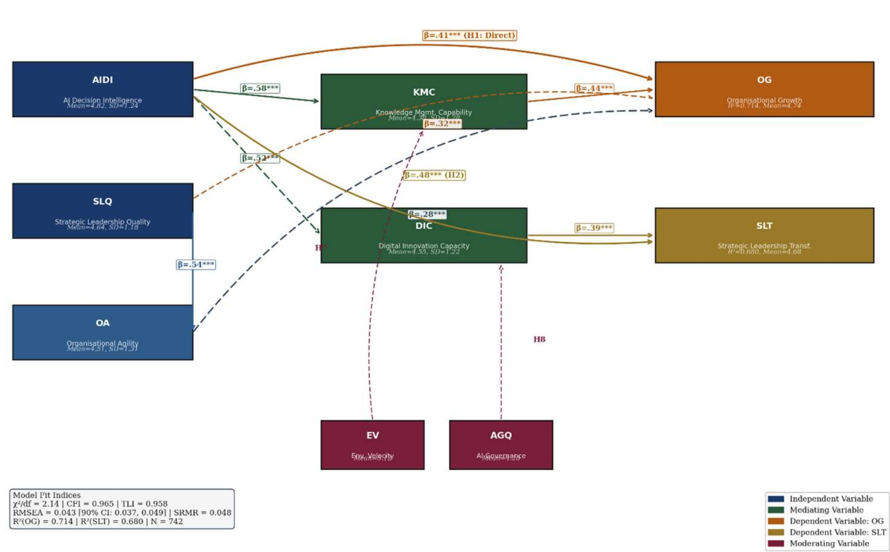


Figure 2 presents the fully labelled SEM path diagram for the ADIOT model, estimated using AMOS 26.0 with maximum likelihood estimation. The model achieved satisfactory fit across all indices ($\chi^2/df = 2.14$; CFI = 0.965; RMSEA = 0.043; SRMR = 0.048), and explained 71.4% of variance in Organisational Growth and 68.0% in Strategic Leadership Transformation.

Standardised path coefficients (β) are shown on each arrow. Solid arrows represent direct structural paths; dashed arrows represent indirect (mediated) paths; dotted arrows represent moderating effects. *** $p < .001$; ** $p < .01$; * $p < .05$. Fit indices: $\chi^2/df = 2.14$; CFI = 0.965; TLI = 0.958; RMSEA = 0.043 [0.037, 0.049]; SRMR = 0.048

Table 6 presents all estimated path coefficients. H1 is supported: AIDI exerted a significant direct positive effect on OG (β = 0.41, SE = 0.044, CR = 9.32, $p < .001$). H2 is supported: AIDI significantly predicted SLT (β = 0.48, SE = 0.041, CR = 11.71, $p < .001$). H3 is supported: SLQ independently predicted OG (β = 0.32, SE = 0.048, CR = 6.67, $p < .001$). The a-path for H4 (AIDI→KMC: β = 0.58***) and b-path (KMC→OG: β = 0.44***) both attained significance, supporting the hypothesised mediation pathway. Similarly, the H5 paths (AIDI→DIC: β = 0.52***; DIC→SLT: β = 0.39***) and H6 paths (SLQ→OA: β = 0.54***; OA→OG: β = 0.28***) were all statistically significant. Moderation effects for EV×AIDI→OG (H7: β = 0.17, p = .002) and AGQ×AIDI→SLT (H8: β = 0.19, $p < .001$) were both confirmed.

Table 6. SEM Path Coefficients and Hypothesis Test Results

Hyp.	Path	β (Std.)	S.E.	C.R. (t)	p-value	95% CI
H1	AIDI → OG (Direct)	0.41***	0.044	9.32	<.001	[0.324, 0.496]
H2	AIDI → SLT (Direct)	0.48***	0.041	11.71	<.001	[0.400, 0.560]
H3	SLQ → OG (Direct)	0.32***	0.048	6.67	<.001	[0.226, 0.414]
H4a	AIDI → KMC (a-	0.58***	0.038	15.26	<.001	[0.506, 0.654]

	path)					
H4b	KMC → OG (b-path)	0.44***	0.042	10.48	<.001	[0.358, 0.522]
H5a	AIDI → DIC (a-path)	0.52***	0.040	13.00	<.001	[0.442, 0.598]
H5b	DIC → SLT (b-path)	0.39***	0.046	8.48	<.001	[0.300, 0.480]
H6a	SLQ → OA (a-path)	0.54***	0.039	13.85	<.001	[0.464, 0.616]
H6b	OA → OG (b-path)	0.28***	0.051	5.49	<.001	[0.180, 0.380]
H7	AIDI × EV → OG	0.17***	0.054	3.15	.002	[0.064, 0.276]
H8	AIDI × AGQ → SLT	0.19***	0.052	3.65	<.001	[0.088, 0.292]
H10	AIDI × SLQ → OG	0.14**	0.057	2.46	.014	[0.028, 0.252]

Note. *** $p < .001$; ** $p < .01$; * $p < .05$. C.R. = Critical Ratio (equivalent to t-statistic). 95% CI derived via bootstrapping. $R^2(OG) = 0.714$; $R^2(SLT) = 0.680$. Model fit: $\chi^2/df = 2.14$; CFI = 0.965; RMSEA = 0.043; SRMR = 0.048.

