

THE LINKAGE BETWEEN OPEN INNOVATION AND DIGITAL TRANSFORMATION IN VIETNAM

Quang Linh Huynh

Ho Chi Minh City University of Industry and Trade, Ho Chi Minh City, Viet Nam

Email: linhhq@huit.edu.vn

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ABSTRACT

This study investigates how open innovation contributes to digital transformation among publicly listed firms in Vietnam, a context characterized by limited resources and nascent digital capabilities. By enabling access to external knowledge and complementary assets, open innovation is expected to facilitate firms' digital capability development and organizational adaptability. Drawing on an integrated theoretical framework that combines open innovation theory, the resource-based view, and dynamic capabilities theory, this study analyzes survey data collected from 312 firms using partial least squares structural equation modeling (PLS-SEM). The data were collected over a 12-week period (October to December 2025) through online questionnaires distributed via Google Forms and Qualtrics. The findings provide robust empirical evidence that open innovation has a positive and significant effect on digital transformation. In contrast, firm size and industry type do not significantly moderate this relationship. This research contributes to literature by empirically bridging open innovation and digital transformation within a unified framework, while highlighting the strategic role of external knowledge in enhancing digital capabilities in emerging market contexts.

Keywords: Open innovation, digital transformation, resource-based view, dynamic capabilities, emerging markets, Vietnam.

1. INTRODUCTION

Open innovation (OI) refers to the purposive inflows and outflows of knowledge across organizational boundaries to improve innovation performance, technological capabilities, and develop market opportunities [1], [2], [3]. By collaborating with external institutions such as universities, startups, customers, and suppliers, firms can access complementary knowledge, alleviate internal R&D constraints, and speed up process innovation and accelerate products and services [4], [5]. Despite the great focus of research on OI literature has grown substantially in developed economies, empirical evidence remains heavily concentrated in Southeast Asia, with comparatively limited insight into how OI operates in emerging-market contexts [6], [7].

Vietnam provides a relevant empirical context for analyzing OI dynamics because of its rapid economic transformation and increasing commitment to digitalization, driven by national digital strategies and rising adoption of digital technologies among firms [8], [9]. However, numerous Vietnamese firms despite operating in increasingly competitive and technology intensive environments continue to face limited internal R&D capacity, low levels of digital maturity, and constrained resources. Prior studies have suggested that such limitations may weaken firms' ability to translate innovation activities into tangible performance of organizational outcomes [10], [11]. In this context, OI represents a critical

strategic approach through which firms can leverage external knowledge to compensate for internal deficiencies [12], [13].

Digital transformation (DT) has emerged as a critical mechanism for converting external knowledge into value creation. DT integrates digital infrastructures and technologies, such as digital platforms, data analytics, automation systems, and digital business models, into organizational processes and structures [14], [15], [16]. Beyond technological adoption, while knowledge acquired through OI can enhance innovation capabilities and operational efficiency, DT enables firms to reconfigure organizational resources and deploy this externally sourced knowledge within their internal processes in response to environmental change, thereby strengthening organizational adaptability and technological capability [17], [18], [19]. From this perspective, externally sourced knowledge acquired through OI may not directly generate value unless firms possess the digital capabilities necessary to assimilate, recombine, and operationalize such knowledge. DT thus serves as a key mechanism that enables firms to internalize and exploit externally generated knowledge for organizational renewal and innovation.

Although both OI and DT have been extensively studied, much of the existing literature has treated them as parallel or outcome independent phenomena [20], [21], and empirical evidence explaining whether—and under what conditions—OI directly facilitates DT remains limited, especially in emerging markets [20], [21], [22], [23]. Furthermore, firm-specific characteristics, particularly firm size (FS) and industry type (IT), may influence how effectively firms integrate external knowledge into digital transformation initiatives. Firm size is associated with differences in organizational flexibility, resource availability, and decision-making speed, which may affect firms' ability to leverage external knowledge for digital transformation [24], [25].

Smaller firms can be more flexible and agile, so they may gain greater benefits from integrating external knowledge, while larger firms suffer structural inflexibility [24], [25]. Similarly, industry type (IT) may matter because service firms tend to be more knowledge- and customer-intensive, whereas manufacturing firms are often more capital-intensive and process-oriented potentially leading to heterogeneous OI–DT dynamics across industries [3], [26]. To address these gaps, this study investigates the association between open innovation (OI) and digital transformation (DT) using data from publicly listed firms in Vietnam. Specifically, it examines (1) The direct effect of OI on DT; (2) The moderating roles of firm size (FS) and industry type (IT). This research contributes to literature in three ways. First, it positions DT as a key organizational outcome of OI, rather than merely a parallel strategic orientation. Second, it provides empirical evidence from an emerging-market context characterized by rapid digitalization but uneven innovation capabilities, thereby extending prior findings largely based on developed economies. Third, it also examines the contextual roles of FS and IT boundary conditions, the study offers insights into the contextual factors that shape the effectiveness of OI for driving digital transformation. The findings provide important implications for both managers and policymakers seeking to design innovative strategies that effectively leverage external knowledge and support DT pressures.

