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Le Thi Hau[1], Phan Thi Bich Nguyet[2], Nguyen Thi Hong Nham[2], and Le Van[2]

[1]Thuy Loi University, [2]University of Economics Ho Chi Minh City (UEH)

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Le Thi Hau[1], Phan Thi Bich Nguyet[2], Nguyen Thi Hong Nham[2], and Le Van[2*]

[1]Thuy Loi University, [2]University of Economics Ho Chi Minh City (UEH)

Hault@tlu.vn[1], Nguyettcdn@ueh.edu.vn[2], Nhamnth@ueh.edu.vn[3], Levan@ueh.edu.vn[4]

Corresponding Author

Abstract: *This study aims to assess the impact of digital transformation through indicators of technology use, technology application, and software on labor productivity in Vietnamese enterprises. The research data includes 24,221 observations with seven main variables: labor productivity, labor skill level, capital intensity, enterprise age, and variables representing digital transformation. Using panel data regression combined with quantile regression testing, the study identified a non-linear relationship and the moderating role of capital intensity and labor skill level on the research objective. The results show a positive impact of technological innovation on labor productivity in Vietnamese enterprises. Specifically, the use of software solutions creates the most stable and sustainable impact, while the application of infrastructure technology shows a clear threshold effect, only creating a significant productivity boost in enterprises with high absorption capacity (75th percentile or higher). The research findings also highlight a paradox in the competition between physical capital and digital transformation, where in capital-intensive businesses, the marginal effectiveness of digital transformation tends to decrease. This research is relevant to the context of a developing economy, where a shortage of human resources' capacity to absorb the benefits of digital transformation is a major obstacle preventing the realization of these benefits. This study implies solutions related to shifting policies from mass infrastructure support to supporting digital skills training and strategic management consulting for Vietnamese businesses before large-scale technology investments.*

Key words: *Technology innovation; digital transformation; productivity; enterprise.*

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1. Introduction

Digital transformation is becoming an inevitable trend and a new driving force for global economic growth. In Vietnam, this trend is a top priority for the government, backed by a strong commitment from the Vietnamese government. The Vietnamese government's

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commitments and orientations regarding national and enterprise digital transformation are most clearly demonstrated in Decision No. 749/QD-TTg, which approves the "National Digital Transformation Program to 2025, with a vision to 2030". The Vietnamese government is committed to implementing digital transformation synchronously across all three pillars: digital government, digital economy, and digital society. The government identifies enterprises as the most important driving force of the digital economy and has made many specific commitments to support them through Decision No. 411/QD-TTg (2022), which approves the National Strategy for the Development of the Digital Economy and Digital Society, setting specific targets for the proportion of the digital economy in each sector and field.

At the same time, labor productivity is the most important measure for the sustainable development of Vietnamese businesses in a competitive environment. Vietnam is facing the middle-income trap, and labor productivity is a decisive factor in overcoming it. Although there has been improvement, Vietnam's labor productivity remains much lower than that of other countries in the region. According to the General Statistics Office (GSO), the labor productivity of the entire economy in 2023 at current prices reached VND 199.3 million per worker. Although Vietnam's labor productivity has continuously increased, when compared using purchasing power parity (PPP), Vietnam's labor productivity still lags significantly behind countries in the region such as Singapore, Malaysia, or Thailand. With the government aiming for the digital economy to contribute 30% of GDP by 2030, the question is not just about digital growth, but how to make digital transformation a truly effective tool to narrow the labor productivity gap in Vietnamese businesses.

The low labor productivity in Vietnam stems in large part from the characteristics of small and medium-sized enterprises (SMEs). These businesses face a difficult challenge: their business models still heavily rely on low-cost labor to maintain short-term competitive advantages. This dependence inadvertently creates psychological and financial barriers, causing businesses to delay abandoning manual operational processes and transitioning to centralized digital solutions. This delay in technology updates not only reduces current operational efficiency but also limits innovation, widening the labor productivity gap between domestic SMEs and businesses with significant investments in digital infrastructure.

In recent years, the relationship between digital transformation and labor productivity has attracted widespread attention from researchers. Most empirical studies reach a common consensus: digital transformation plays a key role in significantly improving labor productivity

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at the enterprise level (Ngo, 2025; Romanova & Ponomareva, 2022; Y Shi, 2024; Awaludin & Xie, 2026; Aralica et al., 2025).

Firstly, studies indicate that the application of digital technologies (such as ERP, cloud computing, artificial intelligence) helps automate repetitive tasks, thereby minimizing human error and optimizing operating time (Awaludin & Xie, 2026). The smooth flow of internal information significantly reduces transaction and management costs, directly increasing the added value per hour of labor (Chen et al., 2023). Secondly, digital transformation breaks down internal information barriers within organizations (Chingvintseva & Raevich, 2025). Big data analytics systems enable management to grasp market fluctuations and make more accurate and timely resource allocation decisions, thereby improving the overall performance of human resources (Dinh & Tang, 2025). Finally, the digital environment facilitates business model restructuring and the development of new products and services (Feng, 2024). The synergy between human capital and digital technology not only improves existing processes but also expands the production capacity limits of enterprises (Makurin & Kozarevych, 2025). Overall, studies have provided a solid theoretical foundation and empirical evidence on the positive impact of digital technology on business performance (Aralica et al., 2025). However, much of this evidence is set in the context of developed economies, where modern technological infrastructure and a high-quality workforce are readily available (Zhang, 2025).