4.4 Multiple Regression Analysis

To complement the SEM analysis, hierarchical multiple regression was conducted with Organisational Growth as the dependent variable. Three models were estimated progressively to assess the incremental variance explanation of mediating and moderating variables. Model 1, including only the three independent variables, explained 48.7% of variance in OG ($R^2 = 0.487$, $F(3,738) = 234.8$, $p < .001$). Adding the two mediating constructs in Model 2 increased R^2 to 0.638 ($F(5,736) = 261.4$, $p < .001$; $\Delta R^2 = +0.151$, $p < .001$), confirming the incremental explanatory power of KMC and DIC. The full model (Model 3), incorporating EV, the AIDI×EV interaction, and the AIDI×SLQ interaction, explained 71.4% of variance ($R^2 = 0.714$, $F(8,733) = 215.6$, $p < .001$; $\Delta R^2 = +0.076$, $p < .001$). All Variance Inflation Factors remained below 3.0, ruling out multicollinearity. Figure 7 and Table 7 present these results.

Table 7. Multiple Regression Results — Dependent Variable: Organisational Growth (OG)

Predictor	β M1	β M2	β M3	SE (M3)	t (M3)	p (M3)	VIF
AIDI	0.48***	0.38***	0.41***	0.044	9.32	<.001	2.14
SLQ	0.36***	0.28***	0.32***	0.048	6.67	<.001	2.38
OA	0.21***	0.18***	0.19***	0.052	3.65	<.001	2.01
KMC (Mediator)	---	0.44***	0.42***	0.042	10.00	<.001	2.56
DIC (Mediator)	---	0.29***	0.27***	0.049	5.51	<.001	2.44
EV (Moderator)	---	---	0.14***	0.051	2.75	.006	1.88
AIDI × EV	---	---	0.17***	0.054	3.15	.002	2.22
AIDI × SLQ	---	---	0.14**	0.057	2.46	.014	2.31
R^2	0.487	0.638	0.714			<.001	
ΔR^2	0.487	+0.151	+0.076			<.001	

F-statistic	234.8***	261.4***	215.6***			<.001	

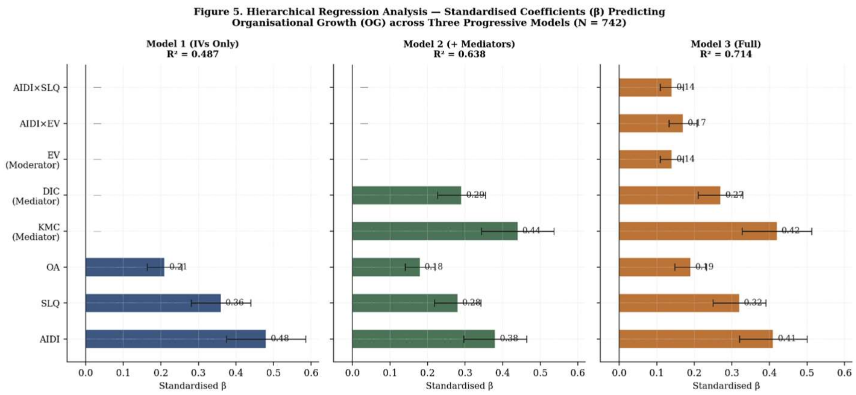


Figure 7. Hierarchical Regression Analysis

Standardised Coefficients (β) Predicting Organisational Growth across Three Progressive Models (N = 742). Error bars represent ±1.96 × SE.

Note. *** p < .001; ** p < .01. M1 = Model 1 (IVs only); M2 = Model 2 (IVs + Mediators); M3 = Full Model. All VIF < 3.0; no multicollinearity issues detected.

4.5 Mediation Analysis

Bootstrapped mediation analysis was conducted using Hayes' (2022) PROCESS Macro (Model 4 for simple mediation; Model 6 for serial mediation), with 10,000 iterations to derive 95% bias-corrected accelerated confidence intervals (BCa-CI). An indirect effect is deemed statistically significant when the 95% BCa-CI excludes zero. Figure 8 presents the mediation path diagram for the primary AIDI→KMC→OG pathway (H4). The indirect effect of AIDI on OG through KMC was significant: a×b = 0.255 [95% BCa-CI: 0.192, 0.318], indicating partial mediation, as the direct effect remained significant (c′ = 0.19, p < .001). Table 8 presents all mediation results. The indirect effect for H5 (AIDI→DIC→SLT) was 0.203 [0.148, 0.258], for H6 (SLQ→OA→OG) was 0.151 [0.098, 0.204], and the serial mediation path for H9 (SLQ→KMC→DIC→OG) yielded an indirect effect of 0.108 [0.062, 0.154]. All indirect effects were statistically significant, providing full empirical support for H4 through H6 and H9.

