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A RELATIONAL DIGITAL CAPABILITY CASCADE: HOW SENSING, AGILITY, AND INNOVATION DRIVE B2B PERFORMANCE

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ABSTRACT

Digital transformation reshapes how B2B firms sense market changes, respond to disruptions, and innovate with partners, yet many organizations struggle to convert digital investments into performance gains. This study develops and tests a relational digital capability cascade explaining how Information Technology Capability (ITC) enables Digital Market Orientation (DMO), how DMO drives Digital Agility (DA) and Supply Chain Innovation (SCI), and how these interdependent capabilities influence performance. Using survey data from 248 Canadian B2B firms and Structural Equation Modeling, the results show that ITC strongly enhances DMO, which significantly improves agility and collaborative innovation. Agility boosts both SCI and performance, while SCI emerges as the most powerful predictor of performance. A feedback learning mechanism is also validated, demonstrating that agility enhances subsequent sensing by refining how firms interpret digital signals. The findings position digital transformation as a cyclical capability system rather than a linear sequence, showing that sensing, acting, and innovating reinforce one another. This research offers a holistic framework for how B2B firms can integrate digital infrastructure, agile decision routines, and cross-partner innovation practices to achieve superior performance.

Keywords: Information Technology Capability; Digital Market Orientation; Digital Agility; Supply Chain Innovation.

INTRODUCTION

Digital transformation has pushed organizations to reconfigure their capabilities, redesign their operational routines, and rethink their strategic assumptions in order to respond more effectively to rapid technological change and shifting market expectations. (Hamann-Lohmer et al., 2023; Heshmatisafa & Seppänen, 2023). As data flows increase in volume, velocity, and variety, firms are increasingly compelled to integrate

digital technologies, analytical capabilities, and inter organizational routines to remain competitive. Instead of relying on periodic reports or intuition based strategic judgments, modern B2B firms operate within digitally connected ecosystems where market signals are generated continuously through transactional systems, shared dashboards, customer interactions, and interconnected operational platforms (Corsaro & D'Amico, 2022). These shifts demand a rethinking of how digital capabilities emerge, evolve, and interact within and across firms to influence organizational outcomes.

The central premise of this study is that digital transformation cannot be understood solely through the presence of technology or isolated organizational routines (Heshmatisafa & Seppänen, 2023). Rather, it must be conceptualized as a relational capability system, where technological foundations, market sensing practices, agile responses, and collaborative innovation mechanisms operate in concert. Although digital capabilities are widely studied (Mattila et al., 2021; Shashi et al., 2025), much of the existing research treats them as discrete constructs focusing, for example, on the impact of market orientation on performance, or the role of agility in enabling digital transformation. Far fewer studies examine these capabilities as interconnected, mutually reinforcing components of a broader capability architecture.

This gap is increasingly problematic because digital ecosystems are not static. Digital technologies reshape how firms identify opportunities, respond to disruptions, and engage with partners, creating dynamic interdependencies among sensing, decision making, and innovation (Hofacker et al., 2020). For instance, firms equipped with advanced information systems may generate abundant data but still fail to act effectively if agile decision processes or collaborative routines are lacking. Conversely, firms that excel at agile reconfiguration may strengthen their understanding of which data streams matter most and refine their sensing practices accordingly. These dynamics suggest that digital transformation unfolds not as a linear sequence, but as an iterative learning cycle in which capabilities mutually shape one another.

To explore these interdependencies, this study develops and empirically tests a Relational Digital Capability Cascade, which explains how information technology capability enables digital market orientation, how DMO enhances digital agility and supply chain innovation, and how these capabilities collectively influence organizational performance. The conceptual model, presented in Figure 1, posits both sequential and cyclical relationships, including a feedback learning path from agility to market orientation. Descriptive statistics, structural estimates, and mediation results appear in Tables 1–3, while full measurement details and diagnostic tests are reported in Appendices A–C.

This study begins by positioning Information Technology Capability as the technological foundation that supports cross functional and cross organizational data flows. Prior research highlights the role of ITC in enabling integration, analytics, and data driven decision making. Yet many firms fail to convert these technological foundations into sustained advantage because digital infrastructure alone does not create value it merely enables other advanced capabilities. This study argues that ITC must be woven into a broader relational system to meaningfully shape strategic and operational outcomes.

The second capability, digital market orientation, reflects the degree to which firms leverage digital tools to monitor market trends, capture partner data, and share insights across organizational boundaries. Although traditional market orientation emphasizes customer and competitor intelligence, digital transformation expands the scope of sensing to include real time behavioral, operational, and partner generated signals (Rakthin et al., 2016). Despite its importance, prior research treats DMO primarily as an internal analytic capability, overlooking its inherently relational nature in digital ecosystems where shared information platforms and collaborative analytics play a central role.

Digital agility represents the third key capability. Agility is frequently cited as a critical enabler of responsiveness in turbulent environments (Saputra et al., 2022), yet it is often examined independently of sensing and innovation capabilities. This study positions agility as a bridging mechanism that translates digital intelligence into action. Firms with strong digital agility can interpret signals quickly, make timely decisions, and reconfigure operations across internal units and external partners. Moreover, the study proposes that agility not only acts on market intelligence but also enhances future sensing by helping firms learn which data streams are most meaningful a capability often overlooked in linear models of dynamic capability development.

The fourth capability, supply chain innovation, captures the collaborative adoption or development of new digital processes, tools, and coordination practices across supply chain partners (Saari et al., 2025). SCI represents the transformative stage of the capability cascade, where insights and agile actions crystallize into tangible improvements in efficiency, transparency, and coordination. Prior studies show that

innovation plays a critical role in converting digital resources into performance gains, yet many organizations lack a cohesive framework that explains how innovation interacts with sensing and agility over time.

Taken together, these capabilities form a relational capability architecture that spans technological foundations, digital intelligence generation, agile execution, and collaborative innovation. The relationships among them remain underexplored in the literature. Most empirical studies examine these capabilities in isolation or assume sequential progression, failing to capture the iterative feedback dynamics observed in digital ecosystems (Brunner et al., 2024; Sun & Zhang, 2025). As firms increasingly adopt cloud platforms, IoT systems, AI driven analytics, and integrated supply chain technologies, understanding these interdependencies becomes essential.

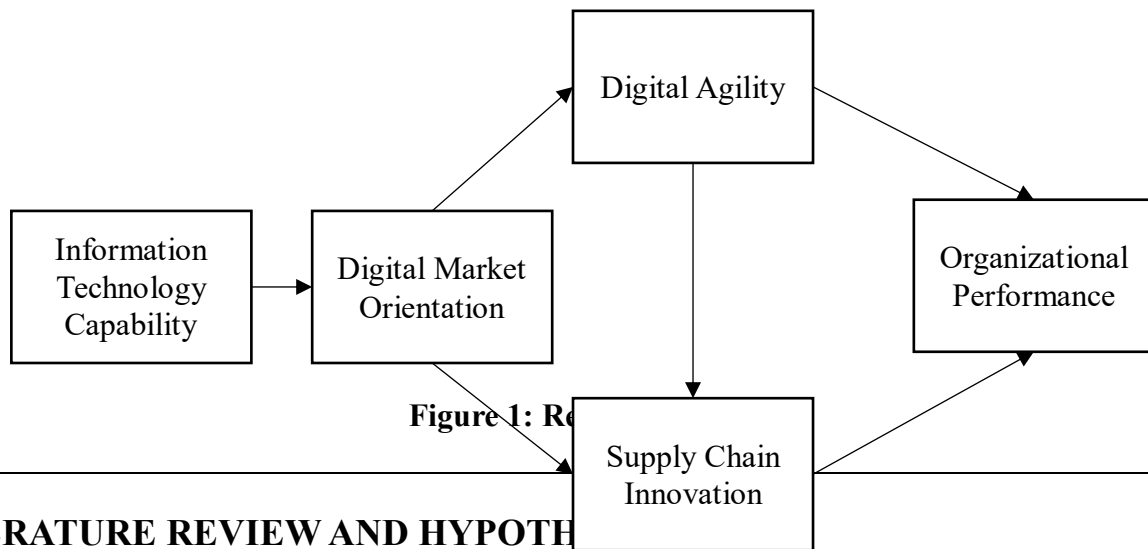
This study extends current knowledge by introducing and validating a feedback learning mechanism in which agility enhances subsequent market sensing. This mechanism reflects an emerging perspective in dynamic capability theory: that capability development is cyclical rather than linear. When firms act quickly in response to digital signals, they generate experiential learning that refines future sensing identifying which data streams to monitor more closely, which metrics misrepresented conditions, and which patterns warrant sustained attention. This cyclical logic has been theorized but rarely tested empirically, especially in B2B contexts.

