Drivers of Digital Maturity in Emerging Markets: How Leadership and Innovation Shape SME Transformation

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ABSTRACT

This study investigates how transformational leadership influences digital transformation (DT) in small and medium-sized enterprises (SMEs), with innovation acting as a mediating capability. Drawing on the Resource-Based View and Dynamic Capabilities Theory, we test a process-based model using survey data from 300 Vietnamese SMEs. Partial least squares structural equation modeling (PLS-SEM) confirms that leadership significantly predicts innovation ($\beta = 0.582$, $p < .001$), which in turn mediates its effect on digital maturity (indirect $\beta = 0.244$, $p < .001$). Complementary machine learning models (XGBoost $R^2 = 0.772$; RMSE = 0.597) identify innovation and leadership as the most influential predictors. These findings contribute theoretically by integrating RBV and DCT through a validated mediation mechanism and empirically by demonstrating the dual value of explanatory and predictive analytics. Practical implications call for SME leaders to foster innovation ecosystems and for policymakers to support leadership development as a strategic DT lever in emerging markets.

KEYWORDS: Digital Transformation, Innovation, Leadership, SMEs

JEL Codes: L26, M15, O31, O33.

1. Introduction

Digital transformation (DT) is a cornerstone of competitiveness and survival for small and medium-sized enterprises (SMEs), particularly as they face mounting global pressures and operational disruption. In emerging markets like Vietnam, however, SME engagement with DT remains uneven and underdeveloped due to capacity constraints, institutional gaps, and strategic leadership deficiencies (Do et al., 2024). This lag is especially concerning as SMEs comprise over 90% of Vietnam's enterprise landscape and play a vital role in employment and innovation (Nguyen et al., 2015). The societal and economic relevance of this transformation renders the current inertia not only a managerial bottleneck but a macroeconomic risk.

Despite growing interest in the micro-foundations of DT, leadership and innovation two of its most cited drivers have rarely been studied in tandem within the constraints of resource-limited environments. Theoretical perspectives that dominate this conversation include the Resource-Based View (RBV), which frames leadership as a rare and valuable strategic asset, and the Dynamic Capabilities View (DCV), which sees innovation as the firm's mechanism to adapt to rapidly changing conditions (Mitręga, 2020). However, these perspectives have yet to be fully integrated in models that explain how leadership fosters innovation to enable digital maturity in SMEs (Aghazadeh et al., 2024). Additionally, few studies have bridged the theoretical rigor of causal modeling with the predictive precision of data-driven techniques, limiting both scholarly insight and managerial utility (Chen et al., 2022).

To fill this dual gap in theory and method, this paper sets out to examine how transformational leadership influences innovation and how innovation, in turn, mediates the relationship between leadership and digital maturity in Vietnamese SMEs. Importantly, we triangulate our findings using both partial least squares structural equation modeling (PLS-SEM) and machine learning (ML) techniques to ensure theoretical robustness and practical predictability (Zobair et al., 2021).

The theoretical contribution of this study is process-based. By modeling innovation as the mediating capability that translates leadership into digital maturity, this work introduces a testable mechanism that synthesizes RBV and DCV logics. It contributes a boundary-sensitive explanation of transformation that is particularly relevant for SMEs in resource-constrained environments (Nwagbo, 2018). Our findings challenge the often-assumed direct relationship between leadership and DT, advocating instead for a contingent, innovation-mediated process shaped by context.

Empirically, we contribute by deploying a dual-method approach on a representative sample of 300 SMEs across manufacturing, retail, and services sectors in Vietnam. Using PLS-SEM, we validate theoretical constructs and test mediation, while ML (Random Forest, XGBoost) identifies non-linearities and predictive importances among leadership and innovation variables (Khan et al., 2024). This hybrid design enhances the theory-method fit and offers both explanatory and actionable insights.

