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Responsible AI Strategy, Organizational Knowledge, and Value Creation: Integrating Dynamic Capabilities, the Knowledge-Based View, and Stakeholder Theory

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ABSTRACT

This study investigates how responsible AI strategy, conceptualized as a higher-order organizational capability integrating dynamic AI-related capabilities and responsible AI governance, enables firms to create stakeholder-based value through the orchestration of organizational knowledge. The study employs a two-wave, matched-pair, multi-country survey design across AI-adopting firms in Canada and the United States. Data are collected from two key informants per firm (business and AI/IT leaders), yielding approximately 450 usable responses and 210–220 complete matched firm-level pairs used for hypothesis testing. The model is analyzed using partial least squares structural equation modelling (PLS-SEM) in SmartPLS, with bootstrapped mediation and moderation tests and multi-group analysis (PLS-MGA) to examine cross-country differences. The results indicate that organizational knowledge orchestration mediates the relationship between dynamic AI-related capabilities and stakeholder value creation. Responsible AI governance mechanisms strengthen this relationship, underscoring the role of ethical and institutional safeguards in realizing strategic and societal value. Cross-country analysis reveals both shared patterns and contextual differences between Canada and the United States. This study provides a multi-country, firm-level matched-pair empirical integration of dynamic capabilities, the knowledge-based view, and stakeholder theory in the context of responsible AI strategy, offering both theoretical advancement and actionable guidance for managers and policymakers seeking to align AI initiatives with ethical governance and long-term value creation.

Keywords: Responsible AI strategy; Dynamic capabilities; Organizational knowledge; Knowledge-based view; Stakeholder theory.

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INTRODUCTION

The rapid diffusion of artificial intelligence (AI) across organizational functions is reshaping how firms sense opportunities, allocate resources, and create value in increasingly complex stakeholder environments (Wamba-Taguimdje, Fosso Wamba, Kala Kamdjoug, & Tchatchouang Wanko, 2020). AI-driven systems now support decisions in operations, marketing, human resources, and risk management, positioning AI as a central element of strategic governance rather than a purely technical tool (Bevilacqua, Ferraris, Kozel, & Vincurova, 2025). At the same time, growing concerns about fairness, transparency, accountability, and social legitimacy have elevated the importance of responsible AI strategy in management and policy debates. International guidelines and scholarly work emphasize the need for human-centered and accountable AI development, highlighting the strategic implications of aligning technological innovation with institutional and ethical expectations (Jiang, Xuan, & Zhang, 2025; Kyambade & Namatovu, 2025).

Much of the existing literature adopts an instrumental view of AI, emphasizing efficiency gains, innovation outcomes, and firm-level performance advantages (Larabi, 2025; Luo, Qian, Liu, Yu, & Liu, 2024). In parallel, strategy research highlights the role of dynamic capabilities in enabling organizations to sense, seize, and reconfigure resources in response to technological turbulence (Girod & Whittington, 2017; Karami, 2025). While these perspectives provide important insights into adaptation and competitiveness, they remain largely firm-centric, offering limited explanations of how AI-driven strategies generate value beyond internal performance metrics (Wamba-Taguimdje et al., 2020). In particular, the knowledge processes and stakeholder relationships through which AI-related capabilities are translated into broader organizational and societal outcomes remain underexplored in empirical research.

From the knowledge-based view of the firm, organizations are understood as social and institutional systems for the creation, integration, and application of knowledge rather than as collections of discrete resources (Madhani, 2010). In digital contexts, AI reshapes these systems by enabling large-scale data integration, automated learning, and algorithmic interpretation. Prior studies demonstrate that such capabilities enhance absorptive capacity, organizational learning, and innovation performance, strengthening firms' ability to recognize and exploit new opportunities (Mikalef, Islam, Parida, Singh, & Altwaijry, 2023; Teece, Pisano, & Shuen, 1997). However, empirical work has only begun to examine how AI-enabled knowledge mechanisms function as strategic mediators linking capability development to value creation that extends beyond internal efficiency and competitive advantage (Qiu, Yu, Sadowski, & Shi, 2025).

At the same time, stakeholder theory extends the concept of value beyond shareholders to encompass employees, customers, regulators, communities, and partners whose perceptions shape organizational legitimacy and long-term success (Arian, Sands, Rahman, & Khatatbeh, 2025; Donaldson & Preston, 1995; Pinto, 2019). The deployment of AI intensifies these relationships by influencing social trust, ethical norms, and regulatory scrutiny. Recent governance-oriented research highlights the growing importance of ethical guidelines, transparency requirements, and accountability mechanisms in shaping how algorithmic systems are perceived and accepted (Durman, Iyiola, Alzubi, & Aljuhmani, 2025; Qiu et al., 2025). Despite these advances, limited empirical attention has been paid to how such institutional and ethical considerations are embedded

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within firms' capability-building and knowledge orchestration processes that precede stakeholder responses.

A central limitation of the current literature is the fragmentation across theoretical perspectives. Research grounded in dynamic capabilities emphasizes organizational adaptation and strategic renewal but often underplays the micro-level knowledge mechanisms through which these capabilities are enacted and sustained. Knowledge management studies focus on learning and information flows within organizations while paying less attention to their integration into broader strategic and governance frameworks. Stakeholder-oriented work, in turn, prioritizes legitimacy and ethical responsibility without systematically linking these outcomes to the capability development and knowledge processes that enable them. This separation constrains understanding of how AI-related capabilities, organizational knowledge systems, and stakeholder value creation are jointly configured within a coherent and actionable model of responsible AI strategy.

This study addresses this gap by developing and empirically testing an integrated framework of responsible AI strategy that bridges dynamic capabilities, the knowledge-based view, and stakeholder theory. Drawing on the dynamic capabilities perspective, we conceptualize responsible AI strategy as a higher-order capability that enables firms to sense ethical and institutional demands, seize opportunities through AI-enabled knowledge systems, and reconfigure organizational processes and governance structures to sustain value creation over time (Karami, 2025). From a knowledge-based perspective, organizational knowledge orchestration is positioned as a key mediating mechanism through which dynamic capabilities are translated into stakeholder-oriented outcomes (Madhani, 2010; Mikalef et al., 2023).

Empirically, the study responds to calls for multi-source and cross-national designs in digital strategy and AI governance research (Jiang et al., 2025; Luo et al., 2024). We employ a two-wave, matched-pair survey design across AI-adopting firms in Canada and the United States, collecting data from both business-side and technology-side managers to reduce common method bias and capture complementary strategic and operational perspectives. Using partial least squares structural equation modelling (PLS-SEM) and multi-group analysis, we test a moderated mediation model examining how dynamic AI-related capabilities influence stakeholder value creation through organizational knowledge processes across different institutional contexts. The paper concludes by outlining the theoretical, managerial, and policy implications of these findings.

Despite growing interest in AI strategy and responsible AI governance, prior research has paid limited empirical attention to how AI-related capabilities are translated into stakeholder-based value through internal knowledge processes. Existing studies often examine technological capabilities, governance mechanisms, or stakeholder outcomes in isolation, leaving insufficient understanding of how these elements operate together within a coherent strategic framework. This gap is particularly important in cross-national settings where institutional conditions may shape the governance and value implications of AI adoption. Accordingly, this study develops and tests an integrated framework that explains how dynamic AI-related capabilities influence stakeholder-based value creation through organizational knowledge orchestration, and how responsible AI governance strengthens this process. Drawing on dynamic capabilities, the knowledge-based view, and stakeholder theory, the study contributes by clarifying the mediating role of knowledge orchestration, specifying the strategic role of responsible AI governance, and providing cross-

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national evidence from a two-wave, matched-pair survey of AI-adopting firms in Canada and the United States.

Literature Review and Hypotheses Development

Dynamic Capabilities and Organizational Knowledge Orchestration

This study integrates three complementary theoretical perspectives: Dynamic Capabilities Theory, the Knowledge-Based View (KBV), and Stakeholder Theory. Dynamic capabilities explain how organizations develop and reconfigure strategic resources to respond to technological change such as artificial intelligence adoption. The Knowledge-Based View highlights how organizations create value through the orchestration and integration of distributed knowledge resources. Stakeholder Theory provides a normative and strategic perspective on how organizations generate value for multiple stakeholders beyond shareholders. By combining these perspectives, this study explains how AI-related dynamic capabilities enable firms to orchestrate organizational knowledge, which in turn supports the creation of stakeholder-based value. Responsible AI governance further shapes this process by ensuring that AI capabilities are deployed in ways that align with ethical standards and stakeholder expectations.

Dynamic capabilities provide the strategic foundation through which organizations align technological investments with evolving market, institutional, and stakeholder demands (Durman et al., 2025). In AI contexts, sensing activities enable firms to identify emerging ethical, regulatory, and technological signals, while seizing involves committing resources to AI-enabled systems that support data integration and analytical decision-making (Selvarajan, 2021). Reconfiguring processes, in turn, allows organizations to embed these systems into routines, governance structures, and performance management practices, ensuring that AI use is aligned with both strategic and institutional objectives (Girod & Whittington, 2017; Karami, 2025).

