“Internal capabilities, digital transformation, and SME export performance: Evidence from Vietnam’s manufacturing industries”

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ARTICLE INFO	Dinh Thi Mung and Tran Hoang Minh (2026). Internal capabilities, digital transformation, and SME export performance: Evidence from Vietnam’s manufacturing industries. *Problems and Perspectives in Management*, *24*(2), 550-561. doi:10.21511/ppm.24(2).2026.37
DOI	http://dx.doi.org/10.21511/ppm.24(2).2026.37
RELEASED ON	Monday, 15 June 2026
RECEIVED ON	Sunday, 28 December 2025
ACCEPTED ON	Wednesday, 20 May 2026

JOURNAL	"Problems and Perspectives in Management"
ISSN PRINT	1727-7051
ISSN ONLINE	1810-5467
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

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INTERNAL CAPABILITIES, DIGITAL TRANSFORMATION, AND SME EXPORT PERFORMANCE: EVIDENCE FROM VIETNAM'S MANUFACTURING INDUSTRIES

Type of the article: Research Article

Received on: 28th of December, 2025
Accepted on: 20th of May, 2026
Published on: 15th of June, 2026

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Abstract

Export upgrading has become a pressing concern for small and medium-sized enterprises (SMEs) in emerging economies. Digital transformation and artificial intelligence (AI) are often presented as fast-track solutions. Yet evidence on whether these technologies actually improve export performance remains inconclusive. In many industries, technology adoption does not automatically translate into stronger foreign market outcomes, especially where internal capabilities differ substantially.

The purpose of this study is to examine how digital transformation, AI adoption, innovation activity, labor productivity, and foreign direct investment (FDI) relate to SME export performance in Vietnam's manufacturing sector over the period 2015–2023. Using industry-level panel data (63 observations) and pooled OLS and fixed-effects estimations, the analysis evaluates both internal capability factors and external structural influences.

The results reveal a clear pattern. Innovation is positively associated with export performance ($\beta = 45.61$, $p < 0.01$), and labor productivity exerts a significant positive effect ($\beta = 24.57$, $p < 0.05$). By contrast, digital transformation, AI adoption, and FDI do not display statistically significant direct effects in the baseline specification. The explanatory power of the model remains substantial (R^2 between 0.642 and 0.701), suggesting that capability-related factors account for a meaningful share of export variation across industries.

Taken together, the findings indicate that technology adoption alone is insufficient. In practice, SMEs cannot simply invest in digital tools and expect immediate export gains. Sustained innovation efforts and productivity-enhancing routines appear to be the more decisive foundations of export competitiveness.

Keywords innovation, productivity, exports, SMEs, digitalization, manufacturing

JEL Classification F14, L25, O33

INTRODUCTION

In emerging economies, export participation among small and medium-sized enterprises (SMEs) can no longer be adequately explained by traditional factors such as scale advantages or cost efficiency alone. Rather, it increasingly reflects firms' underlying capability structure. In practical terms, exporting has evolved into a multidimensional competence test, where firms must simultaneously comply with international technical standards, engage in digitally mediated coordination with global partners, and continuously adapt production routines within highly fragmented global value chains (Gereffi et al., 2005; Porter, 1990). Such pressures are particularly evident in manufacturing sectors that remain deeply embedded in export-led growth models.

Conflict of interest statement:
Author(s) reported no conflict of interest

http://dx.doi.org/10.21511/ppm.24(2).2026.37

Against this backdrop, digital transformation and artificial intelligence (AI) are frequently portrayed as strategic levers capable of accelerating industrial upgrading. Policy narratives and institutional reports tend to emphasize their potential to enhance competitiveness, streamline operations, and reduce structural inefficiencies (Vial, 2019; OECD, 2021). At a conceptual level, these expectations are not without foundation. Digital technologies may indeed improve information processing, facilitate automation, and support more data-driven decision-making (Brynjolfsson & McAfee, 2014). However, a more cautious reading of the evidence suggests that the relationship between technology adoption and export performance is far from straightforward. The mere presence of advanced tools does not necessarily translate into improved outcomes in international markets.