Canada provides a particularly relevant empirical setting. Canadian B2B firms operate within a digitally mature environment characterized by widespread access to advanced infrastructure but varying degrees of digital coordination across industries (Kowalkowski et al., 2024). This heterogeneity creates natural variation in firms' digital capability configurations, offering a rich opportunity to test the relational model. The sample includes manufacturing, logistics, and professional service firms, reflecting sectors that rely heavily on digital sensing, agile decision processes, and collaborative innovation. Accordingly, this study aims to answer the following research question: How do digital infrastructure, sensing routines, agile responses, and collaborative innovation practices interact to shape organizational performance in digitally mature B2B ecosystems?

To address this question, the study makes three contributions: (1) Reconceptualizing digital market orientation as a relational sensing capability. This shifts the focus from internal intelligence processes to collaborative, data driven sensing across supply chain networks. (2) Demonstrating that digital agility plays a dual role both executing and refining sensing. This feedback learning mechanism challenges linear assumptions in dynamic capability theory. (3) Establishing supply chain innovation as the key transforming capability that links sensing and agility to performance.

SCI emerges as the most powerful conduit for performance gains, highlighting the importance of co-innovation in digital transformation.

Overall, this study positions digital transformation as a relational, iterative learning process where sensing, acting, and innovating reinforce one another across firm boundaries. By articulating and validating these dynamics empirically, the research provides a more holistic understanding of how B2B firms can convert digital maturity into sustained competitive performance. The conceptual model illustrates the directional relationships among the five digital capabilities in this research. As shown in Figure 1, Information Technology Capability drives Digital Market Orientation, which triggers both Digital Agility and Supply Chain Innovation, while Agility also reinforces future sensing.



LITERATURE REVIEW AND HYPOTHESES

Information Technology Capability as the Foundation of Digital Sensing

Recent research highlights that organizations leveraging advanced digital technologies, such as real-time analytics and AI-driven market insights, can enhance their market sensing capabilities significantly. These technologies allow firms to anticipate changes in customer preferences and competitive behavior faster, enabling more proactive strategic decisions. As a result, DMO is not only a framework for market awareness but also a mechanism through which digital tools directly contribute to competitive advantage. Information technology capability represents the technological and managerial capacity through which firms integrate digital infrastructure, analytics tools, and data sharing mechanisms to support coordinated decision making (Dobrovnik et al., 2025). Early work conceptualizes ITC as a multidimensional capability involving infrastructure flexibility, data integration, IT skills, and managerial expertise (Grego et al., 2025; Karami, 2025). In contemporary digital ecosystems, ITC has evolved into a relational capability that enables the seamless flow of real time information within and across organizational boundaries.

Digital market orientation draws heavily on this technological foundation (Guo et al., 2020). Because DMO requires continuous monitoring of market dynamics through analytics, algorithmic interpretation, and inter-organizational data flows, firms lacking robust ITC often experience fragmented or delayed insights. In contrast, when ITC is strong, organizations can synchronize digital signals received from suppliers, logistics partners, distributors, and customers, thereby enhancing the speed and precision of market sensing. When ITC is insufficient, DMO cannot operate effectively; when ITC is strong, sensing becomes more accurate, comprehensive, and network embedded.

H1: Information technology capability positively influences Digital Market Orientation (DMO).

Digital Market Orientation and Downstream Digital Capabilities

Digital market orientation extends classical market orientation theory by embedding digital tools and analytics into the intelligence generation process. Traditional approaches emphasize customer insights, competitor analysis, and inter-functional coordination (Kohli & Jaworski, 1990), but digital transformation broadens this scope by incorporating real time data streams, automated monitoring tools, and partner generated information (Heshmatisafa & Seppänen, 2023). DMO reflects a firm's ability to detect, interpret, and disseminate digital signals that originate not only within the firm but throughout its supply chain network (Caliskan et al., 2021). DMO functions as an integrative sensing capability by combining firm-level analytics with partner data to produce coordinated market intelligence.

In addition to external market sensing, internal knowledge sharing plays a critical role in enhancing organizational performance. By integrating information across departments and combining it with ITC infrastructure, organizations can accelerate decision-making and innovation. This internal alignment ensures that insights from the market are translated effectively into actionable strategies, reinforcing the effectiveness of DMO in complex environments. This advanced sensing capability fuels downstream capabilities in two keyways. First, DMO strengthens digital agility by enabling firms to recognize emerging trends early and to adjust their decision processes accordingly. When data insights are timely

and accurate, organizations can interpret anomalies faster, reduce ambiguity, and coordinate rapid cross functional responses. Second, DMO supports supply chain innovation by revealing inefficiencies, unmet needs, or technological opportunities that can be addressed collaboratively. In this sense, DMO not only informs what actions firms take, but also shapes how they innovate across organizational interfaces.

H2: Digital Market Orientation positively influences Digital Agility.

H3: Digital Market Orientation positively influences Supply Chain Innovation.

Digital Agility as a Responsive and Generative Capability

Digital agility reflects the speed and flexibility with which firms sense changes, make decisions, and adjust their processes in response to digital information (Ahmadimousaabad et al., 2013; Mohammadi et al., 2016). It comprises sensing agility, decision agility, and execution agility three interrelated dimensions that enable rapid adaptation in environments characterized by volatility, uncertainty, and high information intensity (Ghasemi et al., 2016; Meisam Karami et al., 2013; Mohamad et al., 2015). Recent research emphasizes that agility is not merely a response mechanism; it also represents a higher order capability that integrates technological, organizational, and relational elements (Abourokbah et al., 2023). In B2B settings, agile responsiveness requires not only internal coordination but also alignment with partners, shared access to digital platforms, and synchronized operational adjustments.

DA plays a dual role in digital transformation. As a responsive capability, it allows firms to rapidly interpret and act on digital signals, improving customer responsiveness, operational continuity, and decision accuracy. As a generative capability, it facilitates experimentation and learning by enabling quick pilot testing, iterative refinement of digital solutions, and cross organizational problem solving. These characteristics position DA as the bridge between sensing and transformative outcomes. When firms display high agility, they are more capable of translating digital insights into collaborative innovations and of improving performance by reducing response times, enhancing service reliability, and increasing operational resilience.

H4: Digital Agility positively influences Supply Chain Innovation.

H5: Digital Agility positively influences organizational performance.