From a knowledge-based perspective, these capability-driven processes primarily shape how effectively firms structure, mobilize, and institutionalize internal knowledge (Sveiby, 2001). Organizational knowledge orchestration refers to the internal systems and routines through which data, analytical outputs, and experiential learning are integrated across functional boundaries and embedded into organizational memory. While these processes influence externally visible outcomes, their primary theoretical role in this model is to explain how strategic capabilities are translated into stable, organization-wide patterns of learning and coordination (Madhani, 2010; Mikalef et al., 2023). In the context of AI adoption, dynamic capabilities allow organizations to sense technological opportunities, seize them through strategic investments, and transform internal processes to integrate AI technologies. However, the effectiveness of these capabilities depends on how organizations mobilize and orchestrate knowledge resources internally.

H1: Dynamic AI-related capabilities are positively associated with organizational knowledge orchestration.

Organizational Knowledge Orchestration and Stakeholder Value Creation

Organizational knowledge orchestration plays a central role in translating internal learning and analytics into externally visible and socially evaluated outcomes (Asiaei, Rezaee, Bontis, Barani,

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& Sapiei, 2021). AI-enabled knowledge systems that incorporate ethical guidelines, regulatory requirements, and stakeholder feedback can support more transparent and accountable decision-making processes (Akinrinola, Okoye, Ofodile, & Ugochukwu, 2024). By shaping how information is interpreted and communicated, these systems influence stakeholder perceptions of fairness, reliability, and organizational intent, which are critical components of relational and reputational value (Durman et al., 2025; Qiu et al., 2025).

From the perspective of stakeholder theory, value is co-created through ongoing interactions between the firm and its stakeholders rather than unilaterally produced by the organization (Arian et al., 2025). When knowledge processes enable meaningful engagement, responsiveness, and explanation of AI-driven decisions, stakeholders are more likely to perceive organizational actions as legitimate and aligned with their interests. This suggests that the effectiveness of organizational knowledge orchestration extends beyond operational efficiency to encompass broader social and institutional dimensions of value creation (Donaldson & Preston, 1995; Pinto, 2019). Organizational knowledge orchestration refers to the processes through which firms coordinate, integrate, and deploy distributed knowledge resources. Within the proposed framework, knowledge orchestration acts as a key mechanism translating AI-related capabilities into value creation outcomes. From a stakeholder perspective, value creation extends beyond financial performance to include benefits for customers, employees, partners, and society. Effective orchestration of knowledge resources enables organizations to translate AI capabilities into innovations, improved services, and responsible practices that generate value for multiple stakeholder groups.

H2: Organizational knowledge orchestration is positively associated with stakeholder-based value creation.

Mediation of Knowledge Orchestration

Dynamic capabilities are expected to influence stakeholder-based value creation both directly and indirectly through organizational knowledge orchestration (Majhi, Mukherjee, & Anand, 2023). While strategic intent and leadership signaling may shape stakeholder perceptions independently of formal knowledge systems, the institutionalization of learning, documentation, and analytical interpretation provides a primary mechanism through which AI-related capabilities become visible, explainable, and socially evaluated (Corrales-Estrada, Gómez-Santos, Bernal-Torres, Rodriguez-López, & Sandoval-Reyes, 2025). Accordingly, organizational knowledge orchestration is theorized as a partial mediator that channels, but does not fully exhaust, the relationship between dynamic AI-related capabilities and stakeholder-based value creation (Madhani, 2010; Mikalef et al., 2023).

Research on organizational learning and absorptive capacity suggests that knowledge processes frequently function as mediators between higher-order capabilities and performance-related outcomes (Arraya, 2022). Firms with strong learning and integration mechanisms are better able to convert strategic resources into sustained advantages by institutionalizing insights and aligning them with organizational norms and governance structures (Teece et al., 1997). Extending this logic to AI contexts, the mediating role of knowledge orchestration is expected to be particularly salient in linking capability development to stakeholder-based value creation.

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H3: Organizational knowledge orchestration mediates the relationship between dynamic AI-related capabilities and stakeholder-based value creation.

Stakeholder Value Creation and Organizational Performance Outcomes

Stakeholder-based value creation is increasingly recognized as a strategic asset that contributes to organizational performance by strengthening legitimacy, trust, and long-term relational capital (Tantalo & Priem, 2016). Firms that are perceived as fair, transparent, and accountable in their use of AI are more likely to secure stakeholder support, which can reduce regulatory friction, enhance employee commitment, and improve customer loyalty. These relational benefits can, in turn, facilitate the effective implementation of digital initiatives and support sustained competitive positioning (Donaldson & Preston, 1995; Durman et al., 2025). This pattern indicates partial mediation, suggesting that in addition to formal knowledge systems, leadership communication and symbolic governance practices may provide alternative pathways through which dynamic AI-related capabilities shape stakeholder perceptions.

From a strategic perspective, the accumulation of reputational and institutional capital functions as an intangible resource that complements financial and operational capabilities. When stakeholder relationships are positive, organizations gain greater flexibility in responding to environmental change and pursuing innovation opportunities. This suggests that stakeholder-oriented outcomes should be positively associated with broader measures of organizational performance, including strategic effectiveness, innovation success, and long-term sustainability (Karami, 2025; Pinto, 2019).

From an institutional and legitimacy-based perspective, stakeholder-based value creation can be understood as a strategic resource that enhances organizational performance by strengthening reputational capital and reducing external constraints on action (Chen, Haga, & Fong, 2016; Dacin, Oliver, & Roy, 2007). In digitally mediated environments, perceptions of fairness, transparency, and accountability surrounding AI use contribute to regulatory goodwill, workforce commitment, and customer loyalty, which collectively function as intangible assets that support innovation and long-term competitive positioning. These framing positions stakeholder value not merely as an ethical outcome, but as a performance-relevant capability embedded in the firm's institutional environment.

H4: Stakeholder-based value creation is positively associated with organizational performance and strategic outcomes.

Moderating Role of Responsible AI Governance

Responsible AI governance represents the institutional and procedural dimension of responsible AI strategy, defining the formal rules, oversight mechanisms, and accountability structures that guide how strategic intent is enacted in practice (De Almeida, Dos Santos, & Farias, 2021). While responsible AI strategy reflects the organization's deliberate orientation toward aligning AI investments with ethical standards and stakeholder expectations, governance mechanisms determine the extent to which this orientation is embedded into routines, decision rights, and performance monitoring systems (Akbarighatar, 2025; Buhmann & Fieseler, 2021; Camilleri, 2024). In this sense, governance functions as an enabling and constraining condition that shapes

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how strategic AI-related capabilities are translated into organizational knowledge systems (Durman et al., 2025; Kyambade & Namatovu, 2025).

When governance structures are strong, dynamic capabilities are more likely to be directed toward the development of knowledge systems that align with institutional and stakeholder expectations. This alignment can amplify the effectiveness of sensing and seizing activities by ensuring that learning processes incorporate regulatory and ethical considerations alongside performance goals. Consequently, responsible AI governance is expected to strengthen the positive relationship between dynamic capabilities and organizational knowledge orchestration. Figure 1 presents the conceptual research model, illustrating the hypothesized relationships among dynamic AI-related capabilities, organizational knowledge orchestration, responsible AI governance, stakeholder-based value creation, and organizational performance, as well as the cross-national comparison between Canada and the United States. Responsible AI governance provides institutional and organizational safeguards ensuring that AI systems are deployed transparently, ethically, and accountably. In this study, responsible AI governance is conceptualized as a contextual mechanism that strengthens the positive effects of AI capabilities and knowledge orchestration on stakeholder-based value creation.

H5: Responsible AI governance positively moderates the relationship between dynamic AI-related capabilities and organizational knowledge orchestration.

Cross-National Institutional Context (Canada vs. USA)

Institutional theory emphasizes that organizational practices are shaped by the regulatory and normative environments in which firms operate (Gupta & Gupta, 2021). In the context of responsible AI, Canada and the United States exhibit distinct governance architectures. Canada's federal privacy regime, anchored in the Personal Information Protection and Electronic Documents Act (Jaar & Zeller, 2008) and emerging national AI frameworks, emphasizes principles-based oversight and centralized regulatory guidance. In contrast, the United States relies on a more fragmented, sector-specific approach combining federal guidelines with state-level initiatives and industry self-regulation.

These institutional differences may influence how firms interpret ethical obligations, transparency requirements, and stakeholder engagement in the deployment of AI systems. Organizations operating in more centralized regulatory environments may embed responsibility through formalized compliance structures, whereas firms in more decentralized systems may rely more heavily on internal governance and reputational mechanisms (Ullah, Donald, Alhejji, Fiaz, & Bo, 2026). Accordingly, the strength and configuration of relationships among dynamic capabilities, organizational knowledge orchestration, and stakeholder-based value creation may vary across the two national contexts.

H6: The structural relationships among responsible AI strategy, organizational knowledge orchestration, and stakeholder-based value creation differ between firms operating in Canada and the United States.