From a theoretical perspective, this ambiguity is not surprising. Classical and modern trade theories consistently highlight productivity as a key determinant of export participation (Melitz, 2003). Firms with higher efficiency are better positioned to absorb fixed export costs and withstand competitive pressures abroad. At the same time, evolutionary economics underscores that innovation capabilities do not emerge uniformly but rather develop cumulatively and unevenly across industries (Nelson & Winter, 1982; Castellacci & Natera, 2016). More recent contributions further indicate that technological change, particularly in the form of automation and AI, may alter production structures without producing homogeneous performance gains across firms (Acemoglu & Restrepo, 2020; Autor & Salomons, 2018). In reality, SMEs operate under heterogeneous conditions. While some industries benefit from relatively strong innovation routines and productivity bases, others remain constrained by limited absorptive capacity and fragmented managerial systems (Cohen & Levinthal, 1990; Zahra & George, 2002). These structural asymmetries arguably play a non-trivial role in shaping export outcomes.

Empirical evidence reflects this underlying tension. On the one hand, innovation and productivity are consistently identified as robust drivers of export performance (Fagerberg, 1988; Love & Roper, 2015; Monreal-Pérez et al., 2012). On the other hand, the effects of digitalization, AI adoption, and foreign direct investment (FDI) appear more contingent and, in many cases, inconclusive, particularly in developing-country contexts where complementary capabilities are unevenly distributed (Cirera et al., 2022; Alfaro et al., 2010). A notable limitation of the existing literature is that these factors are often examined in isolation (Verhoef et al., 2021). As a result, the interaction between internal capabilities and external technological forces remains insufficiently theorized and empirically explored.

This gap becomes especially relevant in manufacturing-oriented economies such as Vietnam. Over the past decade, the country has experienced rapid digital expansion alongside sustained inflows of foreign investment (UNCTAD, 2021; World Bank, 2021). While export volumes have grown considerably, such aggregate trends may obscure substantial heterogeneity across industries. In many SME-dominated sectors, technological adoption is uneven, and the translation of external inputs into competitive advantage is far from automatic. Firms may adopt digital tools or engage with foreign partners yet still struggle to convert these resources into measurable export gains.

Accordingly, the present study departs from purely technology-centered explanations and instead frames export performance as a capability-contingent outcome. More specifically, it addresses the following research problem: under what conditions do digital transformation and external investment become economically meaningful for SME export performance? Furthermore, to what extent are export outcomes driven by internal capability-related factors such as innovation and labor productivity rather than by technology adoption per se? By examining these questions within the context of Vietnam's manufacturing industries, the study seeks to contribute to a more nuanced understanding of export competitiveness in emerging economies.

1. LITERATURE REVIEW

Understanding export performance among small and medium-sized enterprises (SMEs) requires moving beyond aggregate trade indicators toward a more capability-oriented perspective. Early economic theories already hinted at this direction by linking productivity differences to technological progress (Solow, 1957). Subsequent evolutionary approaches deepened this view, suggesting that competitive advantage emerges through cumulative learning processes and firm-specific routines that develop unevenly across industries (Nelson & Winter, 1982; Pavitt, 1984). In a more formalized manner, heterogeneous firm trade theory later established that only firms with sufficiently high productivity can absorb the fixed costs associated with exporting (Melitz, 2003). Taken together, these perspectives converge on a consistent insight: export performance is less a function of scale and more a reflection of underlying productive capabilities.

Within this capability-based view, innovation is commonly regarded as a central upgrading mechanism. Through incremental or, less frequently, radical improvements in products and processes, firms may reposition themselves in international markets and reduce reliance on price-based competition (Fagerberg, 1988; Dosi et al., 2015). From a resource-based standpoint, such innovation-related capabilities constitute strategic assets when they are embedded in organizational routines and are not easily replicable (Barney, 1991). Empirical studies generally confirm a positive association between innovation and export performance among SMEs (Love & Roper, 2015). Nevertheless, this relationship does not appear to be uniform. In many emerging economy contexts, innovation tends to be gradual and path-dependent, implying that its impact on export outcomes may materialize only over time rather than immediately.