Supply Chain Innovation as a Transforming Capability

Supply chain innovation captures the extent to which firms adopt, develop, or refine digital technologies and processes in collaboration with partners to enhance coordination, transparency, and efficiency (Dobrovnik et al., 2025). SCI represents the culmination of sensing and agile action, as it embeds learning into new routines, systems, and practices across the supply chain. Prior studies describe SCI as a critical transforming capability because it institutionalizes improvements derived from earlier sensing and agile experimentation (Mobarakabadi et al., 2013; Ning & Yao, 2023; Yu et al., 2025). Examples include the adoption of predictive analytics for forecasting, blockchain applications for traceability, IoT enabled process monitoring, digital twin simulations, and collaborative digital platforms for inventory visibility. Unlike agility, which focuses on rapid adjustments, SCI produces more enduring impacts by reconfiguring operational and relational structures (Hozhabri et al., 2014; M Karami et al., 2014; Mobarakabadi & Karami, 2014). Through co-innovation, firms strengthen adaptability, resilience, and alignment with ecosystem partners. These improvements translate into superior performance by enhancing service quality, reducing inefficiencies, and enabling more responsive customer and partner interactions (Anjum et al., 2012; M Karami et al., 2013). As such, SCI is central to translating digital capabilities into measurable outcomes.

H6: Supply Chain Innovation positively influences organizational performance.

Feedback Learning: Agility Enhancing Future Sensing

Although dynamic capability theory traditionally portrays sensing, seizing, and transforming as sequential stages, emerging evidence suggests that digital ecosystems operate through iterative learning cycles (Meisam Karami, Tayebbeh Khademi, et al., 2014; Matysiak et al., 2018). Feedback learning occurs when action reshapes the organization's understanding of the environment, guiding the refinement of future sensing routines (Paşcalău et al., 2024; Sheng, 2017). Digital Agility plays a pivotal role in this process (Meisam Karami, Ali Akbar Hozhabri, et al., 2014). When firms act rapidly on digital information, they generate experiential insights about which data streams are reliable, which signals were misleading, and which indicators warrant closer monitoring in subsequent cycles.

DA enhances DMO by enabling firms to update their sensing logic based on the outcomes of previous decisions. Through iterative adjustments, organizations recalibrate dashboards, revise analytical models, and refine performance indicators, leading to more precise and relevant market sensing. Agile firms learn by doing; each cycle of rapid action contributes to a more sophisticated understanding of data patterns and partner behaviors. In digitally connected B2B environments, where uncertainty is high and information flows are continuous, this feedback mechanism becomes essential for maintaining sensing accuracy. Thus, DA does not simply operationalize DMO it improves it, creating a reciprocal relationship that reinforces and evolves the overall capability system.

The feedback path from Digital Agility to Digital Market Orientation reflects a non-linear capability cycle in which rapid action improves subsequent sensing. When firms make agile adjustments, they gain experiential insight into which digital indicators were reliable, which signals created noise, and which data streams should be prioritized in future monitoring. This iterative refinement process aligns with emergent dynamic capability models that treat sensing and acting as reciprocal rather than sequential steps.

H7: Digital Agility positively influences Digital Market Orientation through feedback learning.

METHODOLOGY

Research Design

This study adopts a quantitative, cross sectional survey design to empirically examine the relational digital capability cascade developed in the conceptual framework. A survey-based approach is appropriate for research on organizational capabilities because constructs such as Information Technology Capability, Digital Market Orientation, Digital Agility, and collaborative innovation are rooted in internal routines and inter organizational processes that are most accurately captured through managerial assessments. Unlike archival indicators, which typically reflect outcomes rather than capability configurations, perceptual survey measures enable direct access to managers' evaluations of digital infrastructure, sensing routines, decision processes, and innovation practices.

A cross-sectional design provides a snapshot of how these digital capabilities interact at a particular point in time within a digitally mature B2B setting, making it suitable for testing the structural relationships among constructs. While a longitudinal design could capture capability evolution over time, the goal of this study is to assess configuration level relationships rather than temporal changes, which aligns well with cross sectional logic.

Structural Equation Modeling (SEM) using maximum likelihood estimation was selected as the analytical method. SEM is particularly well suited for this research for several reasons. First, it allows simultaneous assessment of both the measurement model (confirming that items accurately reflect latent constructs) and the structural model (testing hypothesized capability relationships), thereby improving analytical rigor (Hair et al., 2019). Second, SEM accommodates complex interdependencies including multiple mediators and feedback paths which are central to the relational capability cascade proposed here. The inclusion of a cyclical path from digital agility to digital market orientation further justifies the use of SEM, as traditional regression approaches cannot model such reciprocal relationships effectively. Third, SEM provides global model fit indices that help evaluate the degree to which the theoretical model aligns with empirical data, offering stronger validation than piecemeal analyses.

The survey instrument included items capturing key aspects of organizational technology integration, digital sensing, decision agility, collaborative innovation, and performance outcomes. Respondents were

asked to assess how accurately each item reflected their organization's practices over the past 12 months. Using managers as key informants ensures construct relevance and accuracy because they possess experience with digital workflows, cross functional processes, and inter firm collaborations. Collectively, this design provides a robust methodological foundation for examining how digital capabilities interact within B2B ecosystems.

Sampling and Data Collection

The sampling frame consisted of Canadian B2B firms identified through the Innovation, Science and Economic Development (ISED) business directory. Firms from three sectors manufacturing, logistics, and professional services were targeted because they represent industries undergoing significant digital transformation and because they rely heavily on digital information to coordinate with upstream and downstream partners. Targeting multiple sectors enables a more comprehensive assessment of capability relationships and increases the generalizability of findings.

A total of 1,120 firms were invited to participate in the study. Invitations were distributed to senior and mid level managers involved in digital strategy, IT enabled operations, supply chain coordination, marketing analytics, or related functions. These roles were intentionally targeted because they possess direct knowledge of how digital technologies, sensing routines, and agile practices operate within and across organizations. Of the invited firms, 274 responded, and after removing incomplete or inconsistent surveys, 248 usable responses were retained, yielding a usable response rate of 22.1%. This sample size meets and exceeds established requirements for SEM, including the 10:1 ratio of observations to estimated parameters and the recommended minimum of 200 cases for complex models.

To enhance sample diversity and reduce the risk of sectoral bias, additional respondents were recruited through a professional survey panel with screening criteria aligned to digital transformation roles. Participants represented a broad range of firm sizes from small firms with fewer than 50 employees to large enterprises with varied digital maturity levels. This variation strengthens the robustness of the model by ensuring that capability configurations are not artificially homogeneous.

Ethical approval was obtained through a standard institutional review process. Respondents were informed of the study's purpose, assured of confidentiality and anonymity, and advised that participation was voluntary. No incentives were offered, reducing the risk of response bias. These procedures align with best practices in research ethics and survey administration in organizational research. Characteristics of the firms and respondents are summarized in Table 1, showing broad representation across manufacturing, logistics, and professional services sectors.