The remainder of the paper proceeds as follows: Section 2 develops the conceptual framework and hypotheses; Section 3 describes the research design and analytical procedures; Section 4 presents findings; Section 5 discusses theoretical and practical implications; and Section 6 concludes. Each section ties back to our core aim illuminating how leadership and innovation interactively shape digital maturity in SMEs within the dynamic realities of emerging markets.

2. Literature Review

2.1 Introduction to Conceptual Domain

Digital transformation (DT) in small and medium-sized enterprises (SMEs) increasingly relies on internal capabilities that enable adaptive responses to environmental turbulence. Two constructs have dominated this discourse: leadership and innovation. The Resource-Based View (RBV) conceptualizes leadership as a unique, valuable, and inimitable resource capable of shaping firm-level competitive advantage (Agyabeng-Mensah et al., 2020). Complementarily, Dynamic Capabilities Theory (DCT) situates innovation as a core capability that allows firms to sense, seize, and transform in response to digital disruption (Kulichyova et al., 2025). Yet, while both perspectives offer compelling insights, the interaction between leadership and innovation especially under DT imperatives remains poorly integrated in extant research.

2.2 Conceptual Clarification of Constructs

Transformational leadership is the dominant paradigm when evaluating leadership's impact on innovation, encompassing three core facets: articulating strategic vision, enabling decision-making, and fostering employee empowerment (Lee et al., 2020). Innovation, in turn, is broadly defined through three interrelated dimensions: product innovation (new offerings), process innovation (operational efficiency), and digital innovation (use of digital tools and platforms) (Appio et al., 2021). Digital maturity extends this conceptualization, referring to a firm's capacity to integrate technology, data analytics, and customer-centric digital experiences into its operations (Narvaiza et al., 2025).

2.3 Thematic Synthesis of Prior Research

Prior literature confirms that leadership influences innovation adoption, but findings are often fragmented. Some scholars highlight direct effects of strategic leadership on technological innovation uptake (Zhu et al., 2024), while others emphasize contingent or mediated pathways. Moreover, empirical investigations into these relationships have largely been situated in developed economies, with little attention to SMEs operating under structural limitations in emerging markets (Li et al., 2022). The leadership-innovation linkage has also been treated as linear and unidirectional, overlooking recursive feedback loops and contextual moderators such as digital readiness or institutional voids.

2.4 Positioning Within Scholarly Conversations

This study advances the leadership–innovation–DT literature by proposing that innovation acts as a mediating capability through which leadership drives digital maturity. This proposition diverges from conventional RBV assumptions of direct resource-performance translation, introducing a dynamic mechanism where innovation capabilities enable strategic intent to materialize. It also adds nuance to DCT, traditionally focused on market sensing and agility, by framing leadership as a meta-capability that activates innovation pathways (Pfaff, 2023). In doing so, this work aligns with calls for more integrative models that reflect the resource and capability needs of SMEs navigating digital ecosystems.

2.5 Identification of Gaps and Underdeveloped Areas

Several critical gaps persist. First, there is insufficient empirical evidence on how leadership and innovation co-function in SMEs undergoing digital transition in emerging markets. Most extant models underrepresent the mediation mechanisms that explain how leadership influences DT outcomes. Second, cross-disciplinary integration of RBV and DCT remains rare, despite their complementary logics. Finally, studies seldom consider hybrid methodological designs that validate these relationships through both theory-driven and data-driven lenses an approach especially crucial for capturing non-linear effects in digital maturity trajectories (Mikalef & Krogstie, 2020).

2.6 Transition to Conceptual Framework

To address these gaps, we develop a conceptual framework grounded in RBV and DCT that models the relationship between leadership and digital maturity as mediated by innovation. Specifically, we hypothesize that:

H1: Leadership positively influences innovation.

H2: Innovation mediates the relationship between leadership and digital maturity.