Productivity provides a more direct, albeit still complex, pathway. Exporting requires firms to meet strict quality standards, manage coordination costs, and respond to volatile external demand. These conditions impose strong efficiency pressures (Melitz, 2003). Consistent evidence indicates that more productive firms are more likely to enter and sustain export activities (Van Biesebroeck, 2005). At the same time, productivity itself is often the outcome of accumulated innovation efforts and organizational learning (Hall & Rosenberg, 2010). This temporal sequencing introduces an important nuance. While productivity is critical for export participation, its development may lag behind innovation investments, thereby creating a gap between capability building and observable export outcomes.

Recent research extends these discussions to digital transformation and artificial intelligence. Digital technologies are widely expected to enhance coordination, improve information processing, and facilitate integration into global value chains (Vial, 2019). However, empirical findings suggest that their effects are far from uniform. In many cases, technology adoption modifies operational processes without necessarily generating measurable performance gains, particularly in environments characterized by limited absorptive capacity and fragmented organizational structures (Cirera et al., 2022). For SMEs, this challenge is especially pronounced. While acquiring digital tools may be relatively straightforward, embedding them effectively into everyday routines often requires substantial organizational adaptation.

A similar pattern can be observed in relation to foreign direct investment (FDI). Participation in global production networks may provide access to advanced technologies and international market linkages (Gereffi et al., 2005). Yet the benefits of such exposure depend critically on local firms' ability to absorb and utilize external knowledge (Alfaro et al., 2010). Without sufficient internal capability, FDI inflows may coexist with only limited improvements in export competitiveness.

Across these strands of literature, a recurring tension becomes apparent. On the one hand, innovation, digitalization, and FDI are frequently portrayed as drivers of export growth. On the other hand, empirical evidence often reveals indirect, conditional, or even insignificant effects. This divergence suggests that export performance may not be determined by these factors in isolation, but rather by the way they interact with existing organizational capabilities.

From this perspective, dynamic capability theory offers a useful integrative lens. It emphasizes firms'

http://dx.doi.org/10.21511/ppm.24(2).2026.37

ability to reconfigure resources and align technological inputs with strategic objectives over time (Teece, 2007). The critical issue, therefore, is not simply whether firms adopt new technologies or access external capital, but whether they can effectively transform these inputs into productive and innovation-driven outcomes.

Overall, the literature points to an incomplete understanding of how internal capabilities and external forces jointly shape export performance, particularly in emerging economies where capability gaps remain substantial. This limitation motivates a more integrated empirical examination of the relationships among innovation, productivity, digital transformation, artificial intelligence, and foreign direct investment.

Accordingly, the objective of this study is to examine how innovation, labor productivity, digital transformation, artificial intelligence, and foreign direct investment relate to SME export performance in Vietnam's manufacturing industries, with particular attention to the relative roles of internal capabilities and external technological factors.

Based on the above arguments, the study proposes the following hypotheses:

H1: Innovation is positively associated with SME export performance.

H2: Labor productivity has a positive effect on SME export performance.

H3: Digital transformation and artificial intelligence are associated with SME export performance.

H4: Foreign direct investment is associated with SME export performance.

2. METHODOLOGY

This study adopts a quantitative research design to examine the relationships among digital transformation, artificial intelligence (AI), innovation, labor productivity, and export performance within Vietnam's manufacturing sector. Rather than treating technological adoption as an isolated phenomenon, the analysis explicitly considers how internal capabilities and external structural forces jointly influence export outcomes over time. Such an approach is consistent with recent arguments suggesting that the performance effects of digital technologies are inherently context-dependent and mediated by capability structures (Vial, 2019; Nambisan et al., 2019).

Importantly, the study does not rely on firm-level survey data. Instead, it employs an industry-level analytical framework, which arguably provides a more appropriate lens for capturing structural dynamics in SME-dominated environments. In many emerging economies, export performance is shaped not only by firm-specific decisions but also by broader industry conditions, including technology diffusion, productivity regimes, and investment patterns (Fagerberg, 1988; Dosi et al., 2015). By focusing on industry-level variation, the analysis reduces the influence of subjective reporting biases and enables the observation of longer-term structural changes associated with digitalization and international integration.