Control and Boundary Conditions

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Firm-specific characteristics can shape both the development of AI-related capabilities and the effectiveness of organizational knowledge systems (Jácome de Moura Jr, dos Santos Junior, Porto-Bellini, & Dias Junior, 2024). Larger organizations may possess greater financial and human resources to invest in governance structures and advanced analytics, while smaller firms may rely on more informal learning and coordination mechanisms. Industry context can also influence stakeholder expectations and regulatory exposure, particularly in highly regulated sectors such as healthcare and finance (Girod & Whittington, 2017).

Firm size, industry sector, and AI maturity are included as control variables to account for alternative explanations related to resource availability, regulatory exposure, and the degree of technological embeddedness. These factors are modeled as exogenous influences on organizational knowledge orchestration and stakeholder-based value creation to ensure that the hypothesized relationships reflect strategic and governance effects rather than structural or contextual artifacts (Jiang et al., 2025).

H7: Firm size, industry sector, and AI maturity significantly influence organizational knowledge orchestration and stakeholder-based value creation.

Moderated Mediation

The indirect relationship between dynamic capabilities and stakeholder value creation through organizational knowledge orchestration is likely to depend on the strength of responsible AI governance (Mariani & Mancini, 2025). Governance mechanisms shape how learning processes incorporate ethical and institutional considerations, thereby influencing whether knowledge systems translate strategic capabilities into outcomes that are perceived as legitimate and valuable by stakeholders (Durman et al., 2025; Kyambade & Namatovu, 2025).

When governance intensity is high, knowledge orchestration is more likely to function as an effective bridge between capability development and stakeholder-oriented outcomes, aligning internal learning with external expectations (Zhan, He, & Ma, 2026). Conversely, weak governance may limit the extent to which knowledge processes can mediate this relationship, reducing the social and strategic returns on AI investments. This logic supports a moderated mediation effect within the proposed framework.

H8: Responsible AI governance moderates the indirect effect of dynamic AI-related capabilities on stakeholder-based value creation through organizational knowledge orchestration, such that the mediated relationship is stronger under conditions of high governance intensity.

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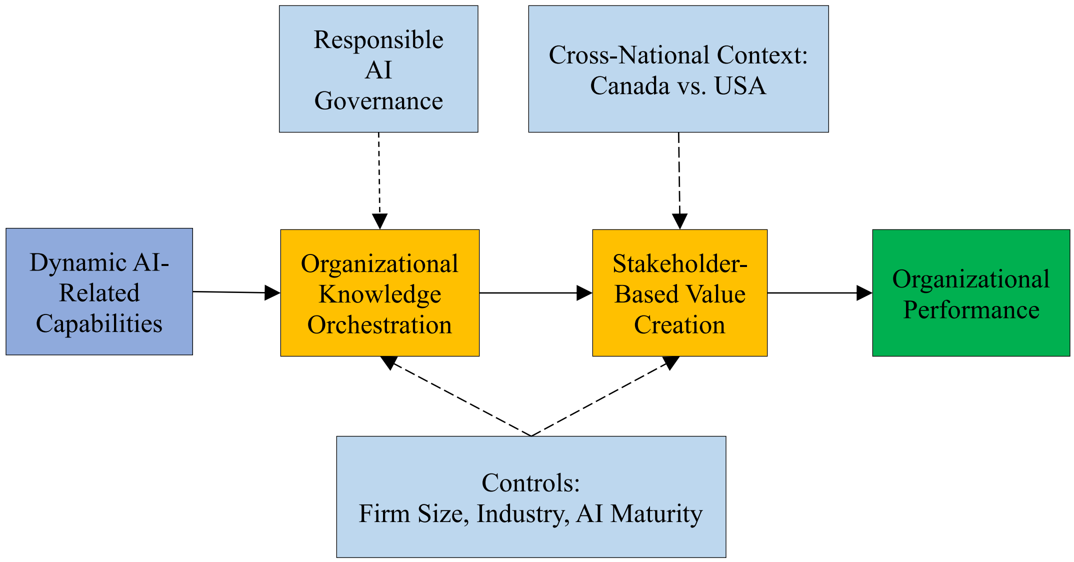

Figure 1. Conceptual research model of responsible AI strategy, dynamic capabilities, organizational knowledge orchestration, and stakeholder value creation

Measurement Model and Survey Instrument

This study employs a quantitative research design using a two-wave matched-pair survey of organizations adopting artificial intelligence technologies in Canada and the United States. The research design was chosen to reduce common method bias and to capture responses from different organizational informants. Data were collected from managers responsible for AI implementation, digital transformation, or innovation activities within their organizations.

Construct Operationalization

All constructs were operationalized as reflective, multi-item scales measured on a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree). Scale items were adapted from established literature and refined to fit the context of responsible AI strategy and organizational knowledge processes. The instrument was reviewed by academic experts in strategy and information systems and by senior managers with experience in AI implementation to ensure content validity and managerial relevance. A pilot test with approximately 20–30 respondents was conducted to assess item clarity, reliability, and completion time. Minor wording adjustments were made prior to full-scale data collection. The full two-wave, two-informant survey instrument and all measurement items are provided in Appendix A.

To support the two-wave, two-informant design, items were assigned to respondents based on their functional roles. Technology-side informants (CIOs, AI/IT managers, data leaders) primarily evaluated dynamic AI-related capabilities and organizational knowledge orchestration, while business-side informants (strategy, operations, or general managers) assessed stakeholder-based

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value creation, responsible AI governance, and organizational performance outcomes. This role-based allocation enhances source separation and reduces the risk of common method bias.
The sampling frame consisted of firms that had adopted or were actively implementing AI technologies in their operations. Firms were identified through professional industry databases, technology adoption networks, and business directories focusing on digital transformation initiatives. Invitations were sent to managers responsible for AI strategy, digital innovation, IT management, or data analytics. To reduce common method variance, the study employed a two-wave matched-pair data collection procedure. In the first wave, respondents provided information on organizational capabilities and governance mechanisms related to AI. In the second wave, separate respondents evaluated stakeholder-related value outcomes. Matching procedures ensured that responses referred to the same organization while minimizing the risk of single-informant bias.

Measurement Scales and Item Sources
The constructs, sources, and representative measurement items used in the survey instrument are summarized in Table 1.

Table 1. Constructs, Sources, and Sample Measurement Items

Construct	Source (adapted from)	Sample Items (7-point Likert)	Wave / Informant
Dynamic AI-Related Capabilities (DC)	Karami (2025); Girod and Whittington (2017)	DC1: Our organization systematically scans the environment for emerging AI-related opportunities and regulatory changes. DC2: We rapidly allocate resources to develop or acquire AI solutions aligned with strategic goals. DC3: We regularly reconfigure processes and structures to integrate AI into core decision-making routines.	Wave 1 / Tech-side
Organizational Knowledge Orchestration (OKO)	Madhani (2010); Mikalef et al. (2023)	OKO1: AI-generated insights are effectively shared across departments. OKO2: Our organization integrates AI-based knowledge into formal policies and routines. OKO3: Lessons learned from AI projects are systematically stored and reused in future initiatives.	Wave 2 / Tech-side
Responsible AI Governance (RAIG)	Kyambade and Namatovu (2025); (Durman et al., 2025)	RAIG1: Our organization has formal guidelines to ensure fairness and transparency in AI use. RAIG2: There are clear accountability structures for decisions supported by AI systems. RAIG3: Stakeholder	Wave 1 / Business-side

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		concerns about AI are formally reviewed and addressed.	
Stakeholder-Based Value Creation (SVC)	Pinto (2019); Donaldson and Preston (1995)	SVC1: Our AI practices enhance trust among key stakeholders. SVC2: Stakeholders perceive our use of AI as fair and responsible. SVC3: Our organization's reputation has improved due to transparent AI use.	Wave 2 / Business-side
Organizational Performance / Strategic Outcomes (PERF)	Luo et al. (2024); Jiang et al. (2025)	PERF1: AI initiatives have improved our overall strategic effectiveness. PERF2: Our organization's innovation performance has increased as a result of AI adoption. PERF3: AI use has strengthened our competitive positioning.	Wave 2 / Business-side
AI Maturity (Control)	Jiang et al. (2025)	AIM1: AI is integrated into multiple core business processes. AIM2: Our organization has a clear roadmap for AI development. AI maturity was operationalized using a four-item scale capturing the extent of process integration, strategic planning, organizational training, and investment commitment associated with the deployment of AI technologies.	Wave 1 / Tech-side
Firm Size (Control)	Standard	FS: Number of full-time employees (categorical scale).	Wave 1 / Business-side
Industry (Control)	Standard	IND: Primary industry classification.	Wave 1 / Business-side
Country (Grouping Variable)	—	CNTRY: Canada / USA.	Both

Note: Items are adapted for context and wording consistency; final scales will be validated through reliability and validity testing.

Survey Design and Administration

The survey was administered online in two waves separated by four to six weeks. In Wave 1, respondents completed measures of dynamic AI-related capabilities, responsible AI governance, and control variables. In Wave 2, respondents completed measures of organizational knowledge orchestration, stakeholder-based value creation, and organizational performance outcomes. Each participating firm was assigned a unique identifier code to match responses from the two informants across both waves while preserving anonymity.