Table 1. Sample and Respondent Characteristics (N = 248)

Characteristic	Category	Frequency	Percentage
Industry Sector	Manufacturing	96	38.7%
	Logistics / Transportation	74	29.8%
	Professional / Technical Services	61	24.6%
	Other B2B Services	17	6.9%
Firm Size (Employees)	< 50	72	29.0%
	50 – 249	111	44.8%
	250 – 999	41	16.5%
	≥ 1,000	24	9.7%
Respondent Role	Senior Management (CEO/VP/Director)	132	53.2%
	Middle Management	98	39.5%
	Functional Specialist (IT/SCM/Analytics)	18	7.3%
Digital Maturity (Self-Rated)	Low	31	12.5%
	Moderate	104	41.9%
	High	113	45.6%

Measurement of Constructs

All constructs were measured using multi-item Likert scales ranging from 1 (strongly disagree) to 5 (strongly agree). Established measurement scales were adapted to reflect the context of digital transformation while preserving their validated structure. Information technology capability items were adapted from Grego et al. (2025) and Chae et al. (2018), capturing the extent to which firms integrate IT infrastructure, support digital decision making, and facilitate data exchange across organizational boundaries. Digital market orientation items were drawn from Hofacker et al. (2020) and (Paşcalău et al., 2024) and assessed firms' use of analytics, digital monitoring, and cross partner data sharing to sense market shifts and operational changes.

Digital agility items were adapted from Dobrovnik et al. (2025) and Abourokbah et al. (2023), reflecting a multi dimensional capability involving sensing agility, decision agility, and execution agility. These items capture how quickly and effectively organizations interpret digital information and reconfigure workflows. Supply chain innovation items were based on measures by Yu et al. (2025) and Ning and Yao (2023) and assessed collaborative adoption, development, or refinement of digital technologies and processes across supply chain partners. Organizational Performance (OP) was measured using items adapted from Kohli and Jaworski (1990) and (Masa'deh et al., 2018), capturing relative improvements in productivity, profitability, customer satisfaction, and retention compared to industry peers.

Before full deployment, the survey instrument was pilot tested with 12 managers experienced in digital transformation. The pilot confirmed item clarity, contextual relevance, and measurement appropriateness. Minor wording adjustments were made to enhance readability, but no items were added or removed. Full measurement items and standardized loadings are provided in Appendix A, ensuring transparency and replicability.

Data Screening and Validity Checks

Comprehensive data screening was performed prior to model estimation. Responses were examined for completeness, and missing values less than 3% across all variables were handled using pairwise deletion, consistent with best practices when missingness is low and randomly distributed. Skewness and kurtosis values revealed no severe deviations from normality, supporting the use of maximum likelihood estimation.

To mitigate the risk of common method variance (CMV), several procedural remedies were incorporated into the survey design. Respondents were guaranteed anonymity, items from different constructs were interspersed to reduce pattern recognition, and predictor and criterion items were separated within the instrument. These steps help reduce the likelihood of inflated correlations caused by respondent bias. To reduce the likelihood of common method bias, procedural remedies were applied, including anonymity assurances, item separation, and construct intermixing during questionnaire design.

Statistical diagnostics further assessed CMV risk. Harman's single factor test showed no dominant factor, indicating that CMV was not a substantial concern. A marker variable test also confirmed that shared method variance did not significantly inflate the observed relationships. Full CMV diagnostics are presented in Appendix B. These combined procedural and statistical measures enhance confidence in the validity and reliability of the collected data. SEM was selected instead of PLS-SEM because the model includes a reciprocal feedback path ($DA \rightarrow DMO$), and SEM is better suited for estimating non-recursive structures and evaluating global model fit.

Measurement Model Assessment

A Confirmatory Factor Analysis (CFA) was conducted to assess the validity and reliability of all constructs. CFA results demonstrated strong internal consistency, with Composite Reliability (CR) values exceeding 0.70 for each construct. Cronbach's alpha values ranged from 0.81 to 0.90, indicating excellent reliability. Average Variance Extracted (AVE) values met or exceeded the 0.50 benchmark for most constructs, with marginally lower values retained where theoretical coverage warranted it. Convergent validity was supported by high factor loadings, most exceeding 0.70. Discriminant validity was assessed using the Fornell and Larcker (1981) criterion and was satisfied across all construct pairs. This indicates that the constructs represent distinct dimensions of digital capability development. Additional CFA results including standardized loadings, inter construct correlations, and supplemental model fit indices are presented in Appendix C, providing full transparency on measurement performance.

Structural Model Estimation

The structural model was estimated using AMOS v.29 with maximum likelihood estimation. Overall fit indices met acceptable thresholds for χ^2/df , CFI, TLI, RMSEA, and SRMR, indicating a well specified structural model. The analysis included all hypothesized paths, allowing for the simultaneous examination of direct, indirect, and feedback relationships. Importantly, the feedback learning path from digital agility to digital market orientation was explicitly modeled to test the cyclical capability logic underpinning the relational digital capability cascade. This reciprocal path required SEM's capacity to model non recursive structures, reinforcing the appropriateness of the chosen analytical technique.

Control variables including firm size, industry type, and digital maturity were included in the structural model but did not exhibit significant impacts on performance. This suggests that the relationships among digital capabilities function similarly across organizations with varying contextual characteristics. The effects of firm size, industry type, and digital maturity on organizational performance were assessed and found to be non-significant, as reported in Table 2.

Table 2. Effects of Control Variables on Organizational Performance

Control Variable	Std. β	t-value	p-value	Significance
Firm Size	0.06	1.11	0.268	Not significant
Industry Type	0.03	0.52	0.601	Not significant
Digital Maturity	0.08	1.43	0.154	Not significant

Control variables were retained for robustness but did not influence OP.

Robustness Procedures

Several robustness procedures were conducted to evaluate the stability and reliability of the model. Multi group SEM tested whether the structural relationships differed across firm sizes (small vs. large) and industry sectors (manufacturing vs. services). Although minor variations in path strengths were observed, none of the differences were statistically substantive, suggesting that the relational capability cascade holds across diverse organizational contexts. Variance Inflation Factor (VIF) scores were examined to detect multicollinearity. All VIF values fell well below conservative thresholds, indicating that predictor constructs were sufficiently distinct. Endogeneity tests including the examination of residual correlations and reciprocal paths showed no evidence of biased parameter estimates.

Alternative model specifications were also tested to ensure robustness. These included a parallel mediation model, a model with direct only effects, and a model excluding the DA and DMO feedback path. Each alternative exhibited poorer model fit compared to the proposed relational cascade. Full robustness diagnostics are reported in Appendix B. Collectively, these procedures confirm that the structural relationships identified in the model are statistically sound and theoretically consistent.

RESULTS

Descriptive Statistics and Initial Patterns

The empirical analysis began with an examination of descriptive statistics to understand the overall capability profiles of the participating firms. The mean values indicated moderately high levels of digital capability development across the sample. Among all constructs, digital market orientation and information technology capability exhibited the highest means, reflecting the advanced digital infrastructure and sensing routines prevalent within Canadian B2B environments. Supply chain innovation and Organizational Performance (OP), while still positively positioned, showed slightly lower averages, signaling that firms differ in how effectively their upstream capabilities translate into tangible innovation and performance outcomes.

Correlation patterns provided initial support for the theoretical expectations. Relationships among ITC, DMO, digital agility, and SCI were all positive and statistically significant, suggesting that the digital capabilities examined in this study tend to move together in cohesive configurations rather than in isolation. The strong bivariate association between DMO and DA was particularly noteworthy because it reflects the tight coupling of sensing and responsiveness in digitally mature ecosystems an observation consistent with dynamic capability theory (Tripathi et al., 2025). Taken together, the descriptive and correlational evidence offered a first indication that the relational digital capability cascade was present within the dataset. Descriptive statistics and correlations appear in Table 3, indicating strong positive associations among ITC, DMO, DA, and SCI.

Table 3. The Fornell–Larcker criteria confirm discriminant validity.