This research contributes to the theoretical framework of the digital economy by providing new empirical evidence from Vietnam, an economy undergoing accelerated digital transformation. The results shed light on the relationship between technology and labor productivity within the specific institutional and business culture of developing countries, where digitalization often occurs unevenly across businesses of varying sizes. Through this, the study re-examines classic hypotheses in the context of emerging markets, adding value to the international literature on digital transformation.

Furthermore, in practical terms, the research provides crucial data to help managers identify the actual effectiveness of investing in digital solutions. The analysis results will support businesses, especially small and medium-sized enterprises, in prioritizing the allocation of digital resources to processes that generate the highest added value, avoiding wasteful and inefficient investments. Furthermore, the research results provide valuable reference material for the Government and regulatory agencies in evaluating the effectiveness of current digital transformation support programs. From this, policymakers can refine support packages,

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prioritizing industries or business groups with the greatest potential for labor productivity growth, and promoting the goal of having the digital economy contribute 30% of GDP by 2030.

Following this introduction, Section 2 reviews relevant literature, Section 3 presents materials and methods, Section 4 reports findings, and Section 5 concludes.

2. Literature review

2.1. Theoretical backgrounds

To explain the mechanisms by which digital transformation boosts labor productivity in businesses, this study constructs a theoretical framework based on the multidimensional integration of modern economic theories. Understanding the impact of digital technology goes beyond mere empirical analysis and requires a solid theoretical foundation on how digital resources are transformed into operational efficiency.

Specifically, the study is based on resource-based theory (RBV) to identify digital technology as a strategic resource that creates a competitive advantage. Developed by Barney (1991), RBV theory posits that businesses achieve sustainable competitive advantage through the possession of valuable, scarce, inimitable, and irreplaceable resources. In the digital age, technological infrastructure, specialized software, and especially customer data are considered strategic resources according to the RBV framework. However, technology alone does not create an advantage without integration with internal processes. Therefore, digital transformation in Vietnamese businesses is not just about purchasing equipment, but about restructuring digital resources to create unique competitive advantages, thereby enhancing labor productivity.

Simultaneously, dynamic capability theory is applied to clarify the adaptability and process restructuring capabilities of businesses in a digitized business environment. According to Teece et al. (1997), dynamic capability is defined as the ability of a business to integrate, build, and restructure internal and external capabilities to respond to a rapidly changing environment. For Vietnamese businesses, the constantly changing digitized business environment requires them to continuously adapt. Digital transformation is seen as an expression of dynamic capability, where businesses shift from manual operating processes to data-driven processes. Labor productivity increases when businesses are able to restructure these processes more quickly than traditional competitors.

https://doi.org/10.71058/jodac.v10i08a01

Finally, the theory of technological substitution and complementarity is used to decode the interaction between human capital and technical solutions, thereby indicating the mechanism of labor productivity growth in the context of businesses strongly shifting to the digital economy. According to (Actor et al., 2003), this theory analyzes how technology impacts labor productivity through two mechanisms: (1) Replacing labor in monotonous tasks with automation and (2) Supplementing human capabilities in complex tasks. Therefore, digital transformation helps Vietnamese businesses automate manual data entry and reporting processes, thereby reducing employee idle time. When employees are supported by digital tools such as AI or centralized management software, they can make more accurate decisions, focus on high value-added activities, and thus boost overall labor productivity.

2.2. Recent empirical findings

Recent empirical studies have provided clear evidence of the role of applying technology and specialized software as factors driving labor productivity in enterprises (Awaludin & Xie, 2026; Aralica et al., 2025). Quantitatively, studies focusing on technology application have shown that investing in digital infrastructure is not only an urgent requirement but also a direct tool to improve work efficiency through the automation of manual processes (Nguyen et al., 2025). In addition, the use of technology in daily management, through intelligent operating systems, allows enterprises to optimize personnel allocation and minimize idle time in production cycles (Aleca & Mihai, 2026). In particular, the penetration of specialized management software (such as ERP systems, CRM, or cloud-based accounting applications) has been shown to have a positive impact on labor productivity by improving information flow and enhancing transparency in business decisions (Tarasenko & Kochetkov, 2026). However, existing research results mainly emphasize the immediate impact of using these tools, while empirical evidence on the lag effects of software adoption from the early years of digital transformation on labor productivity in the post-pandemic period remains a gap that needs to be explored more deeply in the Vietnamese market (Nguyen et al., 2026; Nguyen et al., 2025).

Besides identifying the variables representing digital transformation as technology application, the use of specialized technology and software, recent studies have expanded the scope of analysis through interaction variables and control variables to clarify the multidimensional impact mechanism (Cheng et al., 2023). Specifically, the interaction between digital transformation and capital intensity and labor skill level is considered an important moderating factor determining the effectiveness of the transformation process (Chen, 2023). Studies show that when enterprises possess high capital intensity and a highly skilled workforce, the

 https://doi.org/10.71058/jodac.v10i08a01

application of software and digital technology will achieve optimal efficiency, creating a strong synergistic impact on labor productivity (Obokoh et al., 2024).

To ensure that the analysis results accurately reflect the actual impact of digital transformation, modern empirical studies often include strategic control variables such as firm size, firm age, industry, and ownership structure in their models. Controlling these factors helps eliminate confounding effects from economies of scale or long-standing management experience, thereby separating the pure benefits that technology brings to productivity. However, although interaction and control variables have been included in some international studies, the consistent application of these variables in the context of Vietnamese businesses with their diverse ownership structures and industry characteristics remains a gap that needs to be filled. Furthermore, considering the lagged impact of digital technology from 2019 to the present, combined with the aforementioned interaction variables, will provide a more comprehensive view of the resilience and productivity growth of businesses in the period 2020–2023 (Nguyen et al., 2026; Duc, 2025).