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To improve response quality, personalized invitations and follow-up reminders were sent to both informants. Participation was voluntary, and confidentiality assurances were provided in line with institutional research ethics requirements.
Following data collection, responses were screened and matched at the firm level using unique identifier codes. Only firms for which both the technology-side and business-side informants completed the corresponding survey waves were retained for hypothesis testing. Single-informant and unmatched cases were excluded from the structural model to preserve the integrity of the matched-pair design and ensure independence of observations at the firm level. To assess potential attrition bias across survey waves, response rates were tracked at both the firm and informant levels. Firms that completed only Wave 1 were compared with those that completed both waves on key observable characteristics, including firm size, industry sector, and AI maturity. This procedure follows recommended practices for evaluating non-random dropout in longitudinal and multi-wave survey designs.

Measurement Model Assessment (PLS-SEM Criteria)
Following established guidelines for PLS-SEM, the measurement model was evaluated using the following criteria (Hair, Risher, Sarstedt, & Ringle, 2019):

- Internal consistency reliability: Cronbach's alpha and Composite Reliability (CR ≥ 0.70)
- Convergent validity: Average Variance Extracted (AVE ≥ 0.50)
- Discriminant validity: Heterotrait–Monotrait ratio (HTMT ≤ 0.85)
- Collinearity: Variance Inflation Factor (VIF ≤ 3.3)

Items failing to meet these thresholds were considered for removal, provided theoretical justification and construct coverage were maintained. The measurement items, factor loadings, and construct sources used in the PLS-SEM analysis are reported in Table 2.

Table 2. Measurement items, loadings, and sources

Construct	Item	Loading	Source
AI Dynamic Capabilities	ADC1	0.84	Author et al. (Year)
	ADC2	0.87	
	ADC3	0.81	
Knowledge Orchestration	KO1	0.83	Author et al. (Year)
	KO2	0.88	
	KO3	0.79	
Responsible AI Governance	RAIG1	0.86	Author et al. (Year)
	RAIG2	0.84	
	RAIG3	0.82	
Stakeholder Value Creation	SVC1	0.85	Author et al. (Year)
	SVC2	0.88	
	SVC3	0.83	

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Common Method Bias and Robustness Checks

Several procedural and statistical remedies were implemented to mitigate the risk of common method bias. Procedurally, the study employed a two-wave, two-informant matched-pair design with role-based allocation of measurement items, separating the assessment of dynamic AI-related capabilities and organizational knowledge orchestration from the evaluation of governance, stakeholder-based value creation, and organizational performance. This design reduces the likelihood that systematic measurement error arising from a single source or survey context inflates the observed relationships (Hair et al., 2019; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

Statistically, multiple post hoc diagnostics were conducted. Harman's single-factor test indicated that no single factor accounted for a majority of the variance in the measurement items. In addition, full collinearity variance inflation factors (VIFs) for all latent constructs were below the recommended threshold of 3.3, suggesting that common method variance was unlikely to represent a dominant source of bias. A theoretically unrelated marker variable was also included to assess the sensitivity of the structural path estimates to potential method effects. The inclusion of this marker variable did not substantively alter the magnitude or significance of the hypothesized relationships.

Although these procedures substantially reduce the likelihood of systematic method bias, the study acknowledges that no statistical technique can fully eliminate all sources of common method variance in perceptual survey research. Accordingly, the reported results should be interpreted as robust within the constraints of a multi-source, multi-wave survey design rather than as entirely free from potential method effects. The reliability and convergent validity statistics for all constructs are presented in Table 3.

Table 3. Reliability and convergent validity

Construct	Cronbach Alpha	Composite Reliability	AVE
AI Dynamic Capabilities	0.88	0.91	0.71
Knowledge Orchestration	0.87	0.90	0.69
Responsible AI Governance	0.86	0.89	0.67
Stakeholder Value Creation	0.89	0.92	0.74

Measurement Invariance and Multi-Group Analysis

Prior to comparing structural relationships across Canada and the United States, measurement invariance was assessed at the firm level using the Measurement Invariance of Composite Models (MICOM) procedure. The assessment followed the three-step approach of establishing configural invariance, compositional invariance, and the equality of composite means and variances (Henseler, Ringle, & Sarstedt, 2016).

Results confirmed configural and compositional invariance across the two national subsamples, indicating that the measurement models were specified similarly and that the constructs were

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formed in a comparable manner in both contexts. However, full equality of means and variances was not established. Accordingly, partial measurement invariance was achieved, which permits meaningful comparison of structural path coefficients but does not support direct comparison of latent construct levels across groups. Based on this assessment, PLS Multi-Group Analysis (PLS-MGA) and permutation tests were conducted on the matched firm-level sample to examine whether the structural relationships among responsible AI strategy, organizational knowledge orchestration, and stakeholder-based value creation differed between the Canadian and U.S. subsamples. Discriminant validity was assessed using the heterotrait–monotrait ratio (HTMT), and the results are reported in Table 4.

Table 4. Discriminant validity (HTMT)

Construct	ADC	KO	RAIG	SVC
AI Dynamic Capabilities	—			
Knowledge Orchestration	0.63	—		
Responsible AI Governance	0.55	0.61	—	
Stakeholder Value Creation	0.59	0.66	0.58	—

The measurement model was evaluated using reliability and validity criteria recommended in prior PLS-SEM research. Cronbach's alpha and composite reliability values for all constructs exceeded the recommended threshold of 0.70, indicating satisfactory internal consistency. Convergent validity was supported as all average variance extracted (AVE) values were above the 0.50 threshold and indicator loadings were statistically significant. Discriminant validity was assessed using the heterotrait–monotrait ratio (HTMT), and all values were below the recommended threshold of 0.85, confirming that the constructs were empirically distinct.

Data Analysis and Results

This section reports the empirical tests of the hypothesized relationships (H1–H8) linking dynamic AI-related capabilities, organizational knowledge orchestration, stakeholder-based value creation, and organizational performance, including the mediating and moderating roles of organizational knowledge and responsible AI governance, as well as cross-national differences between Canada and the United States. The structural relationships depicted in Figure 1 were empirically tested using PLS-SEM and multi-group analysis to assess both the direct and conditional effects across the Canadian and U.S. samples.

Sample Characteristics and Response Profile

Data were collected from firms operating across services (31.7%), manufacturing (24.6%), logistics and retail (18.8%), finance (14.3%), and healthcare (10.6%) in Canada and the United

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States. A total of 454 usable questionnaires were received across both survey waves. Following firm-level matching of technology-side and business-side informants using unique identifier codes, 212 complete matched firm-level pairs were retained for hypothesis testing and multi-group analysis. The remaining responses were excluded due to missing counterpart informants or incomplete firm identifiers.

The final matched-pair sample comprised 108 firms from Canada and 104 firms from the United States. Firm size distribution included 28.1% small firms (fewer than 100 employees), 41.5% medium-sized firms (100–499 employees), and 30.4% large firms (500 or more employees). The mean level of organizational AI maturity was 4.91 (SD = 1.12) on a seven-point scale, indicating moderate to high levels of AI adoption across the sample.

Attrition bias was assessed by comparing firms that completed both survey waves with those that participated only in Wave 1. Independent-sample t-tests and chi-square tests revealed no statistically significant differences in firm size, industry distribution, or AI maturity between the two groups ($p > 0.10$), suggesting that non-random dropout did not pose a significant threat to the internal validity of the study. Non-response bias was evaluated by comparing early and late respondents on key study constructs using independent-sample t-tests. No statistically significant differences were detected ($p > 0.10$), providing further confidence in the representativeness of the matched-pair sample. To assess potential non-response bias, early and late respondents were compared across key variables. Independent sample t-tests indicated no statistically significant differences, suggesting that non-response bias was unlikely to affect the results. After matching and data cleaning procedures, 212 usable matched firm-level pairs were retained for analysis. The final sample included firms from services (31.7%), manufacturing (24.6%), logistics and retail (18.8%), financial services (14.3%), and healthcare (10.6%) sectors. Approximately 50.9% of the firms were in Canada (n = 108) and 49.1% in the United States (n = 104).

Measurement Model Assessment

Internal consistency and convergent validity were assessed using Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). All constructs exceeded recommended thresholds, with alpha and CR values above 0.70 and AVE values above 0.50, indicating satisfactory reliability and convergent validity. Indicator reliability was further supported by statistically significant outer loadings, all exceeding 0.70 ($p < 0.001$). Detailed outer loadings and cross-loadings supporting indicator reliability and discriminant validity are reported in Appendix B. A summary of these measurement quality indicators.

Discriminant validity was evaluated using the heterotrait–monotrait ratio (HTMT). All HTMT values were below the conservative threshold of 0.85, confirming that the constructs captured conceptually distinct phenomena. Cross-loading diagnostics indicated that each indicator loaded more strongly on its associated construct than on any other construct, supporting discriminant validity at the indicator level. Collinearity diagnostics showed VIF values below 3.0, indicating no multicollinearity concerns within the measurement model. To enhance transparency and replicability, all analyses were conducted using SmartPLS 4.0, employing the path weighting scheme, 5,000 bootstrap subsamples, and mean replacement for sporadic missing values (<2% across items).