The empirical analysis is based on secondary data covering the period from 2015 to 2023. The selected timeframe spans both pre- and post-digital transformation policy phases, thereby allowing for a more meaningful assessment of structural shifts rather than short-term fluctuations.

The unit of analysis consists of manufacturing industries classified according to Vietnam's official industrial classification system. This focus is deliberate. Manufacturing accounts for a dominant share of national export activity, and SMEs represent the majority of firms operating within these industries (World Bank, 2021; OECD, 2021). As such, industry-level indicators can reasonably approximate export dynamics in SME-intensive contexts. The analysis does not extend to service sectors or high-technology industries beyond manufacturing, and the findings should be interpreted within this empirical boundary.

With regard to variable operationalization, export performance is treated as the dependent variable and measured by the annual export value of each manufacturing industry. This indicator captures aggregate export outcomes and facilitates consistent comparisons across industries and overtime.

The key explanatory variables include digital transformation, AI adoption, innovation, labor productivity, and foreign direct investment (FDI). Digital transformation is proxied by industry-level investment in digitalization and automation-related activities, reflecting the extent to which digital technologies are embedded within production and managerial processes (Vial, 2019). AI adoption is measured by the proportion of firms within an industry that implement AI-based applications, thereby capturing the diffusion of advanced analytical and decision-support systems.

Innovation is operationalized as the share of firms engaging in product, process, or business model innovation, representing the internal improvement capacity of each industry (Love & Roper, 2015). Labor productivity is measured as output per worker, indicating the efficiency with which labor inputs are transformed into economic value. FDI is captured by the realized value of foreign investment at the industry level, reflecting the presence of external capital and potential knowledge spillovers (Alfaro et al., 2010). To account for unobserved heterogeneity, industry and year identifiers are included to control for time-invariant characteristics and common temporal shocks.

To estimate the proposed relationships, panel data regression techniques are employed. This approach exploits both cross-sectional variation across industries and temporal variation within industries, making it particularly suitable for analyzing structural and technological dynamics. The empirical strategy begins with pooled ordinary least squares (OLS) estimations to establish baseline relationships. Subsequently, fixed-effects and random-effects models are estimated to address potential biases associated with unobserved heterogeneity. Model selection is guided by standard diagnostic procedures, ensuring that the chosen specification reflects the underlying data structure rather than purely statistical convenience.

The general form of the empirical model is expressed as:

$$\begin{aligned} ExportPerformance_{it} &= \alpha + \beta 1 AI_{it} \\ &+ \beta_2 Digital_{it} + \beta_3 LabourProductivity_{it} \\ &+ \beta_4 FDI_{it} + \beta_5 Innovation\_it \\ &+ \gamma_i + \delta_t + \varepsilon_{it}, \end{aligned} \tag{1}$$

where i denotes industry and t represents time. The model incorporates both industry-specific effects (γ_i) and time-specific effects (δ_t) to account for unobserved heterogeneity and common macroeconomic shocks.

While the specification treats export performance as the dependent variable and innovation and productivity as key explanatory factors, it is important to acknowledge that the direction of influence may not be strictly unidirectional. In particular, higher export performance could, at least in part, stimulate subsequent innovation activities and productivity improvements through learning-by-exporting mechanisms widely discussed in the trade literature. This introduces a potential simultaneity concern that cannot be fully ruled out.

Admittedly, the panel structure, combined with the inclusion of industry and time fixed effects, helps mitigate biases arising from time-invariant characteristics and shared temporal dynamics. However, these controls do not entirely eliminate endogeneity risks. For this reason, the estimated relationships should be interpreted with caution. Rather than establishing definitive causality, the empirical model is better understood as capturing theoretically grounded associations that are consistent with a capability-based perspective. Within this framework, innovation and labor productivity are treated as foundational conditions shaping export competitiveness, even if reciprocal effects may coexist.