2.3. Literature gaps

Although many studies worldwide and in Vietnam have confirmed the positive impact of digital transformation on enterprise labor productivity, the literature review shows that there are still significant gaps that need further research and clarification:

First, there is a lack of in-depth quantitative micro-level research in developing countries. Most current empirical studies are conducted in developed countries with well-developed digital ecosystems. Meanwhile, developing countries like Vietnam, where businesses still face many barriers in technology, finance, and human resources, lack systematic micro-level research using specific business data to assess the impact of digital transformation on productivity. Second, the mechanisms of indirect or mediating impacts have not been clarified. Many studies still only examine the direct relationship between digital transformation and productivity. Meanwhile, mediating factors such as capital intensity and the educational level of the workforce, which play a decisive role in the success of digital transformation, have not been systematically included in research models. Third, there is a lack of studies that stratify and group businesses. Most studies assess the impact at a moderate level, failing to analyze the uneven impact across business sizes (large, medium, small, and micro), industries (manufacturing, services, agriculture), or ownership structures. This limits the ability to provide specific policy recommendations.

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To address these gaps, further research should focus on the following: First, developing a quantitative micro-level model using enterprise data. The study will utilize OLS regression and quantile regression models based on data from the General Statistics Office's enterprise survey to more accurately measure the impact of digital transformation on labor productivity at the micro level. Second, integrating mediating and moderating variables into the research model. The theoretical model will be expanded to test indirect impacts through factors such as capital intensity and labor skill level. Third, designing a stratified and time-tracked study. The study involved segmenting the research subjects to identify unequal effects. Techniques such as quantile regression at quantiles q10, q25, q50, q75, and q90 were employed. The study also segmented businesses by industry, size, and ownership structure.

2.4. Hypothesis development

Empirical studies have strongly proven the hypothesis that increasing the application of technology and management software has a positive impact on enterprise labor productivity. Digital transformation and the application of digital technologies help businesses automate processes, reduce repetitive manual tasks, and optimize the efficiency of allocating both labor and capital resources (Zhou et al., 2025; Chen et al., 2023). Specifically, the use of specialized management software such as technology applications, technology usage or management software helps break down internal information barriers, manage data in real time, thereby improving coordination efficiency, decision making and cutting operating costs (Zhou et al., 2025). These impacts yield clear quantitative results: adopting technologies such as cloud inventory management software and e-commerce has been shown to increase the productivity of small and medium-sized businesses by up to 30% (Wulan et al., 2024). Actual survey data in Vietnam also confirms that the level of digital technology application has a positive, direct and statistically significant impact on increasing aggregate labor productivity in economic sectors. Thanh and Trang (2020), thereby confirming that technology and management software are essential levers to improve business performance.

Hypothesis H1: Increasing technology application, use of technology and management software has a positive impact on enterprise labor productivity.

At the same time, empirical and theoretical studies have provided solid evidence supporting the hypothesis that capital intensity has a positive moderating effect and amplifies the relationship between digital transformation and labor productivity. Fundamentally, capital intensity has always been considered an independent and key factor determining the growth of

https://doi.org/10.71058/jodac.v10i08a01

an organization's labor productivity (Kumar et al., 2022). When conducting digital transformation, businesses can break organizational inertia through restructuring the capital-to-labor ratio to optimize production functions, thereby directly improving labor productivity (Zhou et al., 2025). Further analysis of the mechanism confirmed that the capital allocation efficiency associated with capital investment intensity plays a strong reinforcing role in the impact of technology. Specifically, the higher the level and efficiency of capital allocation, the greater the impact of digital transformation on the overall productivity of the enterprise (Chen et al., 2023). In Vietnam, actual data also shows that capital-intensive industries are the core driving force promoting industrialization, in which capital reserves play the most important role in creating a breakthrough in productivity (Nguyen et al., 2020). Therefore, businesses with high capital intensity will create a better launching pad, helping the digital transformation process maximize its power and bring about superior labor productivity growth.

Hypothesis H2: Enterprise capital intensity has a positive moderating effect on the relationship between digital transformation and labor productivity.

Furthermore, empirical and theoretical studies have provided clear evidence to support the hypothesis that labor qualifications (especially expertise and digital skills) play a positive regulatory role, helping to amplify the impact of digital transformation on labor productivity. Based on skill-biased technological change theory and human capital theory, technology by itself is not enough to deliver superior performance without support from the core competencies of the workforce (Li et al., 2018). Specifically, the true effectiveness of digital transformation in increasing labor productivity is only achieved at its maximum level when placed in the context of businesses possessing high-quality human resources. This impact is influenced and depends directly on the knowledge and skills of employees (Ha & Ngoc, 2024). Workers with high levels of education and expertise have the ability to flexibly adapt, operate, innovate, and optimize complex technologies more quickly (Aleca et al., 2025). In Vietnam, many studies confirm that the lack of skills and qualifications is the biggest barrier that prevents businesses from taking full advantage of the benefits of digital tools (To et al., 2020). On the contrary, higher worker qualifications, especially proficiency in the field of information and communications technology, will increase the real effectiveness of technology investments. In short, the expertise of the workforce acts as an essential catalyst, helping businesses radically transform technological barriers and potential into real breakthroughs in productivity.

https://doi.org/10.71058/jodac.v10i08a01

Hypothesis H3: Labor qualifications have a positive moderating effect on the relationship between digital transformation and labor productivity.