2. THEORETICAL BACKGROUND

2.1. Theoretical background

A comprehensive understanding of how firms utilize innovative practices to advance their digital capabilities requires an integrated theoretical perspective. Accordingly, this study draws simultaneously on open innovation theory (OIT), the resource-based view (RBV), and dynamic capabilities theory (DCT) to examine the relationship between open innovation (OI) and digital transformation (DT). From the perspective of OIT, innovation outcomes

increasingly depend on purposive inflows and outflows of knowledge across organizational boundaries, rather than exclusive reliance on internal research and development activities [1], [2], [3]. Through inbound and outbound knowledge exchanges, firms can enhance their capacity to recognize and exploit emerging technological opportunities. Complementing this view, the RBV posits that sustained competitive advantage arises from resources that are valuable, rare, inimitable, and non-substitutable [12]. In this regard, open innovation enables firms to access external knowledge and technological expertise that can potentially be assimilated and converted into firm-specific strategic resources. However, RBV alone is insufficient to explain sustained advantages in environments characterized by rapid technological change. Dynamic capabilities theory (DCT) addresses this limitation by emphasizing firms' abilities to sense opportunities, seize them, and continually reconfigure resource bases in response to environmental dynamism [27], [28]. Within this theoretical framework, digital transformation can be interpreted as an outcome of dynamic capabilities, reflecting a firm's capacity to embed digital technologies into operational activities, business models, and innovation systems [14], [15], [29]. Moreover, DCT plays a critical role in translating externally acquired knowledge through OI, generating value only when firms possess the capability to integrate and deploy it effectively. Consequently, digital transformation is conceptualized in this study not only as a direct organizational outcome of open innovation activities but also as an enabling mechanism through which firms strengthen and renew their digital capabilities.

2.2. Open innovation and digital transformation

Digital transformation typically unfolds within complex innovation ecosystems composed of interconnected actors, technologies, and platforms [17], [30]. Through collaboration with a diverse set of external partners, such as technology vendors, digital start-ups, and research organizations, firms can access advanced digital knowledge and technological competencies that are difficult costly, or time-consuming to develop internally [14], [16], [17], [18], [30]. The development and diffusion of digital technologies typically occur within complex innovation ecosystems composed of interdependent actors, platforms, and networks. By adopting open innovation (OI) practices, firms can engage more effectively in these ecosystems and explore emerging digital opportunities [17].

From a dynamic capabilities theory (DCT) viewpoint, OI strengthens firms' abilities to sense and seize technological opportunities by enabling the combination of internally help expertise with externally sourced digital knowledge [19]. This integration enhances firms' capacity to recognize, evaluate, and implement digital innovations across organizational processes, thereby accelerating digital transformation (DT) [19]. Similarly, open innovation theory (OIT) suggests that external collaboration provides access to complementary digital resources and technological capabilities that lie beyond firm boundaries, making OI a crucial catalyst for DT. Empirical studies increasingly support a positive relationship between external collaboration and digital transformation outcomes particularly in emerging-market and SME contexts [6], [14], [19], [25], [31]. Building on these theoretical arguments and empirical insights, this study posits that open innovation positively influences firms' digital transformation. H1: Open innovation positively affects digital transformation.

2.3. The moderating role of firm size

Firm size (FS) is widely recognized as a critical organizational characteristic that shapes strategic behavior, resource endowments, and capability development. Larger firms generally possess greater financial capacity, more sophisticated technological infrastructures, and well-established governance and control mechanisms, which enable the large-scale implementation of digital initiatives [24]. By contrast, smaller firms often exhibit greater organizational flexibility, faster decision-making processes, and stronger entrepreneurial orientation,

allowing them to respond more rapidly to emerging innovation opportunities despite resource constraints [9], [16], [25]. These structural and behavioral differences suggest that firm size may shape the extent to which firms are able to convert external knowledge derived from open innovation (OI) can be transformed into digital transformation (DT) outcomes. While larger firms may benefit from superior absorptive capacity and structured integration mechanisms, smaller firms may compensate through agility and adaptability in deploying externally sourced digital solutions. Consequently, firm size is expected to influence the strength of the relationship between open innovation in driving digital transformation may vary depending on firm size. H2: Firm size moderates the relationship between open innovation and digital transformation.