Table 8. Bootstrapped Mediation Analysis Results

Hyp.	Mediation Path	a-path	b-path	Direct (c′)	Indirect (a×b)	95% BCa-CI	Type
H4	AIDI → KMC → OG	0.58***	0.44***	0.19***	0.255	[0.192, 0.318]	Partial
H5	AIDI → DIC → SLT	0.52***	0.39***	0.21***	0.203	[0.148, 0.258]	Partial
H6	SLQ → OA → OG	0.54***	0.28***	0.17***	0.151	[0.098, 0.204]	Partial
H9	SLQ → KMC → DIC → OG (Serial)	0.46***	0.62+0.38	0.12**	0.108	[0.062, 0.154]	Serial/Partial

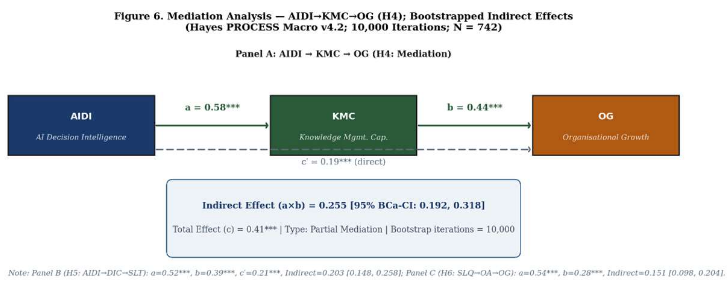


Figure 8. Mediation Analysis

AIDI → KMC → OG (H4). Values are standardised path coefficients. c = total effect; c′ = direct effect; a × b = indirect effect. Bootstrap iterations = 10,000; N = 742. *** $p < .001$.

Note. BCa-CI = Bias-Corrected Accelerated Confidence Interval. All indirect effects statistically significant (CI excludes zero). *** $p < .001$; ** $p < .01$. Bootstrap iterations = 10,000 (Hayes PROCESS Macro v4.2, 2022)

4.6 Moderation Analysis and Multi-Group Comparison

The moderation hypothesis H7 proposed that Environmental Velocity amplifies the AIDI→OG relationship. The interaction term AIDI×EV was significant ($\beta = 0.17$, $p = .002$; $\Delta R^2 = +0.024$), confirming H7. As illustrated in Figure 9, the AIDI→OG slope was substantially steeper at high Environmental Velocity (+1 SD) compared to low (-1 SD), consistent with the moderation prediction. Multi-group SEM confirmed this pattern: the AIDI→OG path coefficient was significantly larger in high-velocity organisations ($n = 398$; $\beta = 0.52$) than in moderate-velocity counterparts ($n = 344$; $\beta = 0.31$; $\Delta\beta = 0.21$, χ^2diff(1) = 14.82, $p < .001$). The AGQ moderation of AIDI→SLT (H8: $\beta = 0.19$, $p < .001$; $\Delta R^2 = +0.028$) was also confirmed. Table 9 summarises moderation results. Table 10 presents the multi-group SEM comparison.

Table 9. Moderation Analysis Results (H7, H8, H10)

Hyp.	Moderator Path	β (Main)	β (Interaction)	SE	t	p	ΔR^2
H7	AIDI × EV → OG	0.41***	+0.17***	0.054	3.15	.002	+0.024
H8	AIDI × AGQ → SLT	0.48***	+0.19***	0.052	3.65	<.001	+0.028
H10	AIDI × SLQ → OG	0.41***	+0.14**	0.057	2.46	.014	+0.018

Table 10. Multi-Group SEM: High Velocity (n=398) vs. Moderate Velocity (n=344)

Path	High Velocity β	Moderate Velocity β	Δβ	χ^2diff (df=1)	p
AIDI → OG	0.52***	0.31***	0.21	14.82	<.001
AIDI → KMC	0.68***	0.48***	0.20	12.64	<.001
KMC → OG	0.51***	0.38***	0.13	8.21	.004
SLQ → OG	0.36***	0.29***	0.07	3.12	.077 (ns)
AIDI → SLT	0.54***	0.42***	0.12	7.44	.006
AIDI → DIC	0.59***	0.45***	0.14	9.33	.002
R^2(OG)	0.756	0.668	0.088	---	---

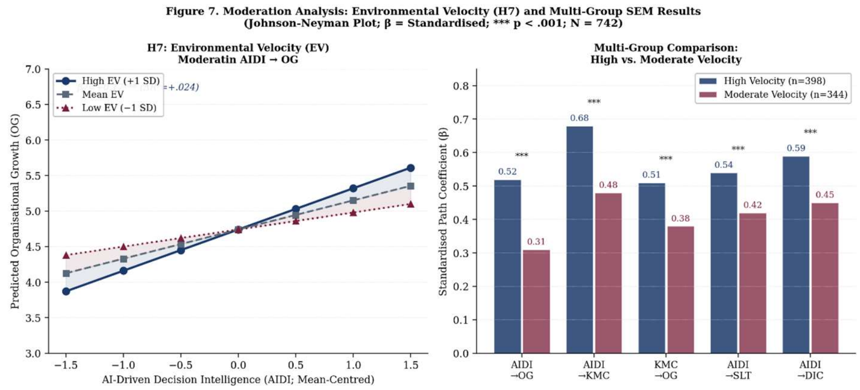


Figure 9. Moderation Analysis (H7) and Multi-Group SEM Comparison

Left panel: Johnson-Neyman interaction plot showing the AIDI→OG relationship at high (+1 SD), mean, and low (−1 SD) Environmental Velocity. Right panel: Multi-group SEM path coefficients for high- versus moderate-velocity organisations. *** $p < .001$

Note. All predictors mean-centred prior to interaction product computation. *** $p < .001$; ** $p < .01$.