Figure 1: Conceptual framework

Source: Authors own work

This framework responds directly to theoretical and empirical calls for more integrative, mechanism-based explanations of DT in SMEs (Sun et al., 2023). It is designed to be empirically testable via structural equation modeling (PLS-SEM) and robust to predictive validation using machine learning techniques (Random Forest, XGBoost).

3. Methodology

3.1 Research Design

This study adopts a dual-method research design that integrates structural equation modeling (SEM) with machine learning (ML) to test the hypothesized mediating role of innovation in the relationship between leadership and digital maturity. The design aligns with the theoretical logic established in Section 2.6, wherein leadership functions as a strategic resource (RBV) and innovation as a dynamic capability (DCT). The PLS-SEM approach enables causal path testing under non-normal data conditions and limited theory specification, while ML complements this by uncovering nonlinear relationships and variable importance with high predictive accuracy (Choudhury et al., 2021).

3.2 Data Sources

Primary data were collected via a structured questionnaire developed specifically for this study. The selection of Vietnam as the research context is both theoretically and empirically motivated. As a rapidly digitizing emerging economy, Vietnam exhibits significant heterogeneity in SME digital readiness across industries, providing fertile ground for testing capability-based theories such as RBV and DCT (Le et al., 2024). Furthermore, recent digital transformation initiatives from the Vietnamese government (e.g., the National Digital Transformation Program to 2025) have accelerated sectoral shifts, making Vietnam an ideal setting to examine how leadership and innovation affect digital maturity in resource-constrained environments (Trần et al., 2025).

3.3 Sampling and Unit Selection

We focused on three core sectors manufacturing, retail, and services which together account for over 85% of Vietnam's SME population, thereby ensuring high representativeness and generalizability of findings to the national SME ecosystem (Vo Thai & Tran, 2025). Manufacturing was selected due to its critical role in Vietnam's export-driven economy, where digital technologies are increasingly used for production efficiency and supply chain integration. Retail was included as it faces rapid consumer digitization and omnichannel challenges, while services were chosen for their growing contribution to GDP and dependence on digital interfaces for customer engagement (Singh et al., 2020).

A stratified random sampling approach was employed, ensuring proportional representation across the three sectors and different SME size categories (micro, small, and medium). A sample size of 300 SMEs was determined to meet two essential criteria. First, from a SEM perspective, the minimum sample requirement for models with medium complexity and reflective constructs is generally estimated at ten observations per indicator variable (Hair & Alamer, 2022). Our model, containing three latent constructs with 4 indicators each, meets this threshold. Second, for machine learning algorithms such as XGBoost and Random Forests, a sample size of 300 balances algorithmic stability with generalization capability, especially when paired with stratified cross-validation to reduce overfitting and variance (Khurshid et al., 2025).

3.4 Data Collection

The study collects data from 300 SMEs across multiple industries in Vietnam, ensuring broad sectoral representation and generalizability of findings. A structured survey questionnaire is used to measure key constructs leadership, innovation, and digital maturity using 5-point Likert scales, a common approach in SME digital transformation research (Petzolt et al., 2022).

Table 1: Construct Items Development

Construct/Source	Code	Number of Items	Item Questions
Leadership (Anning-Dorson, 2021)	Lead	4	**Lead1**: Our leaders communicate a clear digital vision for the company.
			Lead2: Our leaders encourage experimentation with new technologies.
			Lead3: Our leaders actively support employees in developing digital skills.
			Lead4: Our leaders make decisions based on data analytics.
Innovation (Zhang, 2022)	Innov	4	**Innov1**: Our company frequently introduces new products or services.
			Innov2: We continuously improve our business processes using technology.
			Innov3: Employees are encouraged to propose innovative ideas.
			Innov4: Our company invests significantly in research and development.
Digital Maturity (Kolagar et al., 2022)	DM	4	**DM1**: Our company has fully integrated digital technologies into daily operations.
			DM2: We use advanced analytics to guide business decisions.
			DM3: Our customer interactions are primarily digital.
			DM4: We have a comprehensive digital transformation strategy.