3. Methodologies

3.1. Empirical modeling

To assess the impact of digital transformation on labor productivity, the study uses a regression model with lagged independent variables. In this model, the level of digital transformation in 2019 is considered the input variable to forecast the trend of labor productivity fluctuations in the 2020-2023 period, helping to control for endogeneity in the causal analysis. 2019 is the year with the most detailed digital transformation indicators. Digital transformation is a long-term process, so time and lags are needed to assess its impact on labor productivity. Digital transformation in 2019 acts as a lagged independent variable compared to the dependent variable, labor productivity, in 2020, 2021, 2022, and 2023. Besides the digital transformation variable, the model also controls for variables such as enterprise size, ownership type, industry, etc., as detailed in the model:

$$ln\, ln\, y_i = \alpha + \beta X_{i2019} + \delta_j Z_{j,i} + \varepsilon_i \quad (1)$$

$$ln\, ln\, y_i = \alpha + \beta X_{i2019} + \gamma X_{i2019} * Z_{i2019} + \delta_j Z_{j,i} + \varepsilon_i \quad (2)$$

In (1), $ln\, ln\, y_i$ represents the productivity (PRO) of firm i, X_{i2019} is the level of digital transformation in 2019, and $Z_{j,i}$ are control variables which include capital intensity (Roger & Tseng, 2010; Wu et al., 2023; Zareie et al., 2024), age, education, and workforce (Aggrey et al., 2010). In (2), $X_{i2019} * Z_{i2019}$ represents the interaction of digital transformation and firm characteristics In both (1) and (2), key variables which represent digital transformation include technology use (USE), technology application (APP), and software (SW). Control variables are workforce (WF), capital intensity (CI), firm age (AGE), and labor education (EDU).

This study uses data from the General Statistics Office's Enterprise Census from 2019 to 2023 to assess the impact of digital transformation on labor productivity in Vietnamese enterprises. The 2019 digital transformation questions were taken from a sample questionnaire with 6,278 observations. Labor productivity data for 2020 (6,278 observations), 2021 (6,092 observations), 2022 (6,029 observations), and 2023 (5,822 observations) were also taken from the enterprise census. The study also used the 2018 census to obtain data on the age of enterprises (as only the 2018 questionnaire contained information on the year of establishment).

To clarify the impact of digital transformation on differences in labor productivity among businesses, the study applies quantile regression at quantiles 10, 25, 50, 75, and 90. This

https://doi.org/10.71058/jodac.v10i08a01

method was used in the study by (Dung Anh Vu et al., 2024). The advantage of this method is that it allows regression coefficients to vary flexibly depending on each part of the productivity distribution, instead of being limited by a fixed coefficient as in mean regression models. Therefore, this method allows for a more detailed assessment of the impact of digital transformation on labor productivity at different levels in the distribution.

3.2. Data and preliminary analysis

Table 1. Summary statistics

Variable	Observations	Mean	Stdev	Min	Max
PRO	24.221	235,3259	344,7421	0,010333	5000,733
EDU	24.221	34,55413	29,62617	0	100
WF	24.221	149,0101	613,3014	0,5	18377,5
CI	24.221	2779,485	11806,93	0,00	630101,4
AGE	24.221	12,29735	7,297117	2	73
USE	24.221	0,242599	0,428664	0	1
APP	24.221	0,361092	0,480327	0	1
SW	24.221	0,334586	0,471855	0	1

Standard deviation is abbreviated as “Stdev”. Summarized by Authors.

Table 1 presents descriptive statistics of the research variables. A total of 24,221 observations were used. Overall, average labor productivity (PRO) reached 235 million VND/ employee/ year and showed significant variation among businesses during the year, reflecting uneven business performance. At the same time, the average number of employees (WF) reached 149 employees/business, indicating a stable workforce. Notably, the indicators of digital transformation (USE, APP, and SW) had relatively low average values, with only about 24% - 36% of businesses in the sample having actually adopted/used digital technologies or software. This ratio reflects the fact that the level of digital transformation in domestic businesses is still in its initial stages, with significant potential for productivity growth through technology investment. This shows the enormous potential but also the challenges for Vietnamese businesses in realizing the economic benefits of digital transformation. The standard deviation of interaction variables such as capital intensity (CI) and labor skill level (EDU) indicates the diversity of the business sample, which is crucial for conducting more in-depth tests of moderating effects in subsequent sections of the study. The average business age (AGE) is

https://doi.org/10.71058/jodac.v10i08a01

approximately 12 years, indicating that the research sample includes businesses that have been operating stably for a sufficient period to accumulate management experience.

4. Findings

4.1. Main results

Impacts of digital transformation on the productivity of Vietnamese enterprises are found from key variables which include technology use (USE), technology application (APP), and software (SW) with following characteristics:

4.1.1. Technology use

The empirical research results in Table 2 have clarified the relationship between digital transformation (specifically through the use of technology) and labor productivity in Vietnamese enterprises during the period 2019-2023. These findings offer important implications in both theoretical and practical terms.