2.4. The moderating role of industry type

Industry type represents an important contextual factor that shapes firms' innovation strategies and the way innovative practices are implemented. Variations in technological intensity, capital investment requirements, and underlying knowledge bases across industries lead to heterogeneous approaches to innovation and technology adoption. Manufacturing firms typically prioritize technological advancement and production efficiency-related innovation, whereas service firms tend to rely more greater emphasis on knowledge exchange, customer engagement, and data-driven process-oriented innovation [10], [26], [30]. These sectoral differences imply that firms operating in different sectors may differ in their ability to exploit external knowledge for digital transformation purposes (DT). Existing studies indicate that both the adoption rate and the organizational impact of digital technologies adoption differ significantly across industries [21]. As a result, industry type is expected to influence how effectively open innovation activities translate into digital transformation outcomes. H3: Industry type moderates the relationship between open innovation and digital transformation.

Overall, the research model is presented in Figure 1

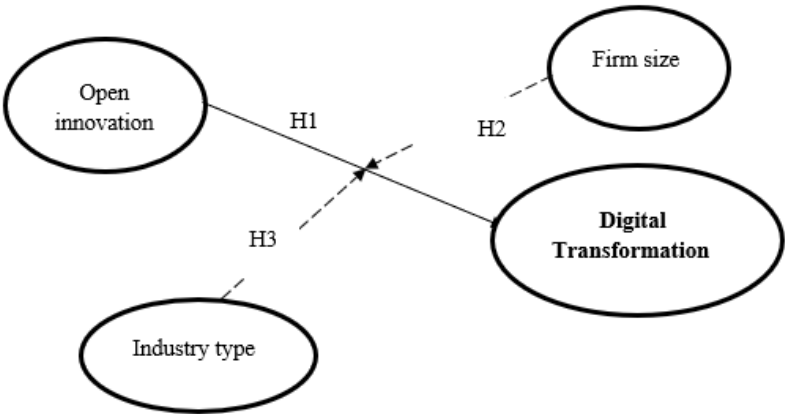


Figure 1. Research model. Source: Authors' elaboration

3. METHODOLOGY

3.1. Main variables

All primary variables were operationalized using multi-item reflective measures and measured using a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). OI was adapted from Huizingh [2]. This construct expresses how extensively firms use external knowledge and collaborative behaviors in support of innovation. The scale included 6 items that investigate different dimensions of OI practices within firms. Consistent with prior conceptualizations of open innovation, the measurement captures both inbound and outbound

dimensions of openness. Items (1)–(3) reflect inbound open innovation practices, emphasizing firms' acquisition and integration of external knowledge from partners and customers, whereas items (4)–(6) represent outbound open innovation, focusing on the external commercialization and sharing of internal knowledge assets. The items include: (1) The firm continuously collects ideas, knowledge, and technologies from external partners; (2) The firm actively collaborates with universities, research institutes, and startups to innovate in product or service development; (3) The firm systematically incorporates customer feedback into innovation processes; (4) The firm licenses its internal technologies or intellectual property to external firms; (5) The firm regularly shares its internal knowledge with external partners to achieve mutual benefits; (6) It participates in joint ventures or strategic alliances to commercialize innovations. This approach ensures that the construct comprehensively reflects bidirectional knowledge flows, which are particularly relevant in the context of listed firms engaging with diverse external stakeholders.

Digital transformation (DT) was adapted from Kane et al. [32] and Reis et al. [20], captures the extent to which firms integrate digital technologies into business processes and strategic decision-making is measured by this construct. Five items per measure: (1) The use of digital technologies to greatly improve business processes; (2) The use of digital platforms for customer interaction and engagement; (3) Digital tools impact the way the firm designs new products or services; (4) Inclusion of data analytics in strategic decisions; (5) Continuous investment in the digitization of business technologies.

3.2. Moderation variables

FS and IT were also the two moderating variables incorporated into the model. FS was adapted from the enterprise size categorizations offered by Beck et al. [24] and Government of Vietnam [33]. Respondents reported the number of employees, and firms were categorized into three groups: small, medium, and large. Specifically, small firms include those with fewer than 50 employees in the service sector and fewer than 100 in manufacturing; medium-sized firms include 50–100 employees (service) and 100–200 employees (manufacturing); and large firms exceed these thresholds.

IT was guided by the United Nations [34] standard classification framework which classifies industries based on their nature. Respondents were prompted to specify the main sector in which their business is found. There are two categories of variables: manufacturing sector and service sector. Both firm size and industry type were incorporated as moderating variables in the structural model as moderators. Following established moderation analysis procedures, interaction terms ($FS \times OI$ and $IT \times OI$) were created to examine whether the strength of the relationship between OI and DT varies across firm sizes and industry sectors.