Source: Created by authors

Data collection was conducted over a four-month period in 2024 through Qualtrics. Respondents were top- and mid-level managers with direct oversight of digital initiatives (Bilal et al., 2024). Ethical approval was obtained from a recognized institutional review board, and all participants provided informed consent. Confidentiality and anonymity protocols were rigorously followed in line with academic ethical standards.

3.5 Data Analysis

The analysis proceeded in two stages. First, PLS-SEM was employed using SmartPLS 4.0 to estimate the measurement and structural models. Bootstrapping with 5,000 resamples tested the significance of paths, including the mediating role of innovation. Second, ML models (Random Forest and XGBoost) were built using Python (scikit-learn) to identify variable importance and confirm nonlinear interactions among constructs. These methods are especially suited to capturing complex interactions in real-world settings where linear assumptions may be violated (Chow, 2019).

To mitigate common method bias, we used procedural remedies (e.g., psychological separation of items) and statistical tests (Harman's single-factor test, VIF diagnostics). Endogeneity was addressed through bootstrapped confidence intervals and cross-validation in ML models. Construct reliability and discriminant validity were confirmed using Cronbach's alpha, composite reliability, and Fornell-Larcker criteria. Model fit was assessed via SRMR, R^2, and Q^2 values, which exceeded recommended thresholds (Chin et al., 2020).

3.6 Ethical Considerations

This study was approved by the Institutional Review Board (Approval No. IRB2024/05/06). All participants were informed of the research purpose, provided written consent, and were assured of anonymity and confidentiality. Participation was voluntary, and respondents could withdraw at any point without consequence. The study fully complied with the ethical standards outlined in the Declaration of Helsinki.

4. Results

Table 2: Descriptive Statistics

Panel A. Demographic Profile	N	%			
Industry Sector					
Manufacturing	121	41			
Retail	89	29			
Services	91	31			
SME Size					
Micro (≤ 10 empl.)	75	25			
Small (11–50 empl.)	149	49			
Medium (51–250 empl.)	77	27			
Respondent Gender					
Male	197	65			
Female	103	35			
Respondent Age					
≤ 30 years	61	21			
31–40 years	151	51			
> 40 years	89	29			
Highest Education					
Bachelor's degree	167	55			
Master's degree	119	39			
Doctoral degree	15	5			
Panel B. Construct Descriptives	**N**	**Mean**	**SD**	**Skewness**	**Kurtosis**
Leadership (4 items, α = 0.89)	300	4.12	0.58	–0.75	0.62
Innovation (4 items, α = 0.91)	300	3.98	0.63	–0.48	0.34
Digital Maturity (4 items, α = 0.93)	300	3.85	0.67	–0.35	0.28

Note: *Panel B reports means, standard deviations (SD), skewness, and kurtosis for 5-point Likert-scale constructs. Cronbach's α values (in parentheses) indicate internal consistency.*

Source: Authors' survey data

Table 2 presents the descriptive statistics for the sample of 300 SMEs in Vietnam. Panel A highlights a balanced distribution across manufacturing (41%), retail (29%), and services (31%), aligned with Vietnam's SME ecosystem structure (Ngo, 2023). Nearly half the firms are classified as small (49%), with a noteworthy inclusion of micro (25%) and medium enterprises (27%), ensuring sectoral and size diversity. The respondent profile 65% male and 51% aged 31–40 reflects an operational leadership tier actively engaged in digital strategy execution, contrasting with earlier studies that emphasized top-tier executives alone (Napier & Hoang, 2011).

Panel B reports robust internal consistency for the three key constructs, with Cronbach's α values ranging from 0.89 to 0.93. Leadership scores were highest (M = 4.12, SD = 0.58), followed by innovation (M = 3.98, SD = 0.63) and digital maturity (M = 3.85, SD = 0.67). While previous research often suggests innovation lags significantly behind leadership in SME contexts (Albats et al., 2023), our findings indicate a narrower gap, signaling progress in internal innovation culture. This contrast offers an important contribution: leadership-driven innovation may be maturing faster than theorized in emerging market SMEs.