Prior to model estimation, descriptive statistics are examined to assess the distributional properties and dispersion of the variables. This step provides an initial understanding of structural variation across industries and overtime. In addition, correlation analysis is conducted to identify potential linear relationships among explanatory variables and to flag early signs of multicollinearity. Such preliminary diagnostics, although sometimes treated as routine, are particularly useful in ensuring that subsequent estimations are not driven by unstable variable relationships.

During the estimation stage, a set of diagnostic tests is implemented to evaluate the robustness of the results. These include checks for multicollinearity, heteroskedasticity, and the stability of

http://dx.doi.org/10.21511/ppm.24(2).2026.37

coefficient estimates across alternative model specifications. The purpose of these procedures is not merely to achieve statistical significance, but rather to ensure that the empirical findings are consistent with the structure of the data and the underlying analytical assumptions. In applied panel data research, this distinction is critical, as statistically significant results may otherwise reflect artefacts of the data rather than substantive economic relationships.

Finally, the dataset used in this study is constructed from publicly available and widely recognized sources, including Vietnam's Statistical Yearbooks, reports from the National Innovation Center, and databases provided by the World Bank. The processed dataset underpinning the empirical analysis is available from the authors upon reasonable request, thereby facilitating transparency and replication.

3. RESULTS

The analysis begins with an examination of descriptive statistics (Table 1) to capture the underlying distributional patterns of the study variables across manufacturing industries.

The descriptive evidence suggests a notable degree of heterogeneity across industries, both in terms of technological engagement and export outcomes. While the average level of export performance indicates a generally strong export orientation, the relatively wide dispersion points to substantial differences in export capacity across sectors. Such variation, at least tentatively, implies that aggregate export growth may mask deeper structural imbalances at the industry level.

From a technological standpoint, the distribution of digital transformation and AI adoption appears uneven. Although average values remain at a moderate level, the observed variability indicates that technology uptake is still in a transitional phase rather than fully diffused. This pattern is consistent with the broader characteristics of SME-dominated manufacturing systems, where adoption tends to be gradual and uneven across industries.

In contrast, indicators associated with internal capabilities, namely innovation and labor productivity, display comparatively more stable distributions. This relative stability may suggest that these capability-related factors are more deeply embedded within existing production structures. Put differently, while digital technologies may be expanding, the foundations of export competitiveness appear to remain closely tied to more established capability dimensions.

Taken together, these preliminary observations point toward an important distinction. External technological inputs exhibit variability and uneven diffusion, whereas internal capabilities demonstrate greater structural consistency. This divergence arguably provides an early indication that the relationship between technology adoption and export performance may be mediated, rather than direct.

To further investigate these relationships, the analysis examines the correlation patterns among the key variables.

The correlation matrix (Table 2) provides initial insights into the relationships among the explanatory variables prior to multivariate estimation. A relatively strong positive association is observed between digital transformation and AI adoption, suggesting that these two dimensions tend to co-evolve within broader digitalization processes.

Table 1. Descriptive statistics of the study variables

Source: Our calculations are based on data from the General Statistics Office of Vietnam, National Innovation Center, and World Bank (2015–2023).

Variable	Mean	Standard deviation	Min	Max
Export performance	9,450.3	3,212.6	3,210	15,820
AI adoption	12.4	5.3	5.1	22.7
Digital transformation	1,230.5	430.8	570	2,150
Labor productivity	115.2	21.4	86.0	147.9
Foreign direct investment	5,742.1	1,390.7	3,200	8,210
Innovation	38.6	9.1	21.5	53.3

Table 2. Correlation matrix of explanatory variables

Variables	AI adoption	Digital transformation	Labor productivity	Foreign direct investment	Innovation
AI adoption	1.000	0.765	0.432	0.281	0.593
Digital transformation	0.765	1.000	0.396	0.244	0.511
Labor productivity	0.432	0.396	1.000	0.120	0.378
Foreign direct investment	0.281	0.244	0.120	1.000	0.165
Innovation	0.593	0.511	0.378	0.165	1.000

This pattern is not unexpected, as investments in digital infrastructure often facilitate the subsequent implementation of AI-based applications.