3.3. Sample and data collection

The current research focuses on firms listed and registered in major equity markets in Vietnam, with the target population being publicly trading companies as of October 2025. These include the Ho Chi Minh Stock Exchange (HOSE) with 404 listed companies, Hanoi Stock Exchange (HNX) with 306 companies, and the Unlisted Public Company Market (UPCoM) with 889 companies. The population includes 1,599 firms. Thus, a targeted sample of 500 firms was selected by screened based on the following criteria: (1) firms operate in manufacturing or service sectors; (2) availability of public data on employees or financial information; and (3) evidence of engagement in innovation and DT activities.

The data were collected over 12 weeks (October to December 2025) through internet questionnaires distributed through Google Forms and Qualtrics. The survey was conducted targeting key informants with strategic knowledge about firm operations, including chief executive officers (CEOs), innovation managers, and DT managers. A total of 347 responses

were received. After data screening for completeness and quality, 312 responses were deemed valid and analyzed, yielding a valid response rate of about 62%. This proportion of responses was enabled by personalized invitation emails and subsequent follow-up reminders. To enhance the accuracy and reliability of the data, the survey targeted senior managers with direct oversight of innovation and digital initiatives, who are presumed to possess comprehensive knowledge of firm-level strategies and practices. This key-informant approach is consistent with prior innovation and digital transformation studies and helps mitigate potential measurement errors associated with survey-based data collection.

3.4. Data analysis techniques

This study adopts a quantitative research design to investigate the relationship between open innovation (OI) and digital transformation (DT) among publicly listed firms in Vietnam. Based on the proposed conceptual framework, hypotheses were developed to examine both the direct effect of OI on DT as well as potential moderating influences.

Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed as the primary analytical technique. This approach is well suited to the objectives of the study due to its strong predictive orientation, its capability to estimate complex structural relationships, including moderation effects and its robustness when applied to relatively moderate sample sizes [35]. The data analysis followed a structured, multi-stage procedure.

In the first stage, the measurement model was evaluated to establish the reliability and validity of the constructs. Several diagnostic tests were conducted, including assessments of common method bias, internal consistency reliability, convergent validity, and discriminant validity [35]. Common method bias was examined using Harman's single-factor test. In addition, procedural remedies were implemented *ex ante* to reduce common method bias, including guaranteeing respondent anonymity, emphasizing the absence of right or wrong answers, and separating the measurement of predictor and criterion constructs within the questionnaire. These measures are recommended to minimize respondents' evaluation apprehension and consistency motifs. Reliability was assessed through outer loadings and composite reliability values, while convergent validity was evaluated using the average variance extracted (AVE). Discriminant validity was verified using multiple criteria, including the heterotrait–monotrait ratio (HTMT), the Fornell–Larcker criterion, and cross-loading analysis. In the second stage, the overall model fit was assessed to determine whether the proposed structural model adequately represented the observed data and met established goodness-of-fit standards [35]. Model fit indicators included the standardized root mean square residual (SRMR), squared Euclidean distance (d_{ULS}), and geodesic distance (d_G). The third stage focused on evaluating the structural model to assess its explanatory and predictive capabilities [35]. Path coefficients were estimated to use a bootstrapping procedure with 5,000 resamples to ensure statistical robustness. The explanatory power of the model was assessed using R^2 values for the endogenous constructs, while effect sizes (f^2) were calculated to determine the relative contribution of each predictor. Predictive relevance was examined using the Stone–Geisser Q^2 statistic to evaluate the model's predictive accuracy.

Finally, hypothesis testing was conducted by examining both direct and moderating effects. The direct relationship between open innovation and digital transformation was evaluated first. Moderation analyses were then performed to assess whether firm size (FS) and industry type (IT) influenced the strength of the relationship between OI and DT. Interaction terms ($OI \times FS$ and $OI \times IT$) were constructed in SmartPLS, and their statistical significance was assessed using bootstrapping procedures in line with established guidelines [35], [36]. While the cross-sectional survey design limits the ability to make strong causal inferences, several steps were taken to alleviate endogeneity concerns. The theoretical model was grounded in established literature to ensure appropriate causal ordering, and key organizational

characteristics were incorporated into the model to reduce omitted variable bias. Moreover, the use of PLS-SEM with a predictive orientation aligns with the study's objective of explaining variance in digital transformation rather than establishing strict causal relationships. Nonetheless, potential endogeneity cannot be entirely ruled out and is acknowledged as a limitation.

4. RESULTS

4.1. Sample characteristics

The chosen firms were classified into FS and IT to illustrate major organizational differences. FS was categorized into small, medium, and large, whereas IT was classified into manufacturing and services. The sample comprises 312 firms, as shown in Table 1. Medium-sized firms are represented by the most representative (48.7%), followed by large firms (41.0%), and small firms (10.3%). Firms from manufacturing represent 44.9% ($N = 140$), while service firms comprise 55.1% ($N = 172$). The findings indicate that all small firms are listed on the manufacturing matrix (32 firms; 22.9% of manufacturing firms). Medium-sized firms are found in a relatively equal distribution across manufacturing sector (79 firms) and services (73 firms). Large firms are more concentrated in the service sector (99 firms) than in manufacturing (29 firms). This distribution provides a suitable basis for examining the potential moderating roles of FS and IT in the relationship between OI and DT.