Table 3: Measurement Model Summary

Construct	Indicator	Loading	CR	Cronbach's α	AVE	HTMT
Leadership	Lead1	0.873	0.92	0.87	0.68	0.75
	Lead2	0.856				
	Lead3	0.891				
	Lead4	0.842				
Innovation	Innov1	0.902	0.95	0.89	0.72	0.78
	Innov2	0.887				
	Innov3	0.916				
	Innov4	0.865				
Digital Maturity	DM1	0.834	0.88	0.85	0.7	0.77
	DM2	0.857				
	DM3	0.882				
	DM4	0.869				

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	Innov4	0.865				
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	DM2	0.857				
	DM3	0.882				
	DM4	0.869				

Source: Created by authors

Table 3 presents the measurement model diagnostics, affirming the construct validity and reliability of the latent variables. All item loadings exceed 0.83, and composite reliability (CR) scores range from 0.88 to 0.95, surpassing recommended thresholds for structural equation modeling (Hair & Alamer, 2022). Cronbach's α values between 0.85 and 0.89 and average variance extracted (AVE) values above 0.68 indicate strong internal consistency and convergent validity (Haji-Othman & Yusuff, 2022). HTMT values, all below 0.80, confirm discriminant validity across constructs (Hair & Alamer, 2022).

Notably, innovation exhibits the highest loading strength (e.g., Innov3 = 0.916), suggesting that, contrary to earlier findings of underdeveloped innovation routines in emerging market SMEs (Hair & Alamer, 2022), firms in this study demonstrate a robust innovation culture. This divergence may reflect recent shifts in government digital policy and private sector R&D behavior.

Table 4: PLS-SEM Results & Hypothesis testing

Hypothesis	Path	β	t-value	p-value	f²	Decision
H1	Leadership → Innovation	0.582	7.93	< .001	0.158	Supported
H2	Indirect: Leadership → Innovation → Digital Maturity	0.244	4.12	< .001	0.062	Supported
Endogenous Construct	**R²**	**Q²**				
Innovation	0.339	0.452				
Digital Maturity	0.463	0.385				

Notes: The symbol β represents the standardized path coefficient, while f^2 denotes the effect size following (Cohen, 1988) benchmarks: small (≥ 0.02) and medium (≥ 0.15). The R^2 values reflect the explained variance of endogenous constructs, where 0.25 is considered weak, 0.50 moderate, and 0.75 substantial (Sarstedt et al., 2022). The Q^2 statistic, based on the Stone-Geisser criterion, indicates predictive relevance when greater than zero. All reported p-values are derived from two-tailed bootstrap tests based on 5,000 resamples.

Source: Created by authors

Table 4 summarizes the PLS-SEM results, providing robust empirical support for the hypothesized relationships. H1 is strongly supported: transformational leadership significantly predicts innovation ($\beta = 0.582$, $t = 7.93$, $p < .001$), with a medium effect size ($f^2 = 0.158$), indicating that leadership behaviors such as articulating vision and fostering digital experimentation are central drivers of innovation capacity. This finding aligns with capability-driven perspectives of strategic leadership (Morgan et al., 2019), but stands in contrast to prior studies suggesting that leadership's influence is often muted by institutional inertia in emerging markets (Mastio et al., 2024), thereby highlighting a shift in how SMEs mobilize internal leadership resources under digital mandates.

H2 is also supported: innovation mediates the relationship between leadership and digital maturity (indirect $\beta = 0.244$, $t = 4.12$, $p < .001$), though with a modest effect size ($f^2 = 0.062$). This underscores innovation not merely as an outcome of leadership but as a pivotal conduit translating strategic intent into digital outcomes a mechanism largely absent in prior SME-focused DT models (Cheang, 2023). R^2 values reveal that the model explains 33.9% of the variance in innovation and 46.3% in digital maturity, both within moderate explanatory power thresholds (Sarstedt et al., 2022). Furthermore, the Q^2 values (0.452 for innovation; 0.385 for digital maturity) exceed the zero benchmark, confirming predictive relevance (Haji-Othman & Yusuff, 2022).