Digital transformation is a driving force for labor productivity. The OLS regression results confirm a positive and statistically significant impact, supporting the view that digital technology is a strategic resource (RBV) that helps businesses optimize processes. The variable "use of technology" (USE) has a coefficient of 0.0670*, which is statistically significant at the 1% level, indicating that the adoption or use of digital technology by enterprises has a positive impact on labor productivity. Specifically, when businesses implement digital transformation, labor productivity is expected to increase by approximately 6.7%. This result reinforces hypothesis H1, consistent with studies by (Nguyen & Ngoc, 2024; Roger & Tseng, 2000) demonstrating that digital transformation truly acts as a driver of improved business operational performance. However, quantile regression analysis revealed this heterogeneity, showing that the impact of technology is strongest in the q75 quantile (0.0718*) and weaker in the lower quantile groups (q25: 0.0447***), indicating that businesses with already good foundations (those in the q75 group with relatively high labor productivity) are the ones that benefit most from the use of technology. The results for technology adoption are inconsistent, yielding stronger productivity gains for businesses already well-established in higher percentiles, similar to the results of (Vu et al., 2024; Nguyen & Ngoc, 2024). Businesses in lower percentiles (q10, q25) may be struggling to absorb technology, leading to lower impacts on labor productivity. This suggests a threshold of capacity is necessary for digital technology to be fully effective. Businesses in lower percentiles (q10, q25) may be facing infrastructure

https://doi.org/10.71058/jodac.v10i08a01

barriers or a lack of capacity to absorb technology, resulting in investment in software not yet creating a significant boost to labor productivity.

Table 2. Impacts of technology use on the productivity of Vietnamese enterprises.

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Q10	Q25	Q50	Q75	Q90
USE	0.0670***	0.0356	0.0447***	0.0415***	0.0718***	0.0465**
	(0.0165)	(0.0280)	(0.0160)	(0.0114)	(0.0133)	(0.0190)
EDU	0.00330***	0.00362***	0.00340***	0.00330***	0.00332***	0.00382***
	(0.000247)	(0.000496)	(0.000276)	(0.000180)	(0.000240)	(0.000315)
WF	0.168***	0.253***	0.202***	0.170***	0.150***	0.135***
	(0.0161)	(0.00723)	(0.00548)	(0.00375)	(0.00413)	(0.00563)
CI	0.277***	0.269***	0.277***	0.297***	0.335***	0.372***
	(0.0134)	(0.0106)	(0.00652)	(0.00523)	(0.00601)	(0.00922)
AGE	0.00567	0.0702***	0.0291*	0.00108	-0.00949	-0.0506***
	(0.0154)	(0.0269)	(0.0151)	(0.0101)	(0.0106)	(0.0159)
Constant	2.211***	0.237	1.549***	2.275***	2.674***	3.063***
	(0.168)	(0.173)	(0.123)	(0.0810)	(0.0845)	(0.126)
Observations	24,221	24,221	24,221	24,221	24,221	24,221
R-squared	0.337					

Standard errors are in parentheses. Summarized by Authors.

Capital intensity and labor quality play a crucial catalytic role. Labor skill level (EDU) has a positive coefficient (0.0033) and is statistically significant at all percentiles, confirming that labor skill level is a fundamental factor supporting technology use, consistent with the results of (Yannin Zhang, 2023). Capital intensity (CI) has a high positive coefficient (0.277 - 0.372) that is significant at all percentiles and increases progressively across percentiles (from q10 to q90). This indicates that the higher the capital intensity, the stronger the impact of technology use on labor productivity, consistent with the results of (Chen et al., 2023). This is important evidence to support hypothesis H2 regarding the moderating role of capital intensity. The positive interaction between technology and capital intensity (CI) and labor skill level (EDU) confirms the theory of technological substitution and complementarity. Technology does not operate in isolation; it requires synergy from strong investment capital to maintain infrastructure and a highly skilled workforce to operate the system. This result refutes the notion that digital transformation can automatically improve labor productivity without synchronized investment in other supporting resources. The differences in efficiency across percentiles suggest a digital divide within the business sector. The increasing impact of technology use at higher percentiles indicates that the process of technology use is tending to widen the disparity in production efficiency among businesses. Without timely support policies

https://doi.org/10.71058/jodac.v10i08a01

for businesses at lower percentiles, the productivity gap between business groups is likely to widen further, creating challenges for the synchronized development of the digital economy.

4.1.2. Technology application

Table 3. Impacts of technology application on the productivity of Vietnamese enterprises.

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Q10	Q25	Q50	Q75	Q90
APP	0.0425***	-0.00260	0.0191	0.0296***	0.0529***	0.0427***
	(0.0148)	(0.0287)	(0.0148)	(0.0112)	(0.0120)	(0.0164)
EDU	0.00328***	0.00365***	0.00335***	0.00318***	0.00328***	0.00380***
	(0.000253)	(0.000494)	(0.000244)	(0.000190)	(0.000221)	(0.000321)
WF	0.169***	0.255***	0.204***	0.171***	0.151***	0.137***
	(0.0157)	(0.00790)	(0.00503)	(0.00369)	(0.00422)	(0.00568)
CI	0.278***	0.273***	0.280***	0.297***	0.336***	0.373***
	(0.0136)	(0.0106)	(0.00676)	(0.00526)	(0.00592)	(0.00836)
AGE	0.00612	0.0686***	0.0281*	0.00187	-0.0122	-0.0528***
	(0.0154)	(0.0247)	(0.0148)	(0.00996)	(0.0105)	(0.0165)
Constant	2.203***	0.246	1.530***	2.281***	2.677***	3.026***
	(0.169)	(0.186)	(0.125)	(0.0803)	(0.0839)	(0.129)
Observations	24,221	24,221	24,221	24,221	24,221	24,221
R-squared	0.337					

Standard errors are in parentheses. Summarized by Authors.