4.2. Measurement model assessment

The assessment of the measurement model followed the guidelines proposed by Hair et al. [35] and focused on evaluating common method bias (CMB), reliability, and construct validity. To examine potential CMB issues, both Harman's single-factor test and the full collinearity variance inflation factor (VIF) approach were applied. Results reported in Table 2 indicate that the largest factor extracted from Harman's test explains 40.45% of the total variance, which is below the recommended threshold of 50%, suggesting that common method variance does not pose a substantial threat to the study. In addition, all full collinearity VIF values fall within the range of 1.442 to 1.890, well below the conservative cutoff value of 3.3, further indicating the absence of serious CMB concerns.

Reliability and convergent validity were evaluated in accordance with the criteria outlined by Hair et al. [35]. As shown in Table 3, nearly all measurement indicators have loadings above 0.70, indicating satisfactory indicator reliability, except for OI6 for OI (0.695), which is still within the acceptable threshold. Both Cronbach's alpha and composite reliability (CR) values exceed the recommended minimum value of 0.70, demonstrating satisfactory internal consistency among the constructs. Moreover, the average variance extracted (AVE) for each construct is above the 0.50 threshold, confirming sufficient convergent validity.

Discriminant validity was assessed using multiple complementary techniques, including the heterotrait–monotrait ratio (HTMT), the Fornell–Larcker criterion, and cross-loading analysis (Table 4). All HTMT values are below 0.90, indicating adequate discriminant validity. Furthermore, the square roots of AVE exceed the corresponding inter-construct correlation coefficients, and all indicators load more strongly on their associated constructs than on others. Collectively, these results provide robust evidence of discriminant validity for the measurement model.

4.3. Model fit assessment

The overall fit of the structural model was examined using the standardized root mean square residual (SRMR), squared Euclidean distance (d_{ULS}), and geodesic distance (d_{G}), in line with established PLS-SEM guidelines [35]. As reported in Table 5, the SRMR value is

0.075, which is below the recommended cutoff value of 0.08, indicating an acceptable level of model fit. In addition, the observed d_ULS (0.519) and d_G (0.151) values are lower than their respective bootstrap-based Hair et al [35] thresholds of 0.532 and 0.158. These results suggest that the discrepancy between the empirical correlation matrix and the model-implied correlation matrix remains within acceptable bounds. Taken together, the fit indices provide evidence of an adequate global model fit, supporting the suitability of the proposed structural model for subsequent analysis.

4.4. Structural model assessment

The structural model was assessed to examine the proposed hypotheses and to evaluate the model's explanatory and predictive capacities [35]. Prior to hypothesis testing, multicollinearity among predictor constructs was examined using variance inflation factor (VIF) values. As reported in Table 6, all VIF values are below the threshold of 3.3, indicating that multicollinearity does not pose a concern for the estimated relationships.

The explanatory power of the model was evaluated using the coefficient of determination (R^2). As shown in Table 7, the model accounts for 21.0% of the variance in digital transformation (DT) ($R^2 = 0.210$), which can be interpreted as a moderate level of explanatory capability. From a practical perspective, this level of explanatory power suggests that open innovation and firm-level characteristics play a meaningful role in explaining firms' digital transformation efforts, while also indicating that DT is influenced by additional organizational, technological, and environmental factors beyond the scope of the present model. This result is consistent with prior digital transformation studies, which emphasize the multifaceted and path-dependent nature of digital change. To further assess the relative importance of individual predictors, effect sizes (f^2) were calculated (Table 8). The results indicate that open innovation (OI) exerts a small-to-moderate and statistically significant effect on DT ($f^2 = 0.104$; $p < 0.05$). Although the effect size of open innovation is classified as small to moderate, it remains substantively meaningful in the context of organizational research, where complex phenomena such as digital transformation are rarely driven by single dominant factors. The findings indicate that even incremental improvements in firms' openness to external knowledge and collaboration can generate observable gains in digital transformation outcomes. In contrast, firm size (FS) shows a small and statistically non-significant effect ($f^2 = 0.013$; $p > 0.05$), while industry type (IT) exhibits a negligible and non-significant effect ($f^2 = 0.002$; $p > 0.05$). Furthermore, the interaction effects between OI and FS as well as between OI and IT are negligible and statistically insignificant, suggesting the absence of moderating effects. The predictive capability of the model was examined using the blindfolding procedure. As reported in Table 9, the Q^2 value for DT is 0.106, indicating that the model demonstrates acceptable predictive relevance for the endogenous construct.