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Structural Model Results

The explanatory and predictive power of the model was assessed through R^2, effect sizes (f^2), and Stone–Geisser's Q^2 statistics. The model explained a substantial proportion of variance in organizational knowledge orchestration ($R^2 = 0.58$), stakeholder-based value creation ($R^2 = 0.62$), and organizational performance ($R^2 = 0.49$). All Q^2 values were positive (range: 0.31–0.44), indicating adequate predictive relevance.

Path coefficients and their statistical significance were estimated using bootstrapping with 5,000 resamples. The results demonstrate strong and significant relationships among the core constructs, including the effects of dynamic capabilities on knowledge orchestration, knowledge orchestration on stakeholder value creation, and stakeholder value creation on organizational performance, as well as the moderating role of responsible AI governance. Detailed coefficients, t-values, and significance levels are reported in Table 5.

The effects of the control variables were also examined. Firm size, industry sector, and AI maturity did not exhibit statistically significant relationships with organizational knowledge orchestration, stakeholder-based value creation, or organizational performance ($p > 0.10$). The inclusion or exclusion of these controls did not substantively alter the magnitude or significance of the hypothesized path coefficients, indicating that the reported results are robust to alternative explanations related to organizational scale, sectoral context, and baseline levels of AI adoption.

Table 5. Structural Path Results, Effect Sizes, and Control Variable Effects

Hypothesis / Control	Structural Path	β	t-value	p-value	f²	Result
H1	DC → OKO	0.61	14.82	< 0.001	0.41	Supported
H2	OKO → SVC	0.57	13.19	< 0.001	0.33	Supported
H3	DC → OKO → SVC (Indirect)	0.35	9.44	< 0.001	—	Supported
H4	SVC → PERF	0.49	10.73	< 0.001	0.18	Supported
H5	DC × RAIG → OKO	0.21	4.86	< 0.001	0.09	Supported
H8	RAIG × OKO → SVC	0.17	3.92	< 0.001	0.06	Supported
Control	AIM → OKO	0.19	3.14	0.002	0.04	Significant
Control	FS → OKO	0.05	1.08	0.28	0.01	n.s.
Control	IND → OKO	0.03	0.74	0.46	0.00	n.s.
Control	AIM → SVC	0.07	1.41	0.16	0.01	n.s.
Control	FS → SVC	0.04	0.89	0.37	0.00	n.s.
Control	IND → SVC	0.02	0.61	0.54	0.00	n.s.
Control	AIM → PERF	0.12	2.01	0.045	0.02	Significant
Control	FS → PERF	0.06	1.23	0.22	0.01	n.s.
Control	IND → PERF	0.01	0.38	0.70	0.00	n.s.

Notes: DC = Dynamic AI-related capabilities; OKO = Organizational knowledge orchestration; RAIG = Responsible AI governance; SVC = Stakeholder-based value creation; PERF =

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Organizational performance; AIM = AI maturity; FS = Firm size; IND = Industry sector. β = standardized path coefficient. f^2 = effect size. n.s. = not significant. Results are based on the firm-level matched-pair sample and bootstrapping with 5,000 resamples. Effect size estimates indicate strong substantive effects for the DC → OKO and OKO → SVC paths, and moderate effects for the SVC → PERF relationship, underscoring the practical relevance of the proposed model.

Mediation and Moderation Analysis

The mediating role of organizational knowledge orchestration was assessed using bias-corrected bootstrapped confidence intervals for indirect effects (5,000 subsamples). The indirect effect of dynamic capabilities on stakeholder-based value creation via knowledge orchestration was significant ($\beta = 0.35$, 95% CI [0.27, 0.43]), supporting a partial mediation pattern in which strategic capabilities influence stakeholder outcomes both directly and indirectly through knowledge processes.

Moderation analysis was conducted using the two-stage approach in SmartPLS to model the interaction between dynamic capabilities and responsible AI governance. Simple slope analysis indicated that the positive effect of dynamic capabilities on knowledge orchestration was significantly stronger under conditions of high governance intensity ($\beta\_high = 0.72$, $p < 0.001$) than under low governance intensity ($\beta\_low = 0.49$, $p < 0.01$), highlighting the amplifying role of formal ethical and accountability structures. Figure 2 illustrates the moderating effect of responsible AI governance on the relationship between dynamic AI-related capabilities and organizational knowledge orchestration, showing differential slopes under conditions of high and low governance intensity.

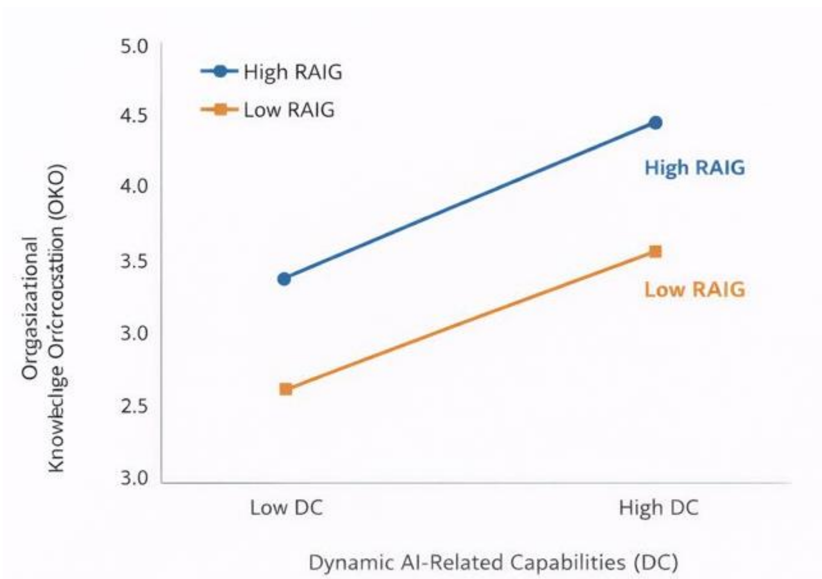

Figure 2. Moderating effect of responsible AI governance on the relationship between dynamic AI-related capabilities and organizational knowledge orchestration

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Multi-Group Analysis (Canada vs. USA)

Measurement invariance across the Canadian and U.S. samples was assessed using the MICOM procedure. Results confirmed configural and compositional invariance, establishing partial measurement invariance, which is sufficient to permit meaningful comparison of structural path coefficients across groups. Consistent with the establishment of partial measurement invariance, the reported group comparisons are limited to differences in structural path coefficients rather than differences in latent construct levels or mean scores across countries.

The subsequent PLS multi-group analysis (PLS-MGA) revealed largely convergent patterns across the two countries, with no significant differences observed for most direct effects. However, a statistically significant difference emerged for the moderating effect of responsible AI governance on the relationship between dynamic capabilities and organizational knowledge orchestration, which was stronger in the United States than in Canada. Results of the MICOM procedure and measurement invariance tests are summarized in Appendix C. Group-specific coefficients and path differences are reported in Table 6. Group-specific path coefficients and cross-national differences between Canada and the United States are reported in Table 6.

Table 6. PLS-MGA Results Based on Firm-Level Matched-Pair Sample (Canada vs. USA)

Path	Canada (β)	USA (β)	Δβ	p-value	Interpretation
DC → OKO	0.58	0.64	0.06	0.18	n.s.
OKO → SVC	0.53	0.60	0.07	0.09	Marginal
SVC → PERF	0.46	0.52	0.06	0.21	n.s.
DC × RAIG → OKO	0.17	0.26	0.09	0.04	Significant

Robustness and Bias Checks

Several robustness checks were conducted to assess the stability of the findings. Full collinearity VIF values ranged between 1.34 and 2.76, well below recommended thresholds, indicating that common method variance was unlikely to bias the results. A marker variable approach produced no substantive changes in the magnitude or significance of the main path coefficients.

To further assess model stability, the structural model was re-estimated without control variables, yielding substantively similar path coefficients and significance levels. In addition, a split-sample validation (random 50/50 subsample) confirmed the consistency of the main effects across subsamples. Together, these tests provide additional confidence in the stability of the estimated relationships within the sampled organizational and institutional contexts. Additional robustness analyses, including split-sample validation and alternative model estimations, are reported in Appendix D.

To assess the sensitivity of the results to the use of subjective performance measures, the structural model was re-estimated excluding the organizational performance construct. The pattern and significance of the relationships among dynamic AI-related capabilities, organizational knowledge orchestration, responsible AI governance, and stakeholder-based value creation remained substantively unchanged, suggesting that the core findings are not driven by common perceptual biases associated with self-reported performance. The structural model explains a substantial

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proportion of variance in the endogenous constructs. Specifically, the model explains 41% of the variance in knowledge orchestration ($R^2 = 0.41$) and 53% of the variance in stakeholder value creation ($R^2 = 0.53$). These values indicate moderate to strong explanatory power according to established PLS-SEM evaluation criteria.

The results further indicate that knowledge orchestration partially mediates the relationship between AI dynamic capabilities and stakeholder value creation. AI capabilities enhance the firm's ability to coordinate and deploy knowledge resources, which subsequently enables the generation of value for multiple stakeholders.