However, the strength of this relationship also warrants careful interpretation. The empirical overlap between digital transformation and AI adoption may blur conceptual boundaries, thereby complicating the identification of their distinct effects in regression analysis. In SME-dominated environments, where technological adoption is often incremental and path-dependent, such overlap is likely to reflect integrated rather than independent technological processes.

By contrast, the correlations between technological variables and internal capability indicators, namely innovation and labor productivity, appear more moderate. This finding tentatively suggests that increased engagement with digital technologies does not necessarily coincide with immediate improvements in innovation intensity or productive efficiency. In other words, technology adoption and capability development may follow different temporal trajectories.

A similar pattern can be observed with respect to foreign direct investment (FDI), which exhibits relatively weak correlations with both technological and capability-related variables. This may indicate that external capital inflows do not automatically translate into stronger internal capability structures at the industry level, at least in the short term.

Taken together, these preliminary patterns point toward a potentially non-linear and conditional relationship between external technological inputs and export performance. The observed correlations provide an important contextual foundation, but they do not allow for definitive conclusions regarding the relative importance of each factor.

Accordingly, a multivariate analytical approach is required to disentangle the individual and joint effects of technological variables, internal capabilities, and external capital on export performance. Table 3 proceeds with regression analysis to examine these relationships in a more systematic manner.

The regression estimates provide consistent evidence regarding the relative importance of internal capabilities and external factors in shaping export performance. Across both model specifications, innovation emerges as the most influential variable, exhibiting a positive and statistically significant effect. Notably, its coefficient remains robust even after the exclusion of potentially over-

Table 3. Pooled OLS regression results

Independent variables	Full model (1)	Reduced model (2)
AI adoption	11.83 (0.115)	–
Digital transformation	0.73 (0.221)	–
Labor productivity	24.57** (0.048)	31.65*** (0.017)
Foreign direct investment	0.92 (0.365)	1.14 (0.241)
Innovation	45.61*** (0.008)	52.48*** (0.005)
Constant	3,420.7	3,182.5
R-squared	0.642	0.701
Observations	63	63

Note: p-values in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

http://dx.doi.org/10.21511/ppm.24(2).2026.37

lapping technological variables, suggesting that its explanatory power is not merely an artefact of model specification.

This pattern lends support to the view that export competitiveness among SMEs is fundamentally grounded in internally developed capabilities. Rather than relying primarily on external technological inputs, firms appear to benefit more from sustained innovation efforts that gradually enhance their ability to compete in international markets.

Labor productivity also displays a positive and statistically significant relationship with export performance, although its magnitude is comparatively smaller than that of innovation. This finding suggests that productive efficiency plays an enabling role, allowing firms to meet cost and quality requirements in export markets. However, the results also imply that productivity alone may not be sufficient to generate sustained export advantages, particularly in the absence of ongoing innovation-driven upgrading.

In contrast, the coefficients associated with digital transformation, AI adoption, and foreign direct investment (FDI) are not statistically significant in the full model. At first glance, this outcome may appear counterintuitive, especially given the prominence of technology-centered narratives in both policy and academic discourse. However, a more cautious interpretation is warranted. The absence of direct significance does not necessarily imply that these factors are irrelevant. Rather, it may indicate that their effects are indirect, conditional, or mediated by internal capability structures.

In the context of Vietnamese SMEs, where organizational capacity and technological integration remain uneven, digital tools and external capital may function more as supporting infrastructures than as immediate drivers of export performance. Their contribution is therefore likely to materialize only when embedded within sufficiently developed innovation routines and productivity-enhancing processes.

The results of the reduced model further reinforce this interpretation. Once highly correlated technological variables are excluded, the coefficients of innovation and labor productivity increase in magnitude and significance, highlighting their central role in explaining export variation. This shift suggests that multicollinearity or conceptual overlap among technological variables may obscure their individual effects, while simultaneously emphasizing the stability of capability-related factors.

To assess the robustness of these findings, additional panel estimations using fixed-effects and random-effects models were conducted. Although not reported in detail for brevity, these alternative specifications yield qualitatively similar results. In particular, the dominant role of innovation and the supportive role of labor productivity remain consistent across models, indicating that the observed relationships are not driven by a specific estimation approach.