4.5. Hypothesis testing

The hypothesis testing results are presented in Table 1. The findings indicate that OI has a positive and statistically significant effect on DT ($\beta = 0.351$; $p < 0.001$), thereby supporting H1. This result confirms the important role of external knowledge sourcing and collaboration in facilitating firms' digital transformation processes.

Regarding the moderating role of FS, the results show that FS has a significant direct effect on DT ($\beta = 0.126$; $p < 0.05$). However, the interaction term between OI and FS is not statistically significant ($p = 0.652$), indicating that firm size does not moderate the relationship between OI and DT. Therefore, H2 is not supported. Similarly, IT does not exhibit a significant influence on DT, as both the direct effect ($p = 0.403$) and the interaction term with OI ($p = 0.512$) are not statistically significant. This suggests that the impact of OI on DT does not vary across industries, leading to the rejection of H3.

Overall, the results demonstrate that while OI plays a key role in promoting DT, the strength of this relationship remains consistent across firms regardless of their size or industry classification. The absence of statistically significant moderation effects suggests that open innovation functions as a broadly applicable mechanism for driving digital transformation across different organizational contexts. In other words, the benefits of open innovation for digital transformation appear to be relatively uniform across firm sizes and industry sectors, rather than contingent upon specific structural characteristics. This finding points to the potential generalizability of open innovation as a strategic approach to digital transformation among listed firms.

Table 1. Sample characteristics

		Industry type		Σ	% of Sample
		Manufacturing	Service		
Firm size	Small	32 (22.9%)	0 (0.0;0%)	32	10.3%
	Medium	79 (56.4%)	73 (42.4%)	152	48.7%
	Large	29 (20.7%)	99 (57.6%)	128	41.0%
Σ		140	172	312	
% of Sample		44.9%	55.1%		

Table 2. Common method bias

Harman's single-factor test			
Factor	Eigenvalue	% of Variance	Cumulative %
Factor 1	4.449	40.450	40.450
Factor 2	1.964	17.852	58.302
Full collinearity VIF			
Path	VIF		
OI -> DT	1.490		
FS -> DT	1.506		
IT -> DT	1.442		
FS x OI -> DT	1.863		
IT x OI -> DT	1.890		

Table 3. Construct reliability and convergent validity

Construct	Item	Outer loading	Cronbach's α	rho_A	rho_C (CR)	AVE
Open Innovation (OI)	OI1	0.807	0.850	0.885	0.887	0.567
	OI2	0.705				
	OI3	0.780				
	OI4	0.743				
	OI5	0.780				

	OI6	0.695				
Digital Transformation (DT)	DT1	0.776	0.815	0.828	0.870	0.572
	DT2	0.740				
	DT3	0.759				
	DT4	0.761				
	DT5	0.745				

Table 4a. Discriminant validity assessment-Heterotrait–Monotrait Ratio: HTMT

	DT	FS	IT	OI	FS x OI	IT x OI
DT						
FS	0.342					
IT	0.275	0.459				
OI	0.477	0.487	0.447			
FS x OI	0.203	0.326	0.255	0.399		
IT x OI	0.216	0.335	0.092	0.378	0.647	

Table 4b. Discriminant validity assessment-Fornell–Larcker Criterion

	DT	FS	IT	OI
DT	0.756			
FS	0.316	1.000		
IT	0.254	0.459	1.000	
OI	0.436	0.456	0.420	0.753

(Bold values represent the square root of AVE)

Table 4.c. Cross Loading

	DT	OI
DT1	0.776	0.427
DT2	0.740	0.343
DT3	0.759	0.287
DT4	0.761	0.262
DT5	0.745	0.281
OI1	0.472	0.807
OI2	0.268	0.705
OI3	0.331	0.780
OI4	0.279	0.743
OI5	0.301	0.780
OI6	0.213	0.695

Table 5. Goodness of fit

Index	Estimated model	HI99
SRMR	0.075	-
d_ ULS	0.519	0.532
d_ G	0.151	0.158

Table 6. Multicollinearity

Item	VIF	Item	VIF
OI1	1.689	DT1	1.512
OI2	1.958	DT2	1.606
OI3	1.841	DT3	1.679
OI4	2.128	DT4	1.818
OI5	1.779	DT5	1.814
OI6	1.689	IT x OI	1.000
FS	1.000	FS x OI	1.000
IT	1.000		

Table 7. Coefficient of determination

Endogenous construct	R ²	Adjusted R ²
DT	0.210	0.197

Table 8. Effect size (f²)