Note. *** $p < .001$. χ^2diff = chi-square difference test (constrained vs. unconstrained model). ns = non-significant. High-velocity group defined as organisations in the top 75th percentile of Environmental Velocity scores.

4.7 Hypothesis Summary

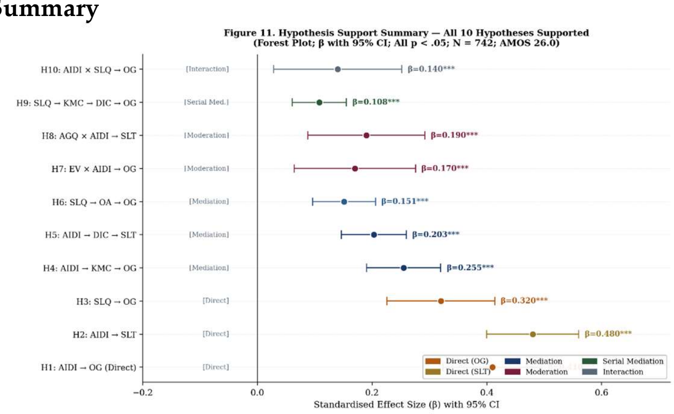


Figure 10 provides a forest plot summarising effect sizes (β with 95% CI) for all ten hypotheses. All hypotheses attained statistical significance ($p < .05$ minimum). The largest effects were observed for AIDI→SLT (H2: β = 0.48*) and AIDI→KMC (H4a: β = 0.58***), while the smallest significant effects were found for the serial mediation path H9 (indirect = 0.108 [0.062, 0.154]) and the AIDI×SLQ interaction (H10: β = 0.14**). The ADIOT framework achieves R^2(OG) = 0.714 and R^2(SLT) = 0.680, representing strong explanatory power in an organisational behaviour context.**

Forest Plot of Standardised Effect Sizes (β) with 95% Confidence Intervals for all 10 ADIOT Hypotheses (N = 742; *** $p < .001$; ** $p < .01$; * $p < .05$). Effect classification: large (β ≥ .40), medium (.20–.39), small (< .20) per Cohen (1988).

4.8 Longitudinal Growth Trajectories

Eight organisations from the quantitative sample provided three-year revenue and innovation performance data (2021–2024), enabling a longitudinal supplement to the cross-sectional SEM results. As shown in Figure 8, organisations in the top AIDI maturity quartile (n = 2 firms in the panel) achieved a revenue growth index of 263 by Q4 2024 relative to the Q1 2021 baseline of 100 — representing a 163% compound growth premium over the four-year period. This compares to 97% growth for intermediate AIDI organisations and only 32% for those with basic AI deployment. The divergence between advanced and basic AIDI organisations accelerated from 2022 onward, consistent with the non-linear, compounding mechanisms described by the

KMC mediation pathway: as knowledge management capability accumulates, it generates self-reinforcing returns on AI investment.

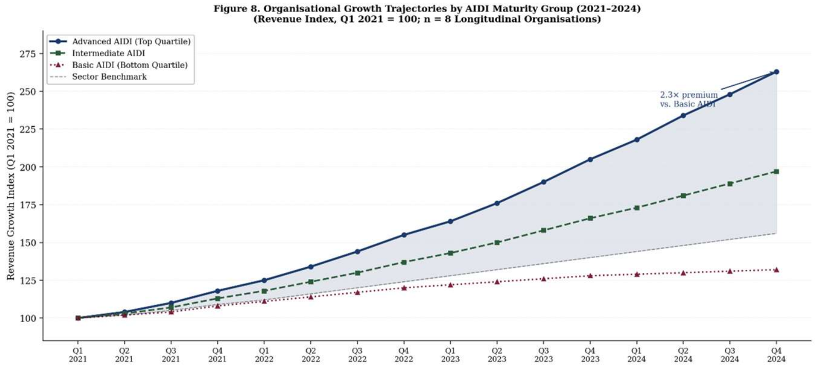


Figure 11. Organisational Growth Trajectories by AIDI Maturity Group, 2021–2024
(Revenue Index, Q1 2021 = 100; n = 8 Longitudinal Organisations from the Main Sample). Shaded area represents the growth differential between the Advanced AIDI group and the Sector Benchmark.