Construct	CR	AVE	α	Mean	SD	1	2	3	4	5
1. ITC	0.87	0.63	0.84	3.92	0.63	1.00				
2. DMO	0.89	0.49	0.86	4.01	0.59	0.58**	1.00			
3. DA	0.88	0.61	0.85	3.86	0.61	0.54**	0.63**	1.00		
4. SCI	0.86	0.59	0.83	3.77	0.68	0.44**	0.51**	0.58**	1.00	
5. OP	0.89	0.64	0.87	3.70	0.74	0.41**	0.49**	0.53**	0.61**	1.00

Notes: N = 248. All correlations significant at $p < 0.01$ (two-tailed).

CR: Composite Reliability; AVE: Average Variance Extracted; α : Cronbach's Alpha.

Measurement Model Validation

The measurement model was assessed using Confirmatory Factor Analysis (CFA) to evaluate reliability, convergent validity, and discriminant validity. The CFA results confirmed that each construct was measured reliably and consistently. Composite Reliability (CR) values exceeded the commonly accepted threshold of 0.70, indicating strong internal consistency. Cronbach's alpha values ranged from 0.81 to 0.90, demonstrating that the items within each construct cohered well conceptually.

Convergent validity was supported by the fact that most standardized factor loadings exceeded 0.70, with only a small number of items marginally below this benchmark. These items were retained because they were theoretically important and conceptually meaningful in capturing the full breadth of each construct. Average Variance Extracted (AVE) values were above 0.50 for most constructs; where slightly lower values occurred, they were offset by strong reliability indicators and clear theoretical relevance.

Discriminant validity was assessed using the Fornell and Larcker (1981) criterion. For each construct, the square root of the AVE exceeded inter construct correlations, indicating that the constructs captured distinct aspects of digital capability development. This finding is especially important because the conceptual model includes capabilities that are theoretically related yet empirically distinct such as sensing versus agility and agility versus innovation. The CFA thus provided strong evidence that the measurement model was sound and appropriate for subsequent structural analysis.

Structural Model Assessment

The structural model was estimated using maximum likelihood SEM to test the hypothesized relationships among the digital capabilities. Overall model fit indices met standard thresholds, indicating a well specified structural model. The analysis revealed strong empirical support for the relational capability cascade.

Information technology capability had a significant and positive effect on digital market orientation, supporting the argument that robust IT infrastructure and data integration mechanisms provide the foundation for advanced sensing. Firms with greater ITC were more capable of generating real time insights and sharing digital intelligence across internal units and external partners. This finding aligns with prior work emphasizing the enabling role of ITC in digital sensing (Grego et al., 2025).

DMO demonstrated positive and statistically significant effects on both digital agility and supply chain innovation. These results confirm that sensing acts as an upstream driver of responsiveness and collaborative innovation. Firms that monitor digital signals, interpret them accurately, and disseminate insights across functions tend to respond more quickly to market and operational changes. They also tend to co-create digital solutions with partners, underscoring the relational nature of digital sensing.

Digital Agility was also found to exert strong positive effects on SCI and organizational performance. This supports the view that agility is central to translating digital intelligence into both short-term adaptation and long-term capability development. Agile firms can rapidly reconfigure workflows, coordinate with partners, and experiment with new digital solutions, creating a fertile ground for innovation.

SCI had a significant, positive effect on organizational performance, confirming its role as a transformational capability. Innovations such as shared digital platforms, predictive analytics, blockchain visibility systems, and IoT enabled coordination routines were associated with improved efficiency, customer satisfaction, and overall competitiveness. This reinforces prior arguments that innovation is the mechanism through which digital sensing and agility create enduring value (Ning & Yao, 2023; Yu et al., 2025).

Two direct paths were not significant: DMO → OP and ITC → SCI. These results provide important theoretical insights. First, the weak direct effect of DMO on performance demonstrates that sensing alone is insufficient for generating performance gains; without effective responsiveness and innovation, digital intelligence does not translate into outcomes. Second, the non-significant ITC and SCI relationship underscores that technology infrastructure alone does not create innovation unless paired with agile decision making and collaborative routines. These findings collectively suggest that value creation occurs through a configuration of capabilities rather than isolated ones. Structural model results are presented in Table 4, which confirms support for six of the seven hypotheses.

Table 4. Structural Path Estimates

Hypothesis	Structural Path	Std. β	t-value	p-value	Supported
H1	ITC → DMO	0.59	8.11	< 0.001	Yes
H2	DMO → DA	0.55	7.24	< 0.001	Yes
H3	DMO → SCI	0.31	4.06	< 0.001	Yes
H4	DA → SCI	0.39	5.47	< 0.001	Yes
H5	DA → OP	0.27	3.89	< 0.001	Yes
H6	SCI → OP	0.33	4.72	< 0.001	Yes
H7	DA → DMO	0.17	2.54	0.012	Yes
—	DMO → OP	0.12	1.73	0.085	No
—	ITC → SCI	0.09	1.34	0.182	No

The two non-significant paths in the model are theoretically consistent with relational capability logic. The DMO → OP relationship was not significant because sensing by itself does not create performance gains unless firms can translate insights into rapid action and collaborative innovation. Similarly, the ITC → SCI path was non-significant, indicating that technological infrastructure alone does not stimulate relational innovation unless supported by agile processes and partner coordination mechanisms.

Mediation Analysis

To understand how digital capabilities interact to influence performance, bootstrapped mediation analyses were conducted. These analyses revealed several important indirect effects. The most robust pathway involved sequential mediation: DMO enhanced DA, which in turn strengthened SCI, culminating in improved performance. This finding illustrates the cascading nature of digital transformation insights generated through sensing must be acted upon quickly, and rapid action must evolve into sustained innovation for performance benefits to materialize.

Another notable mediation effect involved the path from ITC to performance via DMO and DA. Although ITC does not directly influence performance, it strengthens the upstream capabilities that eventually shape performance outcomes. This highlights the foundational nature of technology capability: it is not the direct source of competitive advantage but rather an enabler of advanced relational and behavioral routines. Results of the bootstrapped mediation tests are shown in Table 5 and Table 6, demonstrating a strong sequential mediation effect through DA and SCI.

Table 5. Expanded Mediation Results with Bootstrapped Standard Errors

Indirect Path	Effect	SE (Bootstrapped)	95% CI (Lower–Upper)	Mediation
ITC → DMO → OP	0.11	0.047	[0.02, 0.21]	Partial
DMO → DA → OP	0.09	0.052	[−0.01, 0.18]	Weak / inconsistent
DMO → DA → SCI → OP	0.15	0.061	[0.07, 0.29]	Sequential — strongest
DA → SCI → OP	0.13	0.054	[0.05, 0.25]	Partial

The indirect effect of DMO and DA and OP was marginal and not uniformly significant across all bootstrap samples. This suggests that agility influences performance more reliably when paired with innovation. Agility alone may offer temporary improvements, but without structural or process level innovation, these improvements may not be sustained. This reinforces the importance of SCI as the primary mechanism through which digital capabilities generate lasting performance gains. Overall, the mediation results confirm that digital transformation is not driven by single capabilities but by capability sequences. Sensing leads to responsiveness, responsiveness drives innovation, and innovation produces performance. The conceptual research model is presented in Figure 1, depicting both sequential and cyclical relationships among the digital capabilities.