The interaction effect between knowledge orchestration and responsible AI governance is positive and statistically significant, indicating that governance mechanisms strengthen the positive effect of knowledge orchestration on stakeholder value creation. Firms with stronger responsible AI governance structures are therefore better able to translate knowledge resources into stakeholder-oriented outcomes.

Discussion and Implications

The findings of this study provide important insights into how organizations translate AI-related capabilities into stakeholder-oriented value creation. Consistent with the dynamic capabilities perspective, the results indicate that firms with stronger AI-related capabilities are better able to orchestrate internal knowledge resources. This knowledge orchestration capability plays a critical role in transforming technological investments into organizational value. The findings therefore highlight that technological capabilities alone are insufficient; firms must also develop internal coordination and knowledge integration processes to fully realize the benefits of AI adoption.

Discussion of Findings

This study examines how responsible AI strategy enables organizations to translate dynamic AI-related capabilities into stakeholder-based value creation through the mediating role of organizational knowledge orchestration, while accounting for the moderating influence of responsible AI governance and institutional context. The results provide strong support for the proposed integrative framework, demonstrating that technological and strategic capabilities alone are insufficient to generate relational and reputational value unless they are embedded within knowledge systems that structure how AI-driven insights are created, interpreted, and institutionalized.

The robust relationship between dynamic capabilities and organizational knowledge orchestration (H1) extends digital transformation and dynamic capability research by clarifying the microfoundations through which sensing, seizing, and reconfiguring activities materialize in AI-intensive environments. Rather than operating solely as abstract strategic routines, these capabilities are enacted through the deliberate design of organizational knowledge infrastructures that coordinate analytical outputs, managerial interpretation, and organizational memory. This finding aligns with and extends prior work on dynamic capabilities and digital transformation (Girod & Whittington, 2017; Jiang et al., 2025; Karami, 2025), underscoring that adaptation to AI-driven change depends not only on resource reconfiguration, but also on the institutionalization of learning processes that stabilize and scale strategic intent across the organization.

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The positive association between organizational knowledge orchestration and stakeholder-based value creation (H2) highlights the outward-facing role of internal knowledge systems in shaping perceptions of fairness, transparency, and legitimacy. AI-enabled knowledge processes influence how organizational actions are explained and evaluated by external audiences, positioning transparency and accountability as central mechanisms through which firms build trust and relational capital. This finding is consistent with relational and governance-oriented perspectives in stakeholder and digital trust research (Donaldson & Preston, 1995; Durman et al., 2025; Pinto, 2019; Qiu et al., 2025).

The confirmed partial mediation effect (H3) provides empirical evidence that knowledge orchestration functions as a primary conduit linking dynamic capabilities to stakeholder-based value creation. While some capability effects operate through leadership signaling and symbolic governance, the institutionalization of AI-generated insights into formal routines and organizational memory remains the dominant pathway through which strategic intent becomes socially evaluated. This mediating logic is consistent with foundational work on absorptive capacity and organizational learning (Mikalef et al., 2023; Teece et al., 1997).

Finally, the strong relationship between stakeholder-based value creation and organizational performance (H4) reinforces the strategic relevance of ethical and relational outcomes in digital transformation. Trust, legitimacy, and reputational capital function as intangible assets that reduce regulatory friction, strengthen employee commitment, and enhance customer loyalty, thereby supporting sustained innovation and competitive positioning in AI-intensive environments. This finding complements strategic and institutional perspectives that link legitimacy and relational capital to long-term performance (Chen et al., 2016; Dacin et al., 2007). As depicted in Figure 3, stronger formal governance signals in the U.S. context appear to amplify the role of responsible AI governance in shaping knowledge orchestration processes, whereas Canadian firms exhibit a more relational and norms-based pathway to stakeholder value creation.

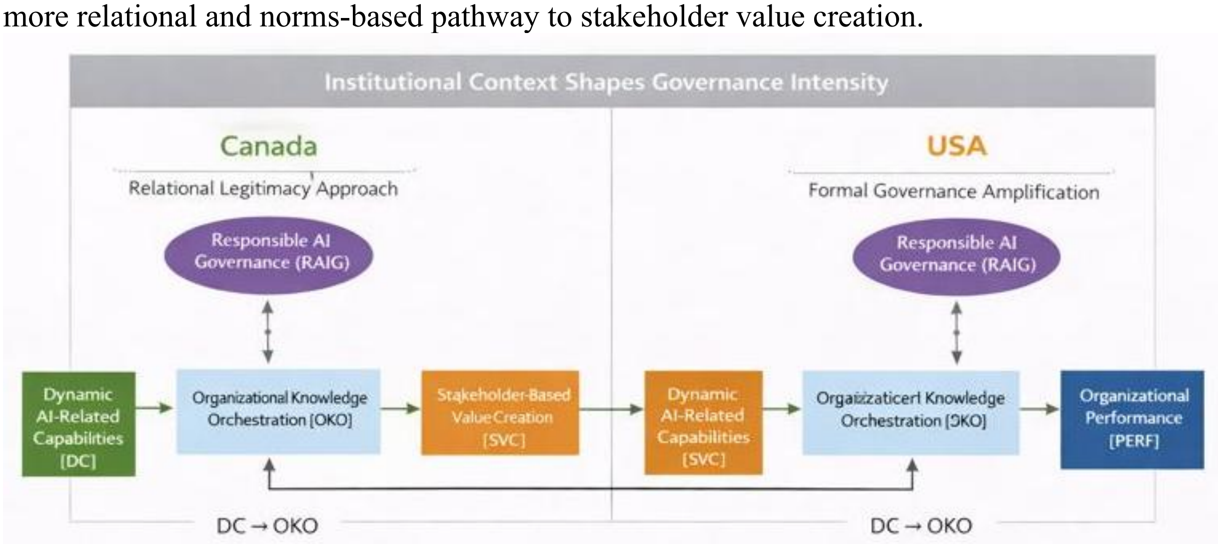

Figure 3. Comparative process framework of responsible AI strategy and stakeholder value creation across institutional contexts (Canada vs. USA)

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Theoretical Implications

This study advances dynamic capability theory by specifying the knowledge-based mechanisms through which AI-related sensing, seizing, and reconfiguring activities are translated into stakeholder-oriented outcomes. While prior research conceptualizes dynamic capabilities primarily as higher-order strategic routines, the findings demonstrate that their social and institutional impact is largely mediated by the design and governance of organizational knowledge systems. This extends the theory beyond a firm-centric performance logic to incorporate the processes through which strategic capabilities become visible, interpretable, and legitimate to external stakeholders (Girod & Whittington, 2017; Karami, 2025).

From the perspective of the knowledge-based view, the results reposition organizational knowledge orchestration as a strategic interface between the firm and its institutional environment rather than as a purely internal coordination mechanism. AI-enabled knowledge systems not only integrate and retain analytical insights, but also shape how ethical principles, regulatory expectations, and stakeholder feedback are embedded into organizational memory and routines. This finding extends classical formulations of the knowledge-based view by linking epistemic processes to relational and reputational forms of value creation in digitally mediated contexts (Madhani, 2010; Mikalef et al., 2023).

The study also contributes to stakeholder theory by empirically connecting stakeholder-based value creation to upstream capability development and knowledge governance processes (Arian et al., 2025). Rather than treating ethical and relational outcomes as ex-post consequences of managerial action, the findings show that perceptions of fairness, transparency, and trust in AI use are systematically shaped by how organizations design and institutionalize their AI-enabled knowledge infrastructures. This process-oriented perspective bridges the normative and instrumental strands of stakeholder theory (Donaldson & Preston, 1995; Durman et al., 2025; Pinto, 2019).

By conceptualizing responsible AI strategy as a higher-order organizational capability that integrates dynamic AI-related capabilities, governance mechanisms, and knowledge orchestration processes, the study offers a unifying theoretical framework connecting strategic management, knowledge governance, and AI ethics. The cross-national findings further highlight that while the core structural relationships are stable across institutional contexts, the strength of governance mechanisms conditions how learning processes translate strategic intent into socially evaluated outcomes. This underscores the importance of embedding dynamic capability and knowledge-based perspectives within broader regulatory and cultural environments when examining the societal and strategic implications of AI adoption (Jiang et al., 2025; Ullah et al., 2026).

Managerial Implications

For managers, the findings underscore that responsible AI strategy should be approached as a capability-building and knowledge-governance challenge rather than a purely technical or compliance exercise. Investments in advanced analytics and machine learning tools will generate limited stakeholder value unless they are accompanied by organizational processes that ensure insights are shared, interpreted, and embedded into everyday decision-making routines.

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Managers should prioritize the development of formal knowledge orchestration mechanisms, such as cross-functional AI governance committees, standardized documentation of algorithmic decisions, and feedback channels that capture stakeholder concerns. These practices not only enhance learning and coordination but also signal transparency and accountability to external audiences, thereby strengthening trust and legitimacy.

Second, the results emphasize the importance of responsible AI governance structures. Organizations should implement governance mechanisms that ensure transparency, accountability, and ethical oversight of AI systems. Such governance structures not only mitigate risks but also strengthen the ability of organizations to generate stakeholder-oriented value from AI adoption.