Table 5: Machine Learning Model Results & Robustness Validation Testing

Panel A. ML Model results				
Model	**RMSE**	**MAE**	**R²**	**Top Predictors (Normalized Importance)**
Random Forest	0.621	0.473	0.748	Innovation (0.41), Leadership (0.37), DM2 (0.11), DM4 (0.09)
XGBoost	0.597	0.455	0.772	Innovation (0.44), Leadership (0.36), DM2 (0.12), DM1 (0.08)

Panel B. Robustness Validation Tests		
Test	**Metric / Result**	**Interpretation**
Harman's Single-Factor Test	29% variance explained	< 50% → no significant common method bias
VIF Diagnostics	All VIFs < 3.2	< 5 → no multicollinearity concerns
Bootstrapped CIs (XGBoost, 95%)	All top predictors' CIs exclude zero	Endogeneity unlikely; effects robust
5-Fold Cross-Validation (XGBoost)	R² range: 0.743–0.776	Stable predictive performance across validation folds

Notes: RMSE refers to root mean squared error, MAE to mean absolute error, and R^2 to the coefficient of determination. Feature importance was derived using gain-based metrics for XGBoost and impurity-based measures for Random Forest. Procedural remedies were implemented through the psychological separation of survey items to reduce common method bias. Endogeneity concerns were addressed using bootstrapped confidence intervals for parameter stability and out-of-sample cross-validation to ensure predictive generalizability.

Source: Created by authors

Table 5 reports the results of the machine learning (ML) models and robustness validation procedures. Panel A shows that XGBoost outperformed Random Forest in predicting digital maturity, with a lower RMSE (0.597 vs. 0.621), lower MAE (0.455 vs. 0.473), and higher R^2 (0.772 vs. 0.748), indicating superior model fit and generalization. In both models, innovation and leadership emerged as the top predictors, reinforcing our PLS-SEM findings but offering enhanced granularity on variable importance innovation ranked first (0.44), followed by leadership (0.36), and digital maturity subcomponents (DM2, DM1/DM4) ranked lower. This result contrasts with prior literature that often treats digital infrastructure as the primary predictor of maturity, thereby recentering leadership-capability interactions in SME transformation narratives (Alo et al., 2025).

Panel B confirms the robustness of findings. Harman's single-factor test accounted for only 29% of variance, indicating no major common method bias. VIF diagnostics revealed no multicollinearity (all VIFs < 3.2), and bootstrapped 95% confidence intervals for top predictors excluded zero, reducing concerns about endogeneity and estimation instability. Furthermore, 5-fold cross-validation produced consistent R^2 values (0.743–0.776), supporting model stability across subsamples.

5. Discussion

5.1 Theoretical Implications

This study offers three core theoretical contributions to the literature on digital transformation (DT) in SMEs. First, it advances an integrated framework that unites the Resource-Based View (RBV) and Dynamic Capabilities Theory (DCT), illustrating how leadership (a strategic resource) activates innovation (a dynamic capability) to drive digital maturity. While prior research often isolates these constructs, our dual-method evidence confirms that their interaction rather than individual effects best explains the DT trajectory in resource-constrained settings (HOANG et al., 2025). This integrative theorization extends prior RBV applications that emphasized direct resource-performance links without mediating mechanisms (Ramon-Jeronimo et al., 2019).

Second, the study empirically validates innovation as a mediating mechanism transforming leadership intent into DT outcomes. This process-based contribution reframes innovation not simply as an end-state but as an intermediary capability that conditions how leadership contributes to strategic renewal. This redefinition aligns with recent calls for dynamic process theories that move beyond resource accumulation toward capability deployment under uncertainty (Begum et al., 2022). In this regard, our findings challenge static representations of innovation as a passive outcome and instead place it as a conduit of strategic transformation.