Path	f ²	STDEV	t	p
OI -> DT	0.104	0.044	2.365	0.018
FS -> DT	0.013	0.014	0.978	0.328
FS x OI -> DT	0.001	0.006	0.124	0.901
IT -> DT	0.002	0.007	0.334	0.739
IT x OI -> DT	0.002	0.007	0.239	0.811

Table 9. Predictive Relevance (Q²)

Endogenous construct	Q ²
DT	0.106

Table 10. Direct and moderation effects

Hypothesis	Path	β	STDEV	T values	P values
H1	OI -> DT	0.351	0.068	5.168	0.000
H2	FS -> DT	0.126	0.060	2.089	0.037
	FS x OI -> DT	0.026	0.059	0.451	0.652
H3	IT -> DT	0.052	0.063	0.836	0.403
	IT x OI -> DT	-0.053	0.081	0.656	0.512

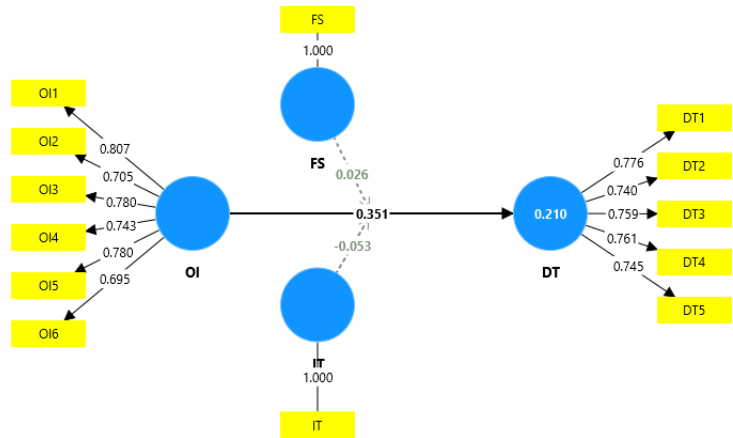


Fig. 2. Results of PLS-SEM analysis-Source: Authors' elaboration

4.6. Discussion

This study examined the relationship between open innovation (OI) and digital transformation (DT) among publicly listed firms in Vietnam. The empirical results provide evidence that OI has a positive and statistically significant effect on DT ($\beta = 0.351$, $p = 0.001$, $f^2 = 0.104$). This finding is consistent with earlier studies highlighting the role of external collaboration, knowledge sharing, and partner engagement in facilitating the adoption and effective use of digital technologies [17], [18], [19]. This finding indicates that companies that actively engage in inbound and outbound open innovation practices appear better positioned to access external knowledge and translate it into digitally enabled processes and business models, the sourcing capabilities and encouraging collaborative innovation should be better able to carry forward their DT progress. From the dynamic capabilities perspective of DCT, the results suggest that OI enhances firms' sensing and seizing capabilities by exposing them to external technological knowledge and innovation opportunities. It helps firms identify suitable digital options and integrate them into business activities. This mechanism is particularly salient in the Vietnamese context, where many firms face limitations in internal skills and technology capabilities are usually lacking. In such environments, open innovation serves as a critical pathway for accelerating digital transformation by compensating for internal capability gaps.

The study also found that firm size and industry type as moderating effects. The empirical results do not support the moderating roles of FS and IT in the relationship between OI and DT. While the direct effect of FS on DT was significant and significantly positive ($\beta = 0.126$; $p < 0.05$), the interacting effect of OI and FS results is not significant, suggesting that FS does not significantly influence the magnitude of the OI-DT association. OI and DT do not differ meaningfully between small, medium, and large firms. In practice, this suggests that firms of different sizes are similarly able to leverage external knowledge through OI to advance their digital transformation efforts. Likewise, IT does not significantly affect DT, and the interaction between IT and OI is also insignificant. These results suggest that the positive influence of OI on DT is relatively stable among manufacturing and service sectors. Although prior literature often highlights sector-specific differences in innovation outcomes and technology adoption, the results prove that OI also has a broader impact on the DT process because of OI-related features across industry environments. One possible explanation is that the pressures associated with digitalization, such as the need for data integration, process automation, and platform-based interaction are increasingly pervasive, reducing sectoral heterogeneity in the way firms exploit external knowledge for digital transformation.