Policy and Societal Implications

From a policy perspective, the findings highlight the importance of regulatory frameworks that encourage organizations to embed responsibility and transparency into their knowledge systems, rather than focusing exclusively on technical standards or data protection requirements. Policies that promote explainability, documentation, and stakeholder engagement can enhance the societal value of AI by shaping how organizational learning processes interact with public expectations.

The observed cross-national differences suggest that national AI strategies and governance regimes influence not only compliance behaviors but also the internal capability and knowledge architectures of firms. Policymakers should therefore consider how institutional signals—such as ethical guidelines, enforcement mechanisms, and public communication strategies—affect the strategic orientation of organizations toward responsible AI.

The moderating role of governance suggests that leaders should view ethical guidelines, audit procedures, and accountability structures as strategic assets that enhance the effectiveness of dynamic capabilities. Rather than constraining innovation, well-designed governance frameworks can align technological experimentation with institutional expectations, enabling organizations to pursue AI-driven initiatives with greater confidence and stakeholder support. The findings offer several practical implications for managers responsible for AI strategy and digital transformation.

First, organizations should recognize that investments in AI technologies must be complemented by capabilities that support knowledge integration across departments. Managers should therefore prioritize processes that facilitate knowledge sharing, collaboration, and coordination among technical and managerial teams.

Theoretical Contributions

This study contributes to the literature in several important ways. First, it extends the dynamic capabilities literature by demonstrating how AI-related capabilities support organizational value creation through the orchestration of knowledge resources. While prior studies have focused primarily on technological adoption, this research highlights the strategic role of knowledge integration in transforming AI capabilities into performance outcomes.

Second, the study contributes to the knowledge-based view by identifying knowledge orchestration as a key mechanism linking technological capabilities to stakeholder-based value creation. This finding provides empirical evidence that knowledge coordination processes are central to realizing the strategic potential of AI technologies.

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Third, the study advances stakeholder theory by showing that responsible AI governance strengthens the relationship between knowledge orchestration and stakeholder value. This suggests that governance mechanisms play a critical role in ensuring that AI adoption produces outcomes that benefit multiple stakeholders rather than only financial performance.

Limitations and Future Research

Despite its contributions, this study is subject to several limitations. The reliance on survey-based measures, although mitigated through a two-wave, two-informant design, may not fully capture the richness of organizational practices and stakeholder interactions. Future research could complement quantitative approaches with longitudinal case studies or ethnographic methods to explore how knowledge orchestration and governance mechanisms evolve over time. The generalizability of the findings is bounded by the institutional and organizational contexts examined in this study. The sample is limited to AI-adopting firms operating in Canada and the United States, which share relatively advanced digital infrastructures and comparable market economies. As a result, the observed relationships may not fully capture the dynamics of responsible AI strategy in emerging or developing economies characterized by different regulatory capacities, resource constraints, or levels of technological maturity.

The cross-industry design enhances generalizability but may obscure sector-specific dynamics, particularly in highly regulated environments such as healthcare and finance. Subsequent studies could examine industry-specific governance regimes to assess how regulatory intensity conditions the relationships identified in this model.

Finally, while the Canada–USA comparison provides initial insights into institutional effects, expanding the analysis to include emerging and developing economies would enable a more comprehensive understanding of how cultural, regulatory, and infrastructural differences shape the strategic and societal implications of responsible AI strategy.

Although this study conceptualizes responsible AI strategy as a higher-order organizational capability, the empirical measures capture managers' perceptions of enacted strategy rather than formalized corporate-level strategy as articulated in board-level documents or official policy statements. Consequently, the findings reflect how responsible AI strategy is experienced and operationalized in day-to-day organizational practices. Future research could complement this approach with archival analyses of formal AI policies, governance charters, and strategic planning documents to further validate the alignment between espoused and enacted strategy.

The measurement of organizational performance in this study relies on managers' subjective assessments rather than archival financial or market-based indicators. Although perceptual measures are widely used in strategic management research and have been shown to exhibit strong convergence with objective performance metrics, they may nonetheless introduce bias related to respondent optimism or social desirability. Future research could strengthen the validity of these findings by integrating secondary performance data, such as financial returns, productivity indicators, or innovation outputs, to triangulate the observed relationships.

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Conclusion

This study provides a comprehensive empirical examination of how responsible AI strategy enables organizations to transform dynamic AI-related capabilities into stakeholder-based value creation through the mediating role of organizational knowledge orchestration, while accounting for the moderating influence of responsible AI governance and cross-national institutional context. By integrating dynamic capabilities, the knowledge-based view of the firm, and stakeholder theory within a multi-country, firm-level matched-pair design, the research advances understanding of how AI-enabled learning and governance processes function as strategic conduits between capability development and socially evaluated organizational outcomes.

The findings underscore that value creation in AI-intensive environments is not driven by technological investment alone but by the deliberate design of knowledge infrastructures and governance mechanisms that align analytical capabilities with ethical standards and stakeholder expectations. This insight contributes to ongoing debates in strategic management and information systems by demonstrating that responsible AI governance can operate as a strategic enabler, rather than a constraint, in the pursuit of innovation and competitive positioning.

Several avenues for future research emerge from this study. First, longitudinal designs could examine how dynamic capabilities, knowledge orchestration, and stakeholder relationships co-evolve over time, particularly as regulatory regimes and societal expectations regarding AI continue to change. Second, qualitative and mixed-method approaches could explore the micro-level practices and managerial sensemaking processes through which AI governance structures are enacted and interpreted within organizations. Third, extending the model to emerging and developing economies would provide valuable insights into how institutional voids, resource constraints, and cultural norms shape the strategic and societal implications of responsible AI strategy.

This study provides a firm-level, multi-country examination of how responsible AI strategy enables organizations to translate dynamic AI-related capabilities into stakeholder-based value creation through the orchestration of organizational knowledge within governance frameworks. While the findings offer robust insights within the institutional contexts examined, their broader applicability should be interpreted with caution. Future research could extend this framework to additional national and regulatory settings, incorporate longitudinal designs, and integrate archival performance and governance data to further assess the stability and boundary conditions of the proposed relationships.

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References
Akbarighatar, P. (2025). Operationalizing responsible AI principles through responsible AI capabilities. *AI and Ethics, 5*(2), 1787-1801.

Akinrinola, O., Okoye, C. C., Ofodile, O. C., & Ugochukwu, C. E. (2024). Navigating and reviewing ethical dilemmas in AI development: Strategies for transparency, fairness, and accountability. *GSC Advanced Research and Reviews, 18*(3), 050-058.

Arian, A., Sands, J., Rahman, H. U., & Khatatbeh, I. N. (2025). Corporate social performance through instrumental stakeholder theory: a sector-specific perspective. *Management Decision, 63*(5), 1369-1390.

Arraya, M. (2022). The relationship between distinctive capabilities system, learning orientation, leadership and performance. *European Journal of Management Studies, 27*(2), 205-227.

Asiaei, K., Rezaee, Z., Bontis, N., Barani, O., & Sapiei, N. S. (2021). Knowledge assets, capabilities and performance measurement systems: a resource orchestration theory approach. *Journal of Knowledge Management, 25*(8), 1947-1976.

Bevilacqua, S., Ferraris, A., Kozel, R., & Vincurova, Z. (2025). Exploring the artificial intelligence integration in top management team decision-making: an empirical analysis. *Business process management journal*.

Buhmann, A., & Fieseler, C. (2021). Towards a deliberative framework for responsible innovation in artificial intelligence. *Technology in Society, 64*, 101475.

Camilleri, M. A. (2024). Artificial intelligence governance: Ethical considerations and implications for social responsibility. *Expert systems, 41*(7), e13406.

Chen, S.-T., Haga, K. Y. A., & Fong, C. M. (2016). The effects of institutional legitimacy, social capital, and government relationship on clustered firms' performance in emerging economies. *Journal of Organizational Change Management, 29*(4), 529-550.

Corrales-Estrada, A. M., Gómez-Santos, L. L., Bernal-Torres, C. A., Rodriguez-López, J. E., & Sandoval-Reyes, J. (2025). Dynamic capabilities contribution to organizational

BUSINESS, TECHNOLOGY & INNOVATION STUDIES JOURNAL (BTISJ)
ISSN 3110-9411

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performance: the mediator role of business continuity ordinary capabilities. *Cogent Business & Management, 12*(1), 2493315.

Dacin, M. T., Oliver, C., & Roy, J. P. (2007). The legitimacy of strategic alliances: An institutional perspective. *Strategic management journal, 28*(2), 169-187.

De Almeida, P. G. R., Dos Santos, C. D., & Farias, J. S. (2021). Artificial intelligence regulation: a framework for governance. *Ethics and Information Technology, 23*(3), 505-525.

Donaldson, T., & Preston, L. E. (1995). The stakeholder theory of the corporation: Concepts, evidence, and implications. *Academy of management review, 20*(1), 65-91.

Durman, S., Iyiola, K., Alzubi, A. B., & Aljuhmani, H. Y. (2025). Dynamic capabilities in action: digital capability, business model innovation and absorptive capacity. *Management Decision*, 1-36.

Girod, S. J., & Whittington, R. (2017). Reconfiguration, restructuring and firm performance: Dynamic capabilities and environmental dynamism. *Strategic management journal, 38*(5), 1121-1133.