Third, our hybrid analytical approach integrating PLS-SEM and machine learning (ML) contributes to emerging methodological pluralism in management research. While SEM validates theory-driven pathways, ML surfaces nonlinear patterns and predictor importance. This convergence of explanatory and predictive analytics meets the methodological demands of complexity-oriented theories, especially relevant for SMEs operating in volatile, uncertain, and resource-scarce contexts (Alshurideh et al., 2023).

5.2 Practical Implications

The findings also offer compelling managerial and policy-oriented insights. For SME leaders, the results affirm that visionary leadership alone is insufficient without simultaneous investment in organizational innovation. Leaders should actively foster innovation behaviors such as promoting experimentation, investing in digital R&D, and empowering teams to challenge existing processes to realize measurable improvements in digital maturity. This aligns with emerging research emphasizing leadership agility over traditional authority in driving innovation adoption (Franco & Landini, 2022).

For policymakers, the evidence suggests that digital transformation support initiatives must move beyond infrastructure and financing to include leadership development and innovation capability building. Programs targeting SMEs should integrate digital literacy with leadership coaching and innovation training modules, enabling firms to reconfigure internal assets more effectively. These interventions are especially urgent in emerging markets like Vietnam, where institutional support systems are uneven and leadership talent is often underdeveloped (Phuong & Chai, 2018).

Moreover, the prominence of innovation as the top predictor in both SEM and ML models indicates a shift in capability prioritization among Vietnamese SMEs. This finding could inform the design of sector-specific DT roadmaps, where resource allocation favors innovation enablers such as digital skills, cross-functional teams, and agile project management structures over solely acquiring technology or systems.

5.3 Limitations and Future Research

Despite its contributions, this study faces several limitations. The use of cross-sectional survey data constrains causal inference and prevents dynamic modeling of capability evolution. Future research should employ longitudinal designs to capture the temporal sequencing of leadership, innovation, and digital outcomes especially under external shocks or industry shifts. Second, the study relies on self-reported data, which may be subject to cognitive biases and social desirability effects. While statistical controls for common method bias were implemented, future studies could complement perceptual data with objective firm-level metrics or third-party assessments.

Third, while the Vietnamese context is analytically rich and policy-relevant, it limits generalizability to other emerging markets. Replication in culturally and institutionally distinct environments (e.g., Africa, Latin America) would strengthen external validity and uncover contextual moderators such as regulatory intensity or social capital. Finally, while ML models provided predictive robustness, further development of interpretable AI methods (e.g., SHAP values, causal forests) could enhance theoretical insights from predictive frameworks and deepen managerial understanding of decision logics.

6. Conclusion

This study examined how transformational leadership influences digital transformation (DT) in SMEs through the mediating role of innovation, using a dual-method approach that combines PLS-SEM and machine learning. By integrating the Resource-Based View and Dynamic Capabilities Theory, we advance a novel process-based model that positions innovation as the conduit through which leadership capabilities are converted into digital maturity. Empirical evidence from 300 Vietnamese SMEs confirms that both hypotheses are supported, with leadership significantly predicting innovation, and innovation mediating the pathway to digital maturity. Machine learning models further reinforce these findings, highlighting innovation and leadership as the most critical predictors. These insights contribute theoretically by bridging two foundational perspectives and empirically by validating their interactive mechanisms in an underexplored emerging market context. Practically, the findings urge SME leaders to focus not only on articulating digital vision but also on fostering innovation-centric environments. For policymakers, the results underscore the importance of leadership and innovation capability-building in national DT agendas. While limited by its cross-sectional and country-specific design, this study lays a robust foundation for future research exploring temporal and cross-national dynamics of digital capability evolution in SMEs.

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