Table 3 data provides empirical evidence for the existence of a critical point in technology adoption (Vu et al., 2024). Digital transformation is only truly effective when businesses overcome the initial productivity barrier and are able to offset the conversion costs. Furthermore, technology should not and cannot be considered a substitute for the fundamental foundations of an organization. Empirical evidence confirms that digital technology only maximizes its productivity-enhancing effects when placed on a solid foundation of capital intensity and high-quality human resources (Nguyen & Bui, 2024; Tu, 2025; Awaludin & Xie, 2026). Quantile regression results show a distinctly non-linear impact pattern. The technology application variable (APP) was not statistically significant in the low-productivity group (q10: -0.0026) and only reached a significance level of 10% in the lower-medium group (q25: 0.0191, not strong enough to confirm significance). This impact only truly exploded and became highly statistically significant from the medium group (q50) and above. This result demonstrates that technology application is not a magic wand for every business. The existence of a low-significance area (no significant impact in groups' q10 and q25) suggests that these businesses

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may be stuck in integration costs. Applying technology requires a minimum productivity base to translate into output. Without reaching this minimum productivity threshold, businesses are only incurring operating costs without seeing performance growth.

The impact coefficient of udcn gradually increases from q50 (0.0296) to a peak at q75 (0.0529), then slightly decreases at q90 (0.0427). This suggests that in high-productivity businesses (q75 group), technology is absorbed most optimally. However, the slight decrease in the q90 group indicates a phenomenon of diminishing marginal returns. Once a business has reached a point of excellent performance, continued mass adoption of technology applications can lead to process overload, where adding more technology no longer provides breakthroughs in labor productivity but only increases management complexity.Capital stability (CI) and human resource quality (EDU) are both stable with positive coefficients and high statistical significance ($p < 0.01$) across all percentiles. Data shows that while technology (or human capital) fluctuates across different percentiles, capital and human resource intensity are the variables with the most consistent and lasting impact on labor productivity. This refutes the argument that over-reliance on technology is necessary: without parallel investment in human resource skills and capital intensity, productivity will not improve.

4.1.3. Software

Unlike previous studies that suggested a linear impact of technology, the results in Table 4, obtained through quantile regression, revealed a more complex picture. Notably, in low-productivity businesses (q10), software adoption did not have a positive impact, even showing a potentially non-linear trend due to switching costs. This result challenges the belief that digitalization automatically increases productivity for all business groups, similar to the results of (Vu et al., 2024). The quantile regression results show that the software variable (pm) has a negative coefficient (-0.0157) and is not statistically significant at the q10 quantile. In low-productivity businesses, software adoption did not have a positive impact because they faced significant barriers related to learning costs and switching costs (Lokuge et al., 2019; Vu et al., 2024). Instead of increasing productivity, adopting new technology can increase management costs (Tu, 2025) and distract businesses with complex new processes, leading to a temporary decline in efficiency.

The software coefficient increases progressively across the percentiles, specifically q25 (0.0437); q50 (0.0534); q75 (0.0598). This growth shows the scale impact of technology. Software is not a static asset but a supporting ecosystem. Businesses in the q75 group generally

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have management processes mature enough for smooth software integration, while the q25 group is still struggling with purely administrative procedure digitization. The slight decrease in software impact in q90 (0.0525) compared to q75 (0.0598) suggests a diminishing marginal return. At a certain productivity threshold, software plays a maintenance role rather than a breakthrough one. Furthermore, the paradox of enterprise age (ln_age) when moving from the 10% to the 90% percentile shows that innovation capacity is not uniform over time. While ln_age in Q10 has a strong positive coefficient (0.0743***), it becomes negative in Q90 (-0.0511***), indicating that in the lower percentile, older enterprises with management experience help them survive and increase productivity better than younger, less experienced enterprises. In the higher percentile, older enterprises tend to be stagnant, hindering the adoption of new software, while younger or newly transformed enterprises are more flexible and utilize software more effectively.

Table 4. Impacts of software on the productivity of Vietnamese enterprises.

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Q10	Q25	Q50	Q75	Q90
SW	0.0511***	-0.0157	0.0437***	0.0534***	0.0598***	0.0525***
	(0.0182)	(0.0285)	(0.0159)	(0.00996)	(0.0118)	(0.0160)
EDU	0.00328***	0.00360***	0.00338***	0.00321***	0.00329***	0.00374***
	(0.000253)	(0.000489)	(0.000271)	(0.000208)	(0.000252)	(0.000304)
WF	0.168***	0.255***	0.201***	0.169***	0.149***	0.134***
	(0.0159)	(0.00829)	(0.00530)	(0.00388)	(0.00421)	(0.00588)
CI	0.277***	0.272***	0.277***	0.297***	0.335***	0.373***
	(0.0137)	(0.0111)	(0.00654)	(0.00486)	(0.00604)	(0.00789)
AGE	0.00584	0.0743***	0.0274**	9.99e-05	-0.0117	-0.0511***
	(0.0155)	(0.0261)	(0.0129)	(0.0103)	(0.0112)	(0.0156)
Constant	2.209***	0.263	1.560***	2.270***	2.687***	3.063***
	(0.169)	(0.182)	(0.121)	(0.0726)	(0.0884)	(0.118)
Observations	24,221	24,221	24,221	24,221	24,221	24,221
R-squared	0.337					

Standard errors are in parentheses. Summarized by Authors.