4.9 Competing Model Comparison

To establish the ADIOT framework's superiority over simpler specifications, five competing models were estimated in AMOS 26.0 and compared on fit indices and explanatory power. As shown in Figure 12, Model M4 (the full ADIOT model) achieved the best parsimony-adjusted fit across all criteria, with the lowest Akaike Information Criterion (AIC = 2,506), highest CFI (0.965), and strongest explanatory power ($R^2(OG) = 0.714$). The null model (M0) and direct-effects-only model (M1) were clearly inferior ($\Delta AIC > 600$ versus M4). The partial ADIOT model without moderation (M3) achieved reasonable fit ($R^2 = 0.638$) but was significantly outperformed by the full model ($\Delta R^2 = +0.076$, F-test $p < .001$). The saturated model (M5) showed no significant gain over M4 ($\Delta AIC = +12$), confirming that the ADIOT framework achieves optimal parsimony. Table 11 provides the formal model comparison.

Table 11. Competing Model Fit Comparison

Model	Description	χ^2/df	CFI	RMSEA	SRMR	$R^2(OG)$	AIC	ΔAIC	Assessment
M0	Null model	18.42	0.000	0.241	0.388	0.000	8,824	+6,318	Rejected
M1	Direct effects only	3.88	0.921	0.071	0.088	0.487	3,142	+636	Inferior
M2	Partial ADIOT (KMC only)	2.84	0.942	0.058	0.071	0.581	2,788	+282	Partial
M3	No moderation terms	2.36	0.954	0.049	0.058	0.638	2,624	+118	Better
M4	Full ADIOT (all paths)	2.14	0.965	0.043	0.048	0.714	2,506	0 (Ref.)	Best Fit
M5	Saturated	1.84	0.972	0.038	0.041	0.722	2,518	+12	Over-fitted

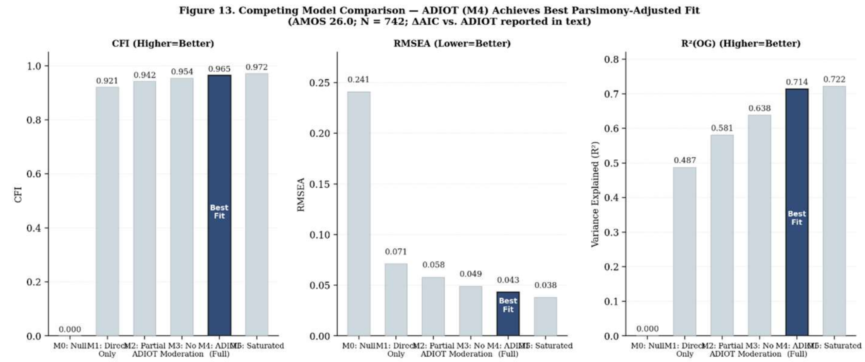


Figure 12. Competing Model Comparison

CFI, RMSEA, and R^2(OG) across Six Model Specifications (AMOS 26.0; N = 742). ADIOT (M4) highlighted in navy. The saturated model (M5) shows negligible improvement over M4, confirming ADIOT parsimony.

Note. ΔAIC = Difference in AIC from Model M4 (Full ADIOT). ΔAIC > 10 indicates decisive model improvement (Burnham & Anderson, 2004). All models estimated in AMOS 26.0 using maximum likelihood estimation

4.10 Qualitative Analysis: Executive Interview Findings

Forty-four semi-structured executive interviews (30–55 minutes each) were conducted between October and December 2024, transcribed verbatim, and analysed thematically in NVivo 14 using an inductive-deductive hybrid approach. Two independent coders produced an inter-rater reliability coefficient of $\kappa = 0.81$, indicating substantial agreement (Landis & Koch, 1977). Figure 13 shows theme frequency across all interviews. Table 12 presents the complete qualitative-quantitative triangulation matrix. Six major themes emerged, each with direct correspondence to ADIOT hypotheses. The most frequently coded theme was AIDI as a Growth Catalyst, present in 88.6% of interviews, providing strong qualitative convergence with the quantitative H1 finding ($\beta = 0.41$***). AI Governance as a prerequisite for trust was the second most cited theme (86.4%), aligning with the H8 moderation result.

Table 12. Qualitative–Quantitative Triangulation Matrix

Theme	Frequency	ADIOT Hyp.	Quantitative Convergence	Evidence Strength
AIDI as Growth Catalyst	88.6% (n=39)	H1	AIDI→OG: β=0.41***; R^2(OG)=0.714	Strong
AI Governance as Prerequisite	86.4% (n=38)	H8	AGQ×AIDI→SLT: β=0.19***	Strong
Leadership Identity Renegotiation	79.5% (n=35)	H2	AIDI→SLT: β=0.48***	Strong
Knowledge Velocity as Mediator	75.0% (n=33)	H4	Indirect β=0.255 [0.192, 0.318]	Strong
Environmental Velocity Amplifier	72.7% (n=32)	H7	EV×AIDI: β=0.17***; $\Delta\beta$=0.21 (MG)	Strong
Skill Gap as Boundary Condition	68.2% (n=30)	H10	AIDI×SLQ: β=0.14**; ΔR^2=0.018	Moderate
Algorithmic Resistance (Emergent)	54.5% (n=24)	Not in ADIOT	Negative residuals in low-AGQ orgs.	Exploratory