The relatively high R-squared values reported in Table 3 further suggest that the model captures a substantial proportion of the variation in export performance across manufacturing industries. Given the structural heterogeneity of the sector, this level of explanatory power is non-trivial and reinforces the relevance of capability-based explanations.

Overall, the regression results point toward a clear empirical pattern. Internal capability-related factors, especially innovation and productivity, exhibit stable and significant associations with export performance. By contrast, external technological and investment-related variables do not appear to exert direct effects in the short term, thereby supporting the argument that export upgrading is inherently conditional and context-dependent.

To further ensure the reliability of these estimates, a series of diagnostic tests is conducted.

Table 4. Variance inflation factor (VIF) results

Variable	VIF
Digital transformation	3.87
AI adoption	3.61
Innovation	2.75
Labor productivity	1.98
Foreign direct investment	1.44

The diagnostic results indicate that the estimated models satisfy key statistical assumptions. In particular, the variance inflation factors (Table 4) remain well below commonly accepted thresholds, suggesting that multicollinearity does not pose a serious concern. This is noteworthy given the relatively strong pairwise correlations observed be-

Table 5. Results of White's test for heteroskedasticity

Test component	Chi-square (χ^2)	Degrees of freedom (df)	p-value
Heteroskedasticity	9.00	8	0.3423
Skewness	4.80	3	0.1868
Kurtosis	2.47	1	0.1160
Joint test	16.27	12	0.1790

tween certain digitalization-related variables. The results therefore imply that, while some degree of overlap exists, it does not materially distort coefficient estimation.

Additional robustness checks further support the reliability of the findings. Tests for heteroskedasticity (Table 5) do not reveal evidence of variance instability, indicating that the estimated coefficients are not driven by heteroskedastic disturbances.

The non-significant p-values across all components of White's test suggest that the null hypothesis of homoskedasticity cannot be rejected. Taken together, these diagnostic outcomes enhance confidence in the empirical results, particularly in light of the relatively limited number of observations available at the industry level. Ensuring the stability of estimates under such conditions is essential to avoid overinterpreting patterns that may otherwise arise from data limitations rather than substantive relationships.

The hypothesis evaluation provides mixed evidence. The empirical evidence indicates that H1 and H2 receive support. Both innovation and labor productivity demonstrate positive and statistically significant associations with export performance across the estimated models. Conversely, the findings do not provide sufficient empirical support for H3 and H4, as the coefficients for digital transformation, AI adoption, and foreign direct investment fail to reach conventional levels of statistical significance. These results suggest that internal capability-related factors play a more immediate role in explaining export outcomes than external technological and investment-related influences.

A closer examination of the regression estimates highlights notable differences in the explanatory strength of the proposed factors. While innovation and productivity maintain stable associations with export performance, the effects of technology adoption and external investment remain comparatively weak. One possible explanation is that the economic value of these resources does not emerge immediately after adoption. Rather, their influence may become visible only when supported by sufficient organizational learning, innovation activities, and productivity-enhancing processes.

As summarized by the hypothesis testing results, H1 and H2 are supported, whereas H3 and H4 are not supported. Accordingly, empirical support is obtained for two of the four proposed hypotheses included in the research model.

4. DISCUSSION

The empirical findings offer insights into the mechanisms underlying SME export performance. Overall, the results indicate that internal capability-related factors, particularly innovation and labor productivity, play a more decisive role than external technological and investment-related inputs. This pattern suggests that export competitiveness is less a direct outcome of resource availability and more a function of how effectively such resources are transformed into productive and adaptive capabilities.

The strong and consistent effect of innovation is broadly aligned with prior research emphasizing its role in enabling firms to upgrade their positions in international markets (Fagerberg, 1988; Love & Roper, 2015). However, the magnitude of its effect observed in this study appears relatively pronounced. One possible explanation is that, in SME-dominated manufacturing contexts, innovation serves not merely as a complementary factor but as a primary mechanism through which firms respond to external competitive pressures. In this sense, the findings extend existing literature by suggesting that inno-

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vation may play a more central role in emerging economies where structural constraints limit alternative sources of competitiveness.