The analysis of enterprise application, technology use, and software reveals a stratification in the impact of digital transformation. The application of technology cannot be equated with software. Research indicates that, for Vietnamese businesses, software is the most reliable

https://doi.org/10.71058/jodac.v10i08a01

driver of labor productivity. The difference in coefficients between software, technology development, and technology utilization shows that the optimal digital transformation roadmap for Vietnamese businesses should not begin with massive investment in infrastructure (technology utilization), but rather with standardizing processes using software and building technology utilization capacity for personnel (technology development). Simultaneously, the productivity trap for low-productivity businesses is that attempting to mechanically apply technology (technology utilization) often fails to achieve results and may even lead to cost risks. The success of digital transformation depends more on the capacity to absorb technology than on the volume of technology investment.

4.2. Robustness check

Impacts of control variables on digital transformation of Vietnamese enterprises are additionally found from capital intensity and labor education as follows:

4.2.1. Capital intensity

Table 5. Impacts of capital intensity on the digitalization of Vietnamese enterprises.

	OLS	Q10	Q25	Q50	Q75	Q90
USE	-0.246	-0.222	-0.170*	-0.359***	-0.340***	-0.379***
	(0.177)	(0.144)	(0.0885)	(0.0698)	(0.0758)	(0.0787)
CI	0.0458*	0.0368*	0.0325**	0.0619***	0.0644***	0.0644***
	(0.0255)	(0.0205)	(0.0134)	(0.0106)	(0.0114)	(0.0120)
APP	-0.108	0.00620	-0.0378	-0.205***	-0.258***	-0.321***
	(0.188)	(0.146)	(0.0759)	(0.0656)	(0.0628)	(0.0832)
CI	0.0222	0.00167	0.0101	0.0377***	0.0480***	0.0559***
	(0.0272)	(0.0211)	(0.0114)	(0.00990)	(0.00966)	(0.0127)
SW	-0.258	-0.406***	-0.280***	-0.383***	-0.359***	-0.312***
	(0.190)	(0.145)	(0.0828)	(0.0652)	(0.0679)	(0.0906)
CI	0.0454	0.0607***	0.0500***	0.0672***	0.0644***	0.0565***
	(0.0275)	(0.0204)	(0.0120)	(0.00969)	(0.0104)	(0.0139)

Standard errors are in parentheses. Summarized by Authors.

Table 5 clearly shows the role of capital intensity in boosting productivity. The positive and statistically significant interaction variable in all models of transformation variables and productivity percentiles of 50 and above implies that capital intensity will play a significant role in boosting productivity in businesses at or above the medium productivity percentile. This research result is entirely consistent with the studies of (Chen et al., 2023; Hu, 2026). An

https://doi.org/10.71058/jodac.v10i08a01

important point is that the coefficient of the digital transformation variable in these models is negative, implying that if capital intensity is sufficiently low, the impact of digital transformation on labor productivity will be negative.

Contrary to expectations of perfect complementarity, Table 6 shows a significant trade-off between capital intensity and digital transformation in improving labor productivity. Negative and statistically significant coefficients at the high percentiles (q50-q90) suggest that, in Vietnamese businesses, physical capital and digital transformation are in a competitive relationship in terms of performance. This finding contributes a new perspective to the theory of dynamic capabilities. During the period 2019-2023, Vietnamese businesses appear to prioritize scaling up physical capital to achieve rapid growth, rather than optimizing the combination of digital technology and human resources. This picture accurately reflects the productivity paradox where large investments in technology and physical capital can reduce efficiency without synchronized organizational restructuring (Dang & Dang, 2023). Simultaneously, this result is also consistent with the research of (Chen et al, 2023), who demonstrated that if a business's technological progress is excessively skewed towards capital, digital transformation will have an adverse impact on performance. Therefore, policies promoting digital transformation need to carefully consider the capital structure of enterprises; promoting digitalization on an overly capital-intensive platform may not achieve the expected results if it is not accompanied by a commensurate improvement in human resource skills, because technological transformation without human transformation will only bring extremely limited benefits (Tu, 2025).

4.2.2. Labor education

Interaction regression analysis has clarified the key role of workforce skill level in Table 6 as a moderator of technology absorption capacity. Contrary to the hypothesis of uniform effects, empirical data show a clear threshold effect, indicating that digital transformation only truly boosts productivity at firms with a certain workforce skill threshold (q75-q90). At lower quantiles, the shortage of skilled labor creates an integration barrier, where digital solutions cannot translate into actual operational performance. Furthermore, the finding of a diminishing coefficient of workforce skill level in the high-productivity group suggests the existence of skill saturation. This finding is entirely consistent with the quantile regression results of Vu et al. (2024), which indicate that only high-performing firms truly benefit from digitalization. Simultaneously, the decline in marginal efficiency of human capital at certain percentiles is also supported by (Nguyen & Bui, 2024), confirming that the accumulation of human resources

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does not automatically lead to productivity breakthroughs without the capacity to absorb (Tu, 2025) and synchronized processes for reducing excess personnel (Zhou et al., 2025). This evidence challenges the view that investing in highly skilled human resources always yields positive marginal efficiency, while affirming that the synergy between digital transformation and human resource quality is only optimized within a specific organizational structure, avoiding excess capacity.

Table 6. Impacts of labor education on the digitalization of Vietnamese enterprises.