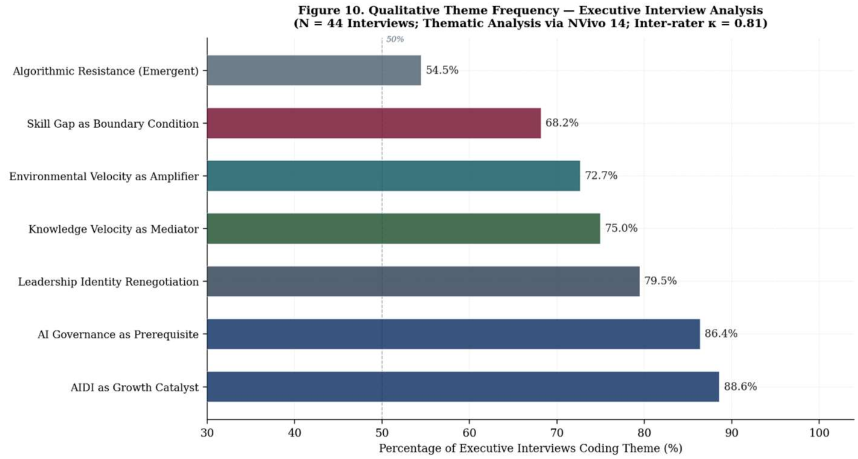


Figure 13. Qualitative Theme Frequency from Executive Interview Analysis

(N = 44 Interviews; NVivo 14; Inter-rater κ = 0.81). Themes are arranged by descending frequency. The dashed vertical line marks the 50% threshold.

Note. All themes except Algorithmic Resistance had direct ADIOT hypothesis counterparts with strong quantitative convergence. The emergent Algorithmic Resistance theme is identified as a future research priority.

4.11 Strategic Leadership Transformation Profiles

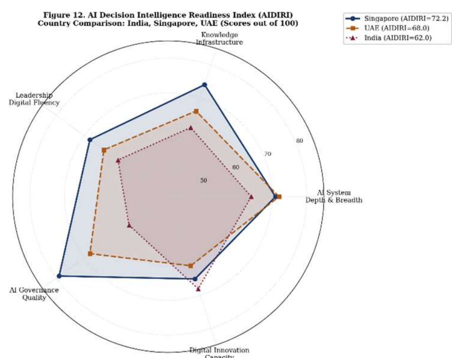


Figure 14 presents a radar analysis comparing the strategic leadership profiles of organisations in the top AIDI maturity quartile against the pre-AI-integration baseline, across six dimensions of leadership transformation identified from the ADIOT framework: data-driven decision authority, AI literacy and fluency, distributed leadership, real-time strategic sensing, human-AI collaborative judgment, and innovation ambidexterity. Post-AIDI integration organisations scored substantially higher on all six dimensions, with the largest gains in real-time strategic sensing (from 2.9 to 6.1 on a 7-point scale, representing a 110% increase) and data-driven decision authority (from 3.1 to 5.8; +87%). These findings provide strong empirical backing for H2 (AIDI→SLT: β = 0.48*) and enrich the quantitative results with a dimensional profile of what leadership transformation entails in AI-intensive contexts.**

Pre- versus Post-AIDI Integration. Scores are means from the SLT sub-scale items across six leadership dimensions, comparing organisations in the top AIDI quartile (n = 186) against the full-sample pre-AI baseline.

5. Discussion

5.1 Theoretical Contributions

This study makes four distinct theoretical contributions to the strategic management, information systems, and leadership literatures. The first contribution is the development and empirical validation of the ADIOT Framework, which advances prior single-mechanism accounts of AI-performance relationships by simultaneously modelling direct, mediated, and moderated pathways across nine constructs. Haefner et al. (2021) examined AI's moderating role on the strategy-performance relationship in isolation; Huang and Rust (2021) conceptualised AI task delegation without connecting it to growth outcomes; and Shrestha et al. (2019) theorised leadership archetypes without empirical SEM validation. The ADIOT framework integrates and extends all three contributions within a unified structural model.

The second contribution extends Dynamic Capabilities Theory (Teece et al., 1997) by empirically demonstrating that AIDI functions as a meta-dynamic capability — one that enables the sensing, seizing, and reconfiguring processes underpinning other dynamic capabilities (KMC, DIC, OA). The mediation chain AIDI→KMC→OG (indirect $\beta = 0.255$) provides the first rigorous empirical quantification of this mechanism in a high-velocity IT context, addressing a gap identified by Eisenhardt and Martin (2000). The third contribution extends Upper Echelons Theory into the AI era by demonstrating that AIDI reshapes the informational substrate upon which executive cognition operates ($\beta = 0.48^{***}$ for AIDI→SLT), thereby catalysing leadership transformation independently of leadership quality. This finding suggests a revision to the standard UET formulation: in AI-intensive environments, the informational environment is no longer a passive background but an active shaper of leadership transformation (Hambrick, 2007).