Similarly, the positive association between labor productivity and export performance is consistent with heterogeneous firm trade theory (Melitz, 2003). More productive industries are better positioned to absorb export-related costs and maintain operational stability. Nevertheless, the comparatively smaller coefficient of productivity relative to innovation indicates that efficiency alone may not be sufficient. This finding supports the view that productivity functions as an enabling condition, while innovation drives longer-term upgrading and differentiation.

By contrast, the absence of statistically significant direct effects for digital transformation, artificial intelligence, and foreign direct investment provides a more nuanced perspective. While some prior studies report positive impacts of these factors on firm performance, the present results are more consistent with recent evidence highlighting the conditional nature of technological and external influences (Vial, 2019; Acemoglu & Restrepo, 2020). Rather than acting as autonomous drivers, these factors appear to operate through indirect or mediated pathways.

A plausible interpretation relates to the uneven distribution of absorptive capacity across industries. As suggested in earlier research, the benefits of digitalization and external knowledge inflows depend on firms' ability to internalize and apply them effectively (Cohen & Levinthal, 1990; Zahra & George, 2002). In contexts where managerial systems and organizational routines remain fragmented, technological adoption may not translate into immediate performance gains. Instead, such inputs may require a period of integration before their effects become observable.

This interpretation is particularly relevant for Vietnam's manufacturing sector. SMEs in this context often rely on incremental adjustments rather than comprehensive technological transformation. As a result, investments in digital tools and AI applications may remain partial or experimental, limiting their short-term impact on export outcomes. In this sense, the findings do not contradict technology-centered arguments, but rather suggest that their effects are contingent upon the maturity of underlying capability structures.

More broadly, the results contribute to reconciling divergent findings in the existing literature. While some studies report strong positive effects of digitalization and FDI, others find weak or insignificant relationships. The present analysis suggests that these differences may reflect variations in capability conditions rather than inconsistencies in theoretical expectations. By emphasizing the role of innovation and productivity as mediating filters, the study provides a more integrated explanation of how internal and external factors jointly shape export performance.

CONCLUSION

This study examines the relationships among digital transformation, artificial intelligence, innovation, labor productivity, and export performance in Vietnam's manufacturing sector. The results consistently indicate that innovation and labor productivity exert significant positive effects, whereas digital transformation, AI adoption, and foreign direct investment do not display statistically significant direct impacts.

These findings suggest that export competitiveness among SMEs is primarily grounded in internal capability development rather than in the mere adoption of advanced technologies or access to external capital. In particular, the results reinforce capability-based perspectives by highlighting the importance of transforming resources into productive and innovation-driven outcomes.

From a managerial perspective, the findings imply that SMEs should prioritize gradual capability development, especially in innovation and productivity, rather than relying on rapid technological adoption as a shortcut to export growth. From a policy standpoint, technology-focused programs are likely to be more effective when combined with initiatives that strengthen organizational capacity, skills development, and innovation systems.

Despite these contributions, several limitations should be acknowledged. The use of industry-level data may not fully capture firm-level heterogeneity, and the measurement of digital transformation and AI remains constrained by data availability. Future research could address these limitations by incorporating firm-level data, applying more advanced estimation techniques, and examining non-linear or time-lagged effects. Extending the analysis to other sectors or conducting cross-country comparisons would also provide further insights into the generalizability of the findings.

AUTHOR CONTRIBUTIONS

Conceptualization: Thi Mung Dinh, Hoang Minh Tran.
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Formal analysis: Thi Mung Dinh, Hoang Minh Tran.
Funding acquisition: Thi Mung Dinh.
Investigation: Thi Mung Dinh, Hoang Minh Tran.
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Writing – original draft: Thi Mung Dinh, Hoang Minh Tran.
Writing – review & editing: Thi Mung Dinh, Hoang Minh Tran.

DECLARATION OF GENERATIVE AI IN THE WRITING PROCESS

In the preparation of this manuscript, generative AI tools were used in a limited capacity for language editing and grammatical refinement. All core elements of the study, including the research design, data analysis, interpretation of results, and conclusions, were developed independently by the authors.

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