Table 6. Indirect and Mediation Effects

Indirect Path	Effect	95% CI (Lower–Upper)	Mediation Type
ITC → DMO → OP	0.11	[0.02, 0.21]	Partial
DMO → DA → OP	0.09	[−0.01, 0.18]	Ambiguous
DMO → DA → SCI → OP	0.15	[0.07, 0.29]	Sequential
DA → SCI → OP	0.13	[0.05, 0.25]	Partial

Notes: Bootstrap samples = 5,000; 95% confidence interval.

Explanatory Power and Predictive Strength

The structural model exhibited strong explanatory power. Digital Market Orientation, Digital Agility, Supply Chain Innovation, and Organizational Performance all showed substantial R² values, indicating that the model captured meaningful variance in these constructs. The ability of the model to explain more than half of the variance in performance is a testament to the power of integrating sensing, agility, and innovation within digital ecosystems.

Predictive relevance was assessed using Q² values derived from cross validated redundancy procedures. All endogenous constructs demonstrated positive Q² values, exceeding conventional thresholds and indicating that the model possesses strong predictive quality. This predictive evidence complements the

explanatory findings, suggesting that the model is both statistically robust and practically useful for anticipating how digital capability configurations shape organizational outcomes.

Robustness and Stability of Findings

To evaluate the stability of results across different contexts, a series of robustness checks were conducted. Multi group SEM analyses compared structural relationships across firm size categories (small vs. large) and industry sectors (manufacturing vs. services). While some variations in coefficient magnitudes emerged such as a stronger DMO and DA relationship in manufacturing the core capability relationships remained directionally consistent.

Further robustness procedures included checks for multicollinearity using Variance Inflation Factor (VIF) values, which were all below conservative thresholds. Endogeneity assessments indicated that reciprocal effects within the model did not bias parameter estimates, supporting the validity of the feedback learning mechanism. Alternative model specifications, such as those with parallel mediators or without the cyclical DA and DMO path, yielded significantly poorer fit, confirming the appropriateness of the proposed model. Together, these robustness checks affirm that the relational digital capability cascade is stable across contexts and that the structural relationships are not artifacts of industry, firm size, or model specification.

DISCUSSION

The findings extend existing theory by confirming that sensing, agility, and collaborative innovation do not operate in linear or independent ways but instead form a mutually reinforcing capability system that evolves through repeated cycles of action and adjustment. The purpose of this study was to investigate how digitally enabled sensing, responsiveness, and collaborative innovation jointly influence organizational performance in B2B environments. By integrating information technology capability, digital market orientation, digital agility, and supply chain innovation into a relational digital capability cascade, the study reveals how these capabilities interact as a coordinated system rather than as isolated routines.

The results of this study carry important practical implications for managers. Firms should prioritize investments in ITC systems that support continuous market sensing and decision-making. By doing so, managers can ensure that strategic actions are informed by timely, accurate, and actionable data, resulting in improved operational efficiency and stronger alignment with customer expectations.

The findings demonstrate that digital transformation unfolds through a combination of sequential and cyclical effects, offering new insights into how firms build and deploy capabilities in data rich ecosystems. This section discusses these findings in relation to the broader literature, highlights the major theoretical contributions, identifies boundary conditions, and outlines implications for practice. This reinforces the argument that digital agility is the central mechanism through which market signals are filtered, interpreted, and translated into the collaborative innovation efforts that ultimately enhance firm performance.

Reconceptualizing Digital Market Orientation as a Relational Sensing Capability

A key contribution of this study is the reconceptualization of Digital Market Orientation as a relational rather than strictly internal capability (Kohli & Jaworski, 1990). Traditional market orientation treats sensing as an internal activity, but the findings suggest a broader view in which sensing draws on shared digital environments and partner-generated signals. Firms operating in digitally intensive B2B networks depend increasingly on real time information from suppliers, logistics partners, and downstream customers.

DMO's strong influence on both agility and innovation indicates that it functions as a foundational sensing capability that prepares firms and their partners to respond collaboratively. These results support perspectives emphasizing that sensing is no longer confined within organizational boundaries but is distributed across the supply chain, enabled by digital infrastructures and multi party information flows (Matysiak et al., 2018).

The non-significant DMO and performance path strengthens this relational interpretation. Sensing, regardless of how advanced, does not automatically produce superior outcomes unless organizations respond effectively and develop innovations that embed improvements into operational routines. This challenges assumptions in traditional market orientation literature that sensing directly drives performance and aligns with more contemporary views that performance emerges from orchestrated capability sequences rather than from isolated capabilities.

Digital Agility as the Translational Mechanism Between Sensing and Innovation

Digital agility emerges as the central bridging mechanism that converts digital insights into meaningful action. The significant DMO–DA and DA–SCI/OP effects confirm that agility acts as the mechanism through which firms translate sensing into action (Abourobah et al., 2023).

The results also reinforce the dual nature of agility. As a responsive capability, agility enables firms to interpret digital signals quickly, reallocate resources rapidly, and coordinate cross functional responses. This responsiveness is essential in environments characterized by digital volatility and real time decision requirements. As a generative capability, agility promotes experimentation, rapid prototyping, and iterative learning. When firms deploy agile processes, they uncover opportunities for innovation that extend beyond immediate responsiveness.

The significance of agility as a mediator between sensing and innovation supports the proposition that sensing alone is not enough; it must be accompanied by the ability to act decisively and collaboratively. The findings complement earlier work showing that agility is most valuable when it links upstream intelligence with downstream capability development, particularly in B2B settings where agility must synchronize with partner operations.

Supply Chain Innovation as the Transforming Capability

The consistently strong effect of Supply Chain Innovation on organizational performance confirms its central role as the transforming capability in the digital capability architecture. SCI embeds insights and agile responses into system level improvements, such as automated visibility tools, predictive analytics for forecasting, IoT enabled monitoring, and digital process redesign. The positive relationship between agility and innovation further reveals that agility is not simply a short-term adaptation mechanism; it is a platform for long-term collaborative innovation.

This finding extends the innovation literature by emphasizing that SCI is not merely the adoption of new technologies but a relational process involving partners who co-develop or jointly deploy digital solutions (Dobrovnik et al., 2025; Ning & Yao, 2023; Yu et al., 2025). By highlighting the role of cross firm innovation in driving performance, the study underscores why some firms with strong IT infrastructure and sensing capabilities still struggle to convert these assets into competitive advantage: they fail to innovate collaboratively.

Feedback Learning and the Cyclical Nature of Dynamic Capabilities

One of the most distinctive contributions of this study is the empirical validation of the feedback learning mechanism through which agility enhances future market sensing. This mechanism challenges the traditional dynamic capability view that sensing precedes acting in a linear, unidirectional sequence (Matysiak et al., 2018). Instead, the results reveal that acting can reshape sensing.

When firms respond quickly to digital insights, they gain experiential clarity about which signals matter, which data streams require recalibration, and which patterns should guide subsequent monitoring efforts. Through iterative cycles of action and reflection, firms refine their sensing routines, improving the relevance and accuracy of digital intelligence. This feedback effect embodies the principle of “learning by doing,” offering a more realistic representation of how digital capabilities evolve in practice.

The significance of the DA and DMO path helps explain why firms with similar technological and sensing capabilities often diverge in capability maturity: those with stronger agility accumulate better learning over time and refine their sensing mechanisms more effectively.

Boundary Conditions: When Does the Capability Cascade Work Best?

Although the results support the hypothesized cascade, they also reveal boundary conditions that shape its effectiveness. These boundary conditions offer additional insight into when and why the capability relationships hold.

First, the non-significant ITC and SCI path suggests that technology alone does not promote innovation unless coupled with robust decision agility. Firms with advanced IT systems but bureaucratic decision structures may lack the ability to translate digital infrastructure into experimentation or co-creation. This boundary condition reinforces the importance of coupling ITC with agile processes.