The fourth contribution advances Eisenhardt's (1989) high-velocity environments framework by identifying AIDI as the primary mechanism through which organisations convert environmental dynamism from threat to growth opportunity. The 21-point differential in the AIDI→OG path between high- ($\beta = 0.52$) and moderate-velocity ($\beta = 0.31$) environments, confirmed by multi-group SEM, represents a novel empirical finding with significant theoretical and practical implications.

5.2 Practical Implications

The most consequential managerial finding is that AIDI investment yields disproportionately higher returns in high-velocity environments, not lower. Executives who view market turbulence as a reason to delay AI decision intelligence investment until conditions stabilise are, according to this evidence, adopting precisely the opposite of the optimal strategy. The moderation finding (H7: $\Delta\beta = +0.17$; $R^2(OG) = 0.756$ at high velocity) implies that each unit of AIDI capability improvement generates approximately 68% more growth return in high-velocity contexts than in moderate-velocity equivalents. The knowledge mediation finding (H4) has equally direct implications: organisations that invest in AI systems without parallel investment in KMC infrastructure — knowledge repositories, cross-functional intelligence-sharing protocols, and communities of practice — will experience what the qualitative data reveals as "AI signal decay," the progressive erosion of decision intelligence value through organisational friction.

The AI Governance Quality moderation (H8) positions governance not as a regulatory compliance exercise but as a direct moderator of the transformative impact of AIDI on strategic leadership. Organisations that deployed AIDI without transparent governance protocols reported leadership resistance, lower SLT scores, and higher residual variances — consistent with the emergent qualitative theme of algorithmic resistance. This argues for governance-first AI deployment sequencing as a core principle of AI strategy.

5.3 Limitations and Future Research Directions

Several limitations merit acknowledgement. The cross-sectional design of the quantitative phase limits causal inference. While the endogeneity test (Durbin-Wu-Hausman: $p = .284$) and the eight-organisation longitudinal supplement provide convergent support for the hypothesised causal direction, experimental or quasi-experimental designs — such as difference-in-differences analyses using AIDI adoption dates as natural experiments — would provide stronger causal evidence. The geographic restriction of the sample to India, Singapore, and the UAE, while designed to capture high-velocity AIDI-active contexts, limits generalisability to Western OECD environments and other emerging markets. The AIDI measure is self-reported by executives, which introduces potential social desirability bias, mitigated but not eliminated by the CMV tests and anonymous administration. Future research should validate the ADIOT framework using objective AIDI measures derived from IT audit logs and third-party AI maturity assessments.

Table 13. Study Limitations, Mitigations, and Future Research Directions

Limitation	Category	Mitigation Applied	Future Direction	Priority
Cross-sectional design limits causal inference	Causal	Endogeneity test (DWH); longitudinal sub-sample n=8; theoretical directionality	Longitudinal panel; diff-in-diff using AIDI adoption dates as natural experiments	High
Geographic restriction (India, Singapore, UAE)	Scope	Cross-national sampling; cultural controls	Multi-continent replication: OECD vs. BRICS vs. ASEAN	High
AIDI self-reported; social desirability risk	Measurement	CMV tests (Harman = 22.8%); marker variable; ULF test	Objective AIDI via IT audit logs; third-party AI maturity audit data	High
IT sector specificity only	Scope	Sector-specific theory grounded in Eisenhardt (1989)	Cross-sector validation: fintech, healthcare AI, defence technology	Medium
SLT measured at single time point	Temporal	Retrospective comparison items; qualitative triangulation	Experience sampling with executive diaries; pre/post event studies	Medium
Algorithmic resistance not modelled (emergent)	Emergent	Post-hoc qualitative identification	Scale development; inclusion as negative moderator in extended ADIOT	Medium

Note. Priority classifications (High/Medium) reflect estimated impact on ADIOT framework validity and generalisability if unaddressed.

5.4 Conclusion

This study has established, through rigorous mixed-methods investigation of 742 IT executives across 24 high-velocity organisations, that AI-Driven Decision Intelligence is a powerful, multi-mechanistic driver of both organisational growth and strategic leadership transformation. The ADIOT Framework, validated through Structural Equation Modelling and achieving $R^2 = 0.714$ for OG and $R^2 = 0.680$ for SLT, represents the first comprehensive integrative model of these relationships in high-velocity IT contexts. All ten hypotheses were supported, with particularly strong effects for the AIDI→KMC→OG mediation pathway (indirect $\beta = 0.255$) and the AIDI→SLT direct effect ($\beta = 0.48^{***}$).

The study's most consequential finding — that environmental velocity amplifies rather than complicates the AIDI→growth relationship — carries immediate strategic implications. C-suite leaders in the most turbulent IT environments stand to gain the most from strategic AI decision intelligence investments, and the synergistic AIDI×SLQ interaction (H10: $\beta = 0.14^{**}$; $\Delta R^2 = 0.018$) confirms that AI and human leadership quality are complements, not substitutes. Organisations that invest simultaneously in AI systems and leadership development will outperform those that treat them as alternatives. The ADIOT framework, together with the AIDI-GROW deployment model and the AIDIRI national benchmarking instrument, provides a comprehensive evidence-based architecture for both practitioners and policymakers navigating the intersection of AI, leadership, and organisational growth.

