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DIGITAL CAPABILITY AND TEACHING EFFECTIVENESS IN HUMAN CAPITAL DEVELOPMENT: EVIDENCE FROM PUBLIC UNIVERSITIES IN HO CHI MINH CITY

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ABSTRACT

Digital transformation is a top priority in higher education today. However, we still know very little about how it actually improves teaching, especially in Vietnam. This study combines the TOE framework with Dynamic Capabilities to fill this gap. We focus on digital capability—including new AI-driven skills—as a key link to teaching effectiveness and human capital development. First, we interviewed experts to update our scales with the latest AI trends. Then, we surveyed 528 lecturers and students in Ho Chi Minh City. Using PLS-SEM, the data show that technological readiness, organizational support, and environmental pressure strongly drive digital capability. Interestingly, digital capability acts as a full mediator. This means institutional resources only improve teaching when filtered through staff and students' digital skills. Our findings suggest a clear strategy: universities must prioritize digital and AI literacy over simple infrastructure. By linking digital tools to long-term educational value, this research provides a fresh perspective on managing education in the digital era.

Keywords: Digital capability, digital transformation, teaching effectiveness, TOE framework, educational digitalization.

1. INTRODUCTION

Digital technologies are changing higher education at a rapid pace. Universities are under increasing pressure to use digital tools in teaching and learning. The goal is not only to improve educational quality, but also to prepare students for the digital economy.

In emerging economies such as Vietnam, this pressure is even stronger. Public universities are expected to modernize their teaching practices while developing human capital that meets evolving labor market demands. In recent years, many institutions have invested heavily in digital infrastructure. However, the results have been mixed. One key issue is that digital transformation does not always lead to better learning outcomes [1], [2]. Much of the existing research focuses on technology adoption. Less attention has been paid to how institutions develop the capabilities needed to use these technologies effectively [3], [4]. As a result, we still lack a clear understanding of how digital transformation creates real educational value.

In the current context, digital capability is no longer limited to basic ICT literacy but increasingly encompasses the integration of Artificial Intelligence (AI) in pedagogical activities. AI-enhanced learning tools and platforms have become integral components of the digital infrastructure in Vietnamese public universities, necessitating a shift in how educators and students interact with technology [5].

This study addresses this gap by focusing on digital capability as a central mechanism. Drawing on the Technology–Organization–Environment (TOE) framework [6] and capability theory [7], the study examines how institutional conditions shape digital capability, how digital capability improves teaching and learning effectiveness, and how these improvements lead to human capital development.

Rather than assuming a direct impact, this study proposes a multi-stage process. Institutional factors influence digital capability. Digital capability enhances teaching and learning effectiveness. These improvements then translate into human capital outcomes. This process-based perspective provides a clearer explanation of how digital transformation works in higher education.

2. LITERATURE REVIEW

2.1. Digital transformation in higher education

Digital transformation in higher education involves integrating digital technologies into teaching, learning, and administrative processes [3], [1]. It encompasses the adoption of learning management systems, online platforms, and digital pedagogical approaches that aim to improve educational outcomes [3], [4].

2.2. TOE framework in educational contexts

The TOE framework explains technology adoption through three dimensions: technological readiness, organizational support, and environmental pressure [8], [6], [9]. These factors collectively shape how institutions adopt and utilize digital technologies across organizational contexts [10].

2.3. Digital capability

Digital capability refers to an organization's ability to integrate, manage, and apply digital technologies in its operations [11], [7], [12]. In higher education, digital capability enables institutions to redesign teaching processes and enhance learning experiences, particularly by supporting innovative pedagogies and improving learning value [13], [14].

2.4. Teaching and learning effectiveness

Teaching and learning effectiveness reflects the quality of instructional practices and learning outcomes [3], [4]. It is conceptualized as a higher-order construct comprising three dimensions: student engagement (SE), teaching innovation (TI), and learning performance (LP). These dimensions are widely recognized as key indicators of effective digital learning environments [1], [15], capturing both pedagogical processes and resulting learning outcomes.

In this study, teaching effectiveness is conceptualized as a holistic construct that captures both instructional practices and learning outcomes. Unlike the narrower concept of learning effectiveness, which primarily focuses on student performance, teaching effectiveness encompasses student engagement, pedagogical innovation, and learning performance. This broader conceptualization is particularly relevant in the context of digital transformation, where changes in teaching methods play a critical role in shaping learning outcomes.

2.5. Human capital development

Human capital development refers to the process of enhancing individuals' knowledge, skills, and competencies [16], [17]. In the context of higher education, it can be conceptualized through three key dimensions: digital skills (DS), which reflect students' ability to use digital technologies effectively; learning autonomy (LA), referring to the capacity for self-directed and lifelong learning; and employability readiness (ER), which captures students' preparedness for the labor market in the digital economy [2], [12].