4.7. Theoretical and Practical Implications

From a theoretical perspective, this study contributes to the literature by reinforcing the role of open innovation as a key antecedent of digital transformation within an integrated model drawing on open innovation theory, the resource-based view, and dynamic capabilities theory. While prior studies have predominantly focused on performance or innovation outcomes of open innovation, this research positions digital transformation in the firm as a core organizational outcomes, through which the value of external knowledge is realized, this work also positions DT as an important outcome of OI, contributing to the literature by bringing a specific direct connection between the two constructs as well, the study advances understanding of how external knowledge flows are converted into digitally enabled capabilities. In addition, the results indicated that the influence of contextual factors, for example firm size and industry type, on the OI–DT relationship is not significantly moderating. the absence of significant moderation effects for firm size and industry type extends existing theory by suggesting that the benefits of open innovation for digital transformation may be more universal than previously assumed. Rather than being contingent on structural characteristics such as organizational scale or sectoral context. This suggests that the effect of OI on DT might appear to be more universal than previously assumed, providing a more general framework for firms to leverage external knowledge in digital transformation. This finding invites future research to reconsider the boundary conditions of open innovation and to explore alternative contextual factors, such as digital maturity, governance structures, or institutional environments that may more strongly condition this relationship.

This research indicates, from a managerial perspective, the findings underscore the importance of actively fostering open innovation practices as a means of advancing digital transformation, managers should actively promote open innovation in the way of collaboration with external partners (customers, technology providers, startups, and research institutions) to improve their companies' digital knowledge and capabilities. Notably, the results indicate that firms can benefit from open innovation. Regardless of company size or industry, suggesting that openness to external collaboration is a viable strategic approach across diverse organizational contexts, a commitment to digital infrastructure, data analytics, and digital platforms is a crucial piece of the puzzle in leveraging external knowledge to its full potential. Firms should also develop enhanced capabilities to assimilate and integrate external knowledge into internal operations, which should facilitate digital transformation efforts. When it comes to policy, officials can help foster digital transformation through innovative ecosystems that facilitate the collaboration of firms with research institutions and technology providers. Such support is vital in emerging markets for digital infrastructure development and knowledge-sharing platforms.

In addition, managers should invest in organizational processes and capabilities that support the assimilation and integration of external knowledge into internal digital initiatives. Developing competencies in data analytics, digital platforms, and digital process redesign can help firms more effectively translate open innovation efforts into tangible digital transformation outcomes. From a policy perspective, the results highlight the value of innovation ecosystems that encourage inter-organizational collaboration. Policymakers in emerging markets can support digital transformation by strengthening digital infrastructure, facilitating knowledge-sharing platforms, and promoting partnerships between firms, universities, and technology providers.

5. CONCLUSION

This study investigated the relationship between open innovation (OI) and digital transformation (DT) among publicly listed firms in Vietnam by integrating insights from open

innovation theory, the resource-based view, and dynamic capabilities theory. The empirical findings demonstrate that open innovation plays a significant and positive role in fostering digital transformation, enabling firms to access, assimilate, and deploy external knowledge to enhance their digital capabilities. OIT, RBV, and DCT theories were used in exploring the relation of OI and DT among listed firms in Vietnam. These empirical results show that OI is one of the key factors in creating and maintaining DT; it makes it possible for firms to extract and exploit external knowledge for growing and developing digital capability. Firms that are active participants in external collaboration appear better equipped to adopt digital technology and improve their organizational capabilities

A further contribution of this study lies in the finding that FS and IT do not significantly moderate the effect of the relationship between open innovation and digital transformation, suggesting that the positive influence of OI on DT is relatively stable across organizational contexts. Accordingly, these results indicate that companies must focus on the integration of external knowledge in digital processes rather than physical factors. This insight reinforces the view of open innovation as a general strategic approach for supporting digital transformation in emerging-market environments.

From a managerial point of view, the findings of this study underscore the need of merging OI practices with investments in digital capacities. Firms should not only focus on acquiring external knowledge but also develop organizational processes and competencies that facilitate the integration of such knowledge into digital transformation initiatives. Building digital infrastructures, strengthening data-driven decision-making and fostering cross-boundary collaboration are critical steps for maximizing the value of open innovation.

This study has some constraints. A cross-sectional study design may make it difficult, if not impossible, to demonstrate causative relationships and the study's focus on publicly listed companies in Vietnam might restrict the external validity of their findings for other types of firms or institutional situations. Longitudinal methods should be used as we further investigate these questions, with the more abundant sample and absorptive capacity, organizational culture, and leadership aspects, which is another topic that can be tackled in future work. In other words, the integration of OI and DT represents the important link to augment the adaptability and competitiveness of the firm in the digitalized knowledge-driven aspect of this economy. Future research could extend the analysis to a broader range of firm types to assess whether the observed relationships hold across different institutional and organizational settings. In addition, further studies may incorporate additional organizational and contextual variables, such as absorptive capacity, organizational culture, leadership, or digital maturity, to better explain heterogeneity in digital transformation outcomes.

Overall, the findings underscore the strategic importance of integrating open innovation and digital transformation as complementary processes. By leveraging external knowledge through collaborative innovation and embedding it within digitally enabled capabilities, firms can enhance their adaptability and competitiveness in an increasingly digital and knowledge-driven economy.

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