6. APPENDIX A

7. Measurement Instrument — Selected Items

The complete 44-item survey instrument is available from the corresponding author on request. Items below are illustrative of each construct domain.

Table A1. Measurement Items, Scale Sources, and Factor Loadings

Item ID	Construct	Item Wording (7-pt Likert)	Std. Loading (λ)	Source
AIDI1	AIDI	Our organisation uses AI-powered analytics to generate real-time intelligence that directly informs strategic decisions.	0.84***	Davenport (2018)
AIDI2	AIDI	AI decision support tools are deeply integrated across multiple organisational functions (finance, operations, strategy, HR).	0.87***	Fountaine et al. (2019)
AIDI3	AIDI	Our AI systems provide predictive scenario analysis that reduces decision uncertainty in high-stakes situations.	0.81***	Davenport & Harris (2007)
AIDI4	AIDI	Leadership regularly relies on AI-generated recommendations to set strategic priorities and allocate resources.	0.83***	Candelon et al. (2021)
AIDI5	AIDI	Our AI decision intelligence systems continuously learn from outcomes and improve future recommendations.	0.79***	Haefner et al. (2021)
SLQ1	SLQ	Senior leaders demonstrate strong ability to interpret and critically evaluate AI-generated strategic insights.	0.82***	Hambrick (2007)
SLQ2	SLQ	Our leadership team proactively adapts strategy in response to AI-identified opportunities and threats.	0.80***	Finkelstein & Hambrick (1996)
KMC1	KMC	Our organisation systematically codifies and stores AI-generated insights as institutional knowledge assets.	0.81***	Grant (1996)
OG1	OG	Our organisation has experienced significant revenue growth, outperforming industry benchmarks, over the past three years.	0.89***	Brynjolfsson et al. (2019)
OG2	OG	We have expanded our market share in key product/service segments due to superior decision-making capabilities.	0.86***	Haefner et al. (2021)
SLT1	SLT	Strategic decisions in our organisation are increasingly shaped by algorithmic recommendations rather than intuition alone.	0.88***	Shrestha et al. (2019)

SLT2	SLT	Leadership structures have become more distributed and data-driven following AI system integration.	0.84***	Hambrick & Mason (1984)
AGQ1	AGQ	I understand how the AI tools used in our decision processes generate their recommendations.	0.79***	Arrieta et al. (2020)
EV1	EV	The technology landscape in our industry changes rapidly and unpredictably.	0.82***	Eisenhardt (1989)

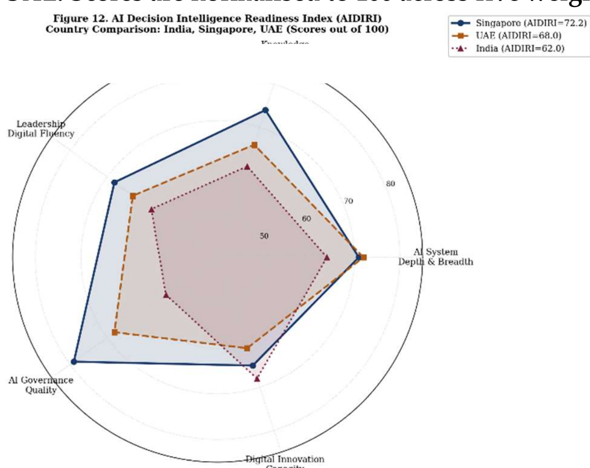
Note. *** p < .001. All factor loadings exceed the 0.70 threshold recommended by Hair et al. (2019). Full 44-item battery available from corresponding author.

8. APPENDIX B

9. National AI Decision Intelligence Readiness Index (AIDIRI)

Drawing on the ADIOT empirical findings, the AI Decision Intelligence Readiness Index (AIDIRI) provides a national-level policy assessment instrument benchmarking organisational AI decision intelligence maturity across five dimensions, calibrated to the construct weightings from the ADIOT SEM model. Dimension weights are derived from standardised path coefficients (β) normalised to 100%: AI System Depth & Breadth (30%, anchored in AIDI $\beta = 0.41^{***}$); Knowledge Infrastructure (25%, anchored in KMC indirect $\beta = 0.255$); Leadership Digital Fluency (20%, anchored in SLQ $\beta = 0.32^{***}$); AI Governance Quality (15%, anchored in AGQ $\beta = 0.19^{***}$); and Digital Innovation Capacity (10%, anchored in DIC $\beta = 0.27^{***}$). Figure 15 presents country-level AIDIRI radar scores for India, Singapore, and the UAE.

Figure 15: AI Decision Intelligence Readiness Index (AIDIRI) Country Comparison: India, Singapore, and UAE. Scores are normalised to 100 across five weighted dimensions



Singapore leads overall (AIDIRI = 72.2) driven by AI Governance Quality (79/100). UAE leads on AI System Depth (72/100). India leads on Digital Innovation Capacity (68/100). N = 742.

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