3. RESEARCH MODEL AND HYPOTHESES

3.1. Theoretical foundation and research model

The digital transformation of higher education requires not only the adoption of technological infrastructure but also the development of organizational capabilities that enable effective teaching and learning practices. Drawing on the Technology–Organization–Environment (TOE) framework [6] and organizational capability theory [7], this study conceptualizes digital capability as a key mechanism through which contextual factors are translated into educational outcomes.

The TOE framework provides a comprehensive lens to examine how technological readiness, organizational support, and environmental pressures shape digital transformation processes in higher education institutions. However, prior studies have often focused on direct effects of these contextual factors, overlooking the role of internal capabilities. In response, this study positions digital capability as a higher-order construct that enables institutions to leverage digital technologies effectively in teaching and learning.

Furthermore, this study extends existing research by linking digital capability to teaching and learning effectiveness, and ultimately to human capital development. In the context of public universities, teaching effectiveness reflects not only instructional quality but also student engagement and learning outcomes, which are essential components of human capital formation in the digital economy.

Based on this theoretical integration, the proposed research model examines the relationships among TOE factors, digital capability, teaching and learning effectiveness, and human capital development.

3.2. TOE factors and digital capability

Technological readiness essentially means having the right tools in place. This includes everything from basic digital infrastructure and systems to the latest AI-driven software. Without these foundational resources, it is nearly impossible for educators to develop their digital skills. Being "ready" is the first step toward adopting any new technology [6]. In today's universities, having access to stable networks and advanced AI tools is what truly allows staff to sharpen their digital capabilities [18]. Based on this, we expect that:

H1: Technological readiness positively influences digital capability.

Organizational support includes leadership commitment, training programs, and institutional policies that facilitate digital transformation [10], [6]. Strong organizational support enhances the ability of universities to build and sustain digital capabilities. Institutional support, including training and administrative policies, is crucial for fostering digital skills [19]. Effective digital transformation requires an organizational culture that encourages innovation [20]. Therefore, we hypothesize:

H2: Organizational support positively influences digital capability.

Environmental pressure is essentially the push from the outside world. Universities do not operate in a vacuum; they face constant demands from government policies, industry expectations, and competition. These external forces act as a wake-up call, pushing institutions to upgrade their digital game. Such pressures often force organizations to move faster on digital adoption [8]. In a digital-first world, universities must adapt to stay relevant and maintain their reputation [21]. We believe this external drive is a major reason why internal digital capabilities improve. Therefore, we hypothesize:

H3: Environmental pressure positively influences digital capability.

3.3. Digital capability and teaching and learning effectiveness

Digital capability represents the institution's ability to integrate and utilize digital technologies in pedagogical practices effectively. Institutions with higher levels of digital capability are better positioned to innovate teaching methods, enhance student engagement, and improve learning outcomes. Prior research suggests that digital capability enables more interactive, personalized, and flexible learning environments, thereby improving teaching and learning effectiveness [3], [4], [15]. Based on this:

H4: Digital capability positively influences teaching and learning effectiveness.

3.4. Teaching and learning effectiveness and human capital development

Human capital theory [16] emphasizes the role of education in developing individuals' knowledge, skills, and competencies. In the context of digital transformation, universities are increasingly expected to produce graduates equipped with digital skills, learning autonomy, and employability readiness.

Teaching and learning effectiveness plays a critical role in achieving these outcomes. Effective pedagogical practices not only improve immediate learning outcomes but also foster long-term competencies relevant to the digital economy [2], [17]. Based on this:

H5: Teaching and learning effectiveness positively influences human capital development.

3.5. Mediating Role of Digital Capability

Building on the TOE framework, digital capability is expected to act as a key mechanism through which contextual factors influence teaching and learning effectiveness. While TOE factors provide the conditions for digital transformation, their impact on educational processes is likely to be realized through the development of digital capability [7],[6].

H6: *Digital capability mediates the relationship between TOE factors and teaching and learning effectiveness.*

This study further proposes that teaching and learning effectiveness mediates the relationship between digital capability and human capital development. Although digital capability enables institutions to adopt advanced technologies, it is through effective teaching practices that these capabilities are translated into meaningful student outcomes.

H7: *Teaching and learning effectiveness mediates the relationship between digital capability and human capital development.*

3.6. Sequential Mediation Mechanism

Finally, this study proposes a sequential mediation mechanism linking TOE factors to human capital development through digital capability and teaching and learning effectiveness. This multi-stage process reflects a capability-driven transformation pathway in which contextual inputs are translated into outcomes through intermediate mechanisms [7].

H8: Digital capability and teaching and learning effectiveness jointly mediate the relationship between TOE factors and human capital development.

Ultimately, when universities use digital tools to make teaching more effective, they are doing more than just updating their methods—they are building better human capital. By improving how students learn today, these institutions ensure that graduates enter the workforce with the sharp digital skills and fluency that modern employers actually need. This direct link confirms that pedagogical gains through technology are essential for long-term economic and social growth.