Second, the weak DMO and performance effect highlights that digital sensing provides limited value without cross functional alignment. In firms where decision bottlenecks, cultural resistance, or siloed analytics functions impede action, sensing may not lead to improvement. DMO's value depends on integration with agility and innovation capabilities.

Third, industry level variation hints that the capability cascade behaves differently across operational contexts. Manufacturing firms showed a stronger DMO and DA effect, suggesting that complex, asset heavy environments may benefit more from digital sensing. In contrast, service firms displayed a stronger DA and performance relationship, reflecting their higher dependence on responsiveness and customer facing interactions.

Fourth, organizational structure may moderate the cascade. Firms with rigid hierarchies, centralized decision making, or low cross functional coordination may be less able to convert sensing into agility and innovation.

These boundary conditions do not weaken the capability cascade; rather, they clarify the contextual environments in which it is most effective.

Integrating the Findings into a Relational Capability Framework

Taken together, the findings confirm that digital transformation is best understood as a relational, iterative capability system. ITC forms the technological foundation; DMO processes this information into meaningful insights; DA enables organizations to act swiftly and experiment effectively; and SCI embeds these actions into enhanced routines and technologies. The cyclical feedback from agility to sensing highlights how capability systems evolve dynamically rather than sequentially. Furthermore, process improvement initiatives should be closely integrated with digital transformation efforts. When these two elements are aligned, organizations can enhance supply chain resilience, reduce operational risks, and respond more rapidly to disruptions. This integration highlights the importance of considering both technological and procedural changes together rather than in isolation.

This integrated framework enriches existing digital transformation research by providing a more holistic, empirically validated model that captures the interconnectedness of sensing, acting, and learning processes. Rather than treating capabilities as discrete constructs, the framework shows how capabilities reinforce each other and how performance emerges from the interplay of technological, analytical, behavioral, and collaborative routines.

Implications for Practice

The findings provide several practical guidelines for managers seeking to strengthen digital transformation efforts. First, firms should prioritize coordinated capability building, recognizing that IT investments alone will not generate returns without complementary sensing, agility, and innovation routines. This calls for cross functional digital strategy teams that integrate IT, marketing, operations, and supply chain perspectives.

Second, organizations should cultivate agile decision structures to accelerate the translation of digital insights into action. This may require redesigning workflows, decentralizing decision authority, and implementing rapid response mechanisms.

Third, firms should embed collaborative innovation practices into supply chain relationships. Because SCI is the primary driver of performance, organizations need governance mechanisms, shared digital platforms, and partner engagement models that support joint experimentation.

Fourth, leaders should institutionalize feedback learning disciplines. Post implementation reviews of agile actions can reveal which digital signals were most accurate, which metrics need refinement, and where sensing processes should be recalibrated.

Finally, firms should evaluate their digital maturity not only through the strength of individual capabilities but through the coherence of their capability system. Capability gaps such as strong sensing but weak agility should be identified and addressed strategically.

Key Contributions

This study advances theory by demonstrating that digital transformation is not a linear process but a cyclical one driven by feedback learning and relational capability interactions. It provides empirical evidence that sensing, acting, and innovating operate as mutually reinforcing components of a dynamic capability system. For managers, the findings highlight the necessity of orchestrating capabilities rather than building them in isolation.

CONCLUSION AND LIMITATIONS

CONCLUSION

This study set out to examine how digitally enabled capabilities interact to shape organizational performance in B2B environments undergoing rapid digital transformation. By integrating information technology capability, digital market orientation, digital agility, and supply chain innovation into a unified relational capability cascade, the research offers a comprehensive explanation of how sensing, acting, and innovating collectively drive performance outcomes. Rather than viewing digital transformation as a linear, technology driven process, the findings highlight that it unfolds through an interconnected and iterative system of capabilities that span technological, analytical, behavioral, and collaborative domains. The results show that ITC serves as the technological foundation upon which advanced sensing routines are built. Firms with stronger ITC exhibit greater capacity to capture and disseminate digital market signals, enabling more accurate and timely market orientation in digital ecosystems. However, technology alone is not sufficient. DMO must be complemented by agility to translate sensing into effective action. Indeed, the study finds that Digital Agility is the central bridging capability: firms that sense well but cannot act quickly fail to unlock the value of their digital intelligence. Agility allows firms to rapidly process information, reconfigure workflows, coordinate across functions, and initiate experimentation behaviors that are critical for navigating turbulent digital environments.

To support practical implementation, firms can take several specific steps. First, they can strengthen digital agility by delegating routine decision authority and enabling real-time coordination among marketing, operations, and IT units. Second, organizations can enhance collaborative innovation by establishing shared digital workspaces, integrated dashboards, or co-development mechanisms with key partners. Third, firms can institutionalize brief post-action learning reviews, allowing teams to refine sensing indicators based on what proved informative during rapid responses.

Supply Chain Innovation emerges as the transformative capability that embeds agile responses into lasting improvements. By jointly adopting or developing new digital technologies and processes with partners, firms convert insights and actions into durable operational and strategic advantages. In this way, SCI functions as the conduit through which upstream sensing and acting capabilities generate measurable performance outcomes. The finding that SCI has the strongest direct effect on organizational performance underscores its role as the anchor capability in digital transformation.

A distinctive theoretical contribution of this study lies in the validation of a feedback learning mechanism, wherein agility enhances subsequent sensing. This reciprocal effect challenges the traditional dynamic capability assumption that sensing precedes acting. Instead, the evidence shows that acting can refine sensing by helping firms discover which data streams matter most, which patterns were misleading, and which environmental cues warrant closer monitoring in the future. These findings position digital

transformation as a cyclical, iterative process rather than a sequential one, reinforcing emerging arguments that firms learn by doing in digital environments (Yu et al., 2025).

Taken together, these insights contribute to a more nuanced and realistic understanding of digital transformation within B2B ecosystems. They demonstrate that performance improvement depends not on any single capability but on the alignment and interaction of multiple capabilities operating across organizational and inter organizational boundaries. This relational and iterative perspective offers a promising avenue for advancing digital transformation theory and provides a more accurate blueprint for practitioners seeking to orchestrate digital capabilities effectively.

Limitations and Future Research Directions

Although the study produces valuable insights, several limitations must be acknowledged. These limitations also highlight opportunities for future research that can deepen understanding of how digital capabilities evolve and interact over time.

The first limitation concerns the cross-sectional research design. While cross sectional data allow for the examination of structural relationships among capabilities, they do not capture how these relationships evolve or how feedback learning patterns play out over multiple cycles of sensing and acting. Future research should adopt longitudinal or time lagged designs to trace how agility driven learning accumulates and influences subsequent rounds of market orientation and innovation. Such studies could also explore whether the feedback loop strengthens, weakens, or varies across different stages of digital transformation. The second limitation involves the reliance on perceptual, self reported measures. Although perceptual measures are common in strategic capability research and appropriate for capturing internal practices, they may introduce potential biases related to optimism, memory recall, or respondent role. Researchers can build on this study by incorporating objective performance indicators, such as operational efficiency metrics, innovation outputs, customer retention data, or digital adoption indices. Mixed method designs that combine quantitative surveys with interviews, digital trace data, or archival indicators would provide a more holistic view of capability interactions.