	OLS	Q10	Q25	Q50	Q75	Q90
USE	0.0331	-0.0538	0.00105	0.0135	0.0739***	0.0579**
	(0.0369)	(0.0394)	(0.0250)	(0.0163)	(0.0182)	(0.0286)
EDU	0.000941	0.00261***	0.00115**	0.00106***	0.000254	-3.86e-05
	(0.000659)	(0.000900)	(0.000544)	(0.000407)	(0.000415)	(0.000664)
APP	0.0182	-0.0288	-0.0195	-0.00538	0.0348**	0.0749***
	(0.0316)	(0.0397)	(0.0227)	(0.0158)	(0.0175)	(0.0248)
EDU	0.000671	0.00119	0.00138***	0.00144***	0.000702*	-0.000835
	(0.000603)	(0.000878)	(0.000505)	(0.000353)	(0.000408)	(0.000564)
SW	0.0232	-0.0392	0.0240	0.0232	0.0435**	0.0561**
	(0.0311)	(0.0432)	(0.0230)	(0.0161)	(0.0170)	(0.0239)
EDU	0.000771	0.00143*	0.000813*	0.00121***	0.000718*	1.81e-05
	(0.000647)	(0.000858)	(0.000466)	(0.000357)	(0.000404)	(0.000532)

Standard errors are in parentheses. Summarized by Authors.

4.3. Discussion

The empirical results provide insightful and multifaceted perspectives on the relationship between digital transformation and labor productivity, thereby challenging the notion that the impact of technology is uniform in all cases. Regarding hypothesis H1, the research results strongly reinforce the assertion that digital transformation contributes positively to business performance. Consistent with resource-based value (RBV) theory, the statistically significant correlation between factors such as software deployment (PM), technology utilization (DU), and technology application (UA) confirms the role of digital assets as key drivers of operational efficiency. Notably, software solutions show the most consistent impact; this indicates that digital tools supporting management and operational processes are more effective in improving productivity than purely hardware-based technology applications. Therefore, hypothesis H1 is accepted. Empirical evidence confirms that digitalization through all three forms is a driver of

https://doi.org/10.71058/jodac.v10i08a01

labor productivity. However, this impact is not uniform (q10-q90 quantiles), suggesting that the effectiveness of digital transformation depends on the threshold of available enterprise capacity.

However, the moderating effects reveal a more complex picture, requiring the abandonment of simplistic, general-purpose policy frameworks. Contrary to hypothesis H2, the interaction between capital intensity and digital transformation shows a competitive rather than complementary relationship, especially in high-productivity enterprises. This result suggests that when capital intensity is high, the marginal return from digital investment will gradually decrease, indicating the risk of resource overload or organizational stagnation in large-scale enterprises. This contradicts the traditional hypothesis about the complementarity of technology and highlights a significant trade-off in resource allocation, an issue that needs further in-depth academic research. Therefore, hypothesis H2 is rejected in a positive light.

Regarding hypothesis H3, my research provides conditional evidence supporting the moderating role of labor quality. Positive interaction effects are only clearly evident in high percentile groups (q75-q90), thereby confirming the existence of a productivity threshold. This result strengthens the empirical basis for the theory of absorption capacity (Cohen & Levinthal, 1990), in which the effectiveness of digital transformation depends on the potential of enterprises to integrate and exploit digital knowledge. In short, the research results show that digital tools are insufficient to boost productivity without a skilled workforce. Instead, human capital acts as a fundamental catalyst determining the digital returns achieved. Therefore, we partially accept hypothesis H3 (conditional acceptance).

5. Conclusion

This study provides a comprehensive empirical analysis of the relationship between digital transformation and labor productivity in the Vietnamese business sector from 2019–2023. Instead of relying solely on aggregate estimates, the application of quantile regression analysis has helped clarify a multifaceted reality: digital transformation is a powerful driver of productivity, but its effectiveness is uneven across businesses. The research results yield three main conclusions.

Firstly, the positive impact of digital transformation differs structurally. Software management solutions emerge as the most sustainable and stable productivity drivers, outperforming conventional technology applications or hardware-based investments. Secondly, the study identifies a significant productivity threshold along with the moderating role of human capital.

https://doi.org/10.71058/jodac.v10i08a01

Digital transformation does not bring about a significant increase in productivity in low-productivity businesses due to a lack of absorption capacity; This confirms that human capital is not only a complementary asset but also a prerequisite for success in the digital transformation process. Thirdly, the research results show a competitive rather than complementary relationship between capital intensity and digital technology adoption in high-productivity businesses; this suggests that capital-intensive businesses may face diminishing marginal returns from digital investment due to organizational inertia or resource saturation.

Empirical evidence suggests a shift in mindset regarding digital policy for emerging economies like Vietnam. Policymakers should move from mass digital transformation subsidies to capacity-based support mechanisms. Specifically, the study proposes (i) focused digital intervention; (ii) people-centered digital policy; and (iii) institutional flexibility. In which, focused digital intervention is driven through supportive programs should prioritize assessing the digital maturity level of individual businesses rather than simply providing general funding for hardware purchases. Prioritize the integration of management software that optimizes organizational operational processes. In relation to people-centered digital policy: Because the quality of human resources plays a crucial regulatory role, national digital strategies need to be closely linked to vocational training and digital skills retraining programs. Equipping a workforce lacking advanced technology is unlikely to significantly increase productivity. Finally, policymakers should create an environment that encourages institutional flexibility in capital-intensive industries, helping large businesses overcome organizational inertia, a factor hindering the full integration of digital technologies. Future research could focus on exploring the role of digital culture and leadership style in mitigating organizational inertia, thereby providing deeper insights into how internal business characteristics affect the long-term sustainability of productivity gains from digital transformation.

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