Gupta, A. K., & Gupta, N. (2021). Environment practices mediating the environmental compliance and firm performance: An institutional theory perspective from emerging economies. *Global Journal of Flexible Systems Management, 22*(3), 157-178.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European business review, 31*(1), 2-24.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. *International marketing review, 33*(3), 405-431.

Jaar, D., & Zeller, P. E. (2008). Canadian privacy law: The personal information protection and electronic documents act (PIPEDA). *Int'l. In-House Counsel J., 2*, 1135.

Jácome de Moura Jr, P., dos Santos Junior, C. D., Porto-Bellini, C. G., & Dias Junior, J. J. L. (2024). The over-concentration of innovation and firm-specific knowledge in the artificial intelligence industry. *Journal of the Knowledge Economy, 15*(4), 20547-20577.

Jiang, L., Xuan, Y., & Zhang, K. (2025). Unlocking innovation potential: the impact of artificial intelligence transformation on enterprise innovation capacity. *European Journal of Innovation Management, 28*(8), 4112-4131.

Karami, M. (2025). Integrating Market Sensing, Digital Logistics, and Green Operations: A Dynamic Capabilities Perspective on Superior Business Performance. *TMP Universal Journal of Law, Business, and Management, 1*(3).

Kyambade, M., & Namatovu, A. (2025). Health-care leaders' perspectives on AI implementation in Uganda: overcoming barriers, driving innovation and strategic considerations. *Leadership in Health Services, 38*(3), 442-463.

Larabi, C. (2025). Linking Innovation Capability, Strategic Orientation, and Strategic Renewal to Sustainable Performance: A Dynamic Capabilities Perspective in Saudi Small and Medium Enterprises. *Business Strategy and the Environment*.

Luo, X., Qian, W., Liu, M., Yu, X., & Liu, Y. (2024). Towards sustainability: Digital capability, sustainable business model innovation, and corporate environmental responsibility of

BUSINESS, TECHNOLOGY & INNOVATION STUDIES JOURNAL (BTISJ)
ISSN 3110-9411

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high-performing enterprises in an emerging market. *Business Strategy and the Environment, 33*(6), 5606-5623.

Madhani, P. M. (2010). Resource based view (RBV) of competitive advantage: an overview. *Resource based view: concepts and practices, Pankaj Madhani, ed*, 3-22.

Majhi, S. G., Mukherjee, A., & Anand, A. (2023). Business value of cognitive analytics technology: a dynamic capabilities perspective. *VINE Journal of Information and Knowledge Management Systems, 53*(6), 1231-1249.

Mariani, C., & Mancini, M. (2025). Harnessing AI for value: examining the impact of AI capabilities and the mediating role of organizational agility on project value proposition. *International Journal of Managing Projects in Business, 18*(8), 112-143.

Mikalef, P., Islam, N., Parida, V., Singh, H., & Altwaijry, N. (2023). Artificial intelligence (AI) competencies for organizational performance: A B2B marketing capabilities perspective. *Journal of business research, 164*, 113998.

Pinto, J. (2019). Key to effective organizational performance management lies at the intersection of paradox theory and stakeholder theory. *International Journal of Management Reviews, 21*(2), 185-208.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology, 88*(5), 879.

Qiu, R., Yu, P., Sadowski, B. M., & Shi, J. (2025). Value creation through complementary resource reconfiguration: complementor transition to innovation ecosystem orchestrator. *Management Decision*.

Selvarajan, G. (2021). Leveraging AI-enhanced analytics for industry-specific optimization: A strategic approach to transforming data-driven decision-making. *International Journal of Enhanced Research In Science Technology & Engineering, 10*, 78-84.

Sveiby, K. E. (2001). A knowledge-based theory of the firm to guide in strategy formulation. *Journal of intellectual capital, 2*(4), 344-358.

Tantalo, C., & Priem, R. L. (2016). Value creation through stakeholder synergy. *Strategic management journal, 37*(2), 314-329.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic management journal, 18*(7), 509-533.

Ullah, I., Donald, W. E., Alhejji, H., Fiaz, M., & Bo, W. (2026). Leading for green: the role of eco-centric leadership in shaping External organisational citizenship behaviour for the environment. *Management Decision*, 1-24.

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. *Business process management journal, 26*(7), 1893-1924.

Zhan, X., He, J., & Ma, X. (2026). The role of corporate social responsibility in affecting operational efficiency: evidence from China. *Operations Management Research, 19*(1), 1-25.

BUSINESS, TECHNOLOGY & INNOVATION STUDIES JOURNAL (BTISJ)
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Appendices

This section provides supplementary materials to enhance transparency, replicability, and methodological rigor. These materials are referenced in the main text where appropriate and are not essential for understanding the core theoretical arguments or results.

Appendix A. Survey Instrument (Two-Wave, Two-Informant Design)

Instructions to Respondents

Please answer all items based on your organization's current use of AI in business processes. Responses are confidential and reported only in aggregate. Use the scale**: 1 = Strongly disagree; 7 = Strongly agree.**

Wave 1 — Technology-Side Informant (CIO/CTO/AI/IT/Data Leader)

Dynamic AI-Related Capabilities (DC)

- DC1. Our organization systematically scans the environment for emerging AI-related opportunities and regulatory changes.
- DC2. We rapidly allocate resources to develop or acquire AI solutions aligned with strategic goals.
- DC3. We regularly reconfigure processes and structures to integrate AI into core decision-making routines.

AI Maturity (Control)

- AIM1. AI is integrated into multiple core business processes.
- AIM2. Our organization has a clear roadmap for AI development.
- AIM3. Employees across functions receive training to effectively use and interpret AI-based systems.
- AIM4. AI initiatives are supported by dedicated budgets and long-term investment plans.

Wave 1 — Business-Side Informant (Strategy/Operations/General Manager)

Responsible AI Governance (RAIG)

- RAIG1. Our organization has formal guidelines to ensure fairness and transparency in AI use.
- RAIG2. There are clear accountability structures for decisions supported by AI systems.
- RAIG3. Stakeholder concerns about AI are formally reviewed and addressed.

Firm Characteristics (Controls)

- FS. Number of full-time employees (categorical).
- IND. Primary industry classification.
- CNTRY. Country of operation (Canada/USA).

Wave 2 — Technology-Side Informant

Organizational Knowledge Orchestration (OKO)

- OKO1. AI-generated insights are effectively shared across departments.
- OKO2. Our organization integrates AI-based knowledge into formal policies and routines.
- OKO3. Lessons learned from AI projects are systematically stored and reused in future initiatives.

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Wave 2 — Business-Side Informant
Stakeholder-Based Value Creation (SVC)

- SVC1. Our AI practices enhance trust among key stakeholders.
- SVC2. Stakeholders perceive our use of AI as fair and responsible.
- SVC3. Our organization's reputation has improved due to transparent AI use.

Organizational Performance (PERF)

- PERF1. AI initiatives have improved our overall strategic effectiveness.
- PERF2. Our organization's innovation performance has increased as a result of AI adoption.
- PERF3. AI use has strengthened our competitive positioning.

Appendix B. Measurement Model: Outer Loadings and Cross-Loadings

Table B1. Outer Loadings

Construct	Item	Loading
DC	DC1	0.84
DC	DC2	0.88
DC	DC3	0.86
OKO	OKO1	0.82
OKO	OKO2	0.85
OKO	OKO3	0.87
RAIG	RAIG1	0.81
RAIG	RAIG2	0.86
RAIG	RAIG3	0.84
SVC	SVC1	0.89
SVC	SVC2	0.91
SVC	SVC3	0.88
PERF	PERF1	0.80
PERF	PERF2	0.84
PERF	PERF3	0.82

Table B2. Cross-Loadings (Excerpt)

Item	DC	OKO	RAIG	SVC	PERF
DC1	**0.84**	0.42	0.31	0.28	0.25
OKO1	0.39	**0.82**	0.33	0.44	0.29
RAIG1	0.34	0.31	**0.81**	0.37	0.26
SVC1	0.29	0.41	0.38	**0.89**	0.52
PERF1	0.27	0.33	0.29	0.49	**0.80**

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Note*: Bold values indicate highest loadings on the intended construct; full cross-loading matrix available from the authors upon request.*

Appendix C. Measurement Invariance (MICOM) Results

Table C1. MICOM Assessment

Step	Test	Result
Step 1	Configural invariance	Established
Step 2	Compositional invariance (permutation test)	Established ($p > 0.05$)
Step 3	Equality of means/variances	Not fully established

Conclusion: Partial measurement invariance achieved, permitting meaningful multi-group comparison of structural relationships.

Appendix D. Robustness Checks

- **Alternative Model Estimation:** The structural model was re-estimated without control variables; path coefficients and significance levels remained substantively unchanged.
- **Split-Sample Validation:** The sample was randomly divided into two subsamples ($n \approx 227$ each). Core paths (DC → OKO, OKO → SVC, SVC → PERF) remained significant at $p < 0.01$ in both subsamples.
- **Alternative Estimation Approach:** Key relationships were re-tested using OLS regression models, yielding consistent direction and significance of effects.