Third, the empirical context Canadian B2B firms presents both strengths and constraints. Canada's digitally mature economy offers a fertile ground for observing advanced digital practices, yet the findings may not fully generalize to emerging economies, highly regulated environments, or platform centric industries. Future studies could replicate this model across different national contexts to test whether the relational capability cascade behaves similarly in countries with lower digital infrastructure, more fragmented supply chains, or distinct institutional pressures. Cross country comparative studies would provide deeper insight into contextual moderators of digital capability development.

Fourth, while the study focuses on five core capabilities, it does not incorporate ecosystem level variables such as digital platform governance, data interoperability standards, regulatory frameworks, or trust across supply chain partners. These factors likely influence how capabilities unfold and interact, especially in multi stakeholder environments. Future research should integrate ecosystem characteristics to examine how external digital infrastructures shape the internal and relational capabilities of firms. Understanding how firm level routines interact with ecosystem level architectures would further enrich theoretical explanations of digital transformation.

Fifth, the model does not differentiate between types of digital innovation. Supply chain innovation encompasses a broad range of activities, including process redesign, technology adoption, collaborative development, and data sharing mechanisms. Future studies could unpack these dimensions to examine whether certain types of innovation (e.g., analytics driven innovation vs. process automation) are more effective in translating digital sensing and agility into performance.

Finally, further research should explore the micro foundations of digital capabilities by examining how individual behaviors, leadership styles, and team level dynamics contribute to sensing, acting, and innovating. Qualitative and case-based research would be especially valuable for uncovering how managers interpret digital signals, coordinate agile responses, and institutionalize learning across organizational layers. Integrating micro level insights with system level analyses would provide a more complete and multi level understanding of digital capability development.

Future research could explore how organizational culture influences the effectiveness of DMO and ITC in different industries. Understanding the role of cultural factors in digital adoption and knowledge sharing

can provide deeper insights into the conditions under which these mechanisms maximize organizational performance. Such studies would offer valuable guidance for managers seeking to implement these strategies in diverse organizational contexts.

Despite these limitations, this study provides a robust and theoretically grounded framework for understanding how digital capabilities interact to support organizational performance in B2B environments. By demonstrating the importance of relational capability configuration and iterative learning, the research offers a foundation for both scholars and practitioners to rethink how digital transformation unfolds in practice and how organizations can better orchestrate digital capabilities to achieve sustainable competitive advantage.

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APPENDIX A — MEASUREMENT SCALES

(All items measured on 5-point Likert scales; standardized loadings shown in parentheses.)

Information Technology Capability

Sources: Grego et al. (2025); (Chae et al., 2018)

- Integrates real time data across departments and partner interfaces. (0.82)
- Supports decision making for internal and external stakeholders. (0.78)
- Enables smooth data exchange with suppliers and customers. (0.74)
- Enhances coordination across the entire supply network. (0.81)

Digital Market Orientation

Sources: Hofacker et al. (2020); (Paşcalău et al., 2024)

- Uses analytics to anticipate needs of partners and customers. (0.83)
- Continuously monitors digital data across the supply chain. (0.79)
- Shares market insights rapidly across departments. (0.66)
- Acts promptly on real time information. (0.73)
- Uses digital feedback to refine decisions. (0.68)
- Collaborates with partners via shared dashboards. (0.84)

Digital Agility

Sources: Dobrovnik et al. (2025); Abourokbah et al. (2023)

- Detects early signals of market or partner changes. (0.80)
- Translates data insights into fast decisions. (0.77)
- Reconfigures workflows quickly when conditions shift. (0.65)
- Coordinates rapid implementation with partners. (0.82)
- Reviews responses to improve future decisions. (0.76)

Supply Chain Innovation

Sources: Yu et al. (2025); Ning and Yao (2023)

- Jointly implements digital solutions that improve efficiency. (0.78)
- Adopts new digital technologies with partners. (0.74)
- Co-develops digital practices for transparency. (0.79)
- Continuously refines operations through collaboration. (0.81)

Organizational Performance (OP)

Sources: Kohli and Jaworski (1990); Matysiak et al. (2018)

- Productivity exceeds comparable firms. (0.83)
- Customer satisfaction is higher than competitors. (0.80)
- Profitability exceeds industry averages. (0.77)
- Digital partnerships enhance customer retention. (0.69)
- Overall performance surpasses key competitors. (0.84)

APPENDIX B. Robustness and Diagnostic Tests

Table B1. Summary of Robustness and Diagnostic Tests

Diagnostic Category	Test / Indicator		Interpretation
Common-Method Variance (CMV)	Harman's Single-Factor Test	Largest factor = 30%	Below 50% threshold; CMV not a major issue
	Marker Variable Test	$\Delta R^2 = 0.014$	Non-significant; CMV unlikely
	Latent CMV Factor	No improvement in model fit	CMV does not distort structural paths
Multicollinearity	VIF (all constructs)	< 3.0	No multicollinearity concerns
Alternative Models	Parallel Mediation	Worse fit vs. final model	Not supported
	Direct Only Model	Unacceptable fit	Not supported
	Model Without Feedback Path	Lower fit	Confirms necessity of DA → DMO feedback
	Proposed Final Model	Best fit	Supported
Multi Group SEM	DMO → DA	Stronger in manufacturing	Data rich settings benefit more from sensing
	DA → OP	Stronger in services	Service firms rely more on fast execution
	Firm Size Effects	No major differences	Model stable across sizes
Endogeneity Tests	Reciprocal Path Distortion	None detected	Endogeneity not a concern
	Residual Patterns	No abnormalities	Model properly specified
Additional Robustness	Sensitivity Analysis	Stable parameters	Model robust
	Bootstrapped SE Stability	Stable SEs	Estimates reliable

APPENDIX C — ADDITIONAL MODEL OUTPUTS

Standardized Factor Loadings (Complete)

ITC: 0.82, 0.78, 0.74, 0.81

DMO: 0.83, 0.79, 0.66, 0.73, 0.68, 0.84

DA: 0.80, 0.77, 0.65, 0.82, 0.76

SCI: 0.78, 0.74, 0.79, 0.81

OP: 0.83, 0.80, 0.77, 0.69, 0.84

Model Fit Summary

$\chi^2/df = 2.21$

CFI = 0.93

TLI = 0.91

RMSEA = 0.057

SRMR = 0.047

Residual Structure Notes

- DMO error terms e2–e4 correlated to improve fit.
- DA → DMO feedback path improved model fit and theoretical alignment

Table C1. Fornell–Larcker Matrix (Square Root of AVE on Diagonal)

Construct	ITC	DMO	DA	SCI	OP
ITC	0.79				
DMO	0.58	0.70			
DA	0.54	0.63	0.78		
SCI	0.44	0.51	0.58	0.77	

OP	0.41	0.49	0.53	0.61	0.80
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Table C2. HTMT Ratios

Construct Pair	HTMT
ITC – DMO	0.73
ITC – DA	0.69
ITC – SCI	0.55
DMO – DA	0.81
DMO – SCI	0.76
DA – SCI	0.79
SCI – OP	0.83
DA – OP	0.72
DMO – OP	0.67

All HTMT values < 0.90 → discriminant validity achieved.

Table C3. CMV Robustness Tests

Diagnostic Category	Test	Value	Decision Rule	Conclusion
Harman's Single-Factor Test	Largest factor	30%	< 50%	CMV not a concern
Marker Variable Test	ΔR^2	0.014	< 0.05 & non-significant	CMV not inflating results
Latent CMV Method Factor	Model fit change	$\Delta CFI = 0.002$	< 0.01	No CMV distortion
Full Collinearity VIF	Max VIF	2.41	< 3.3	No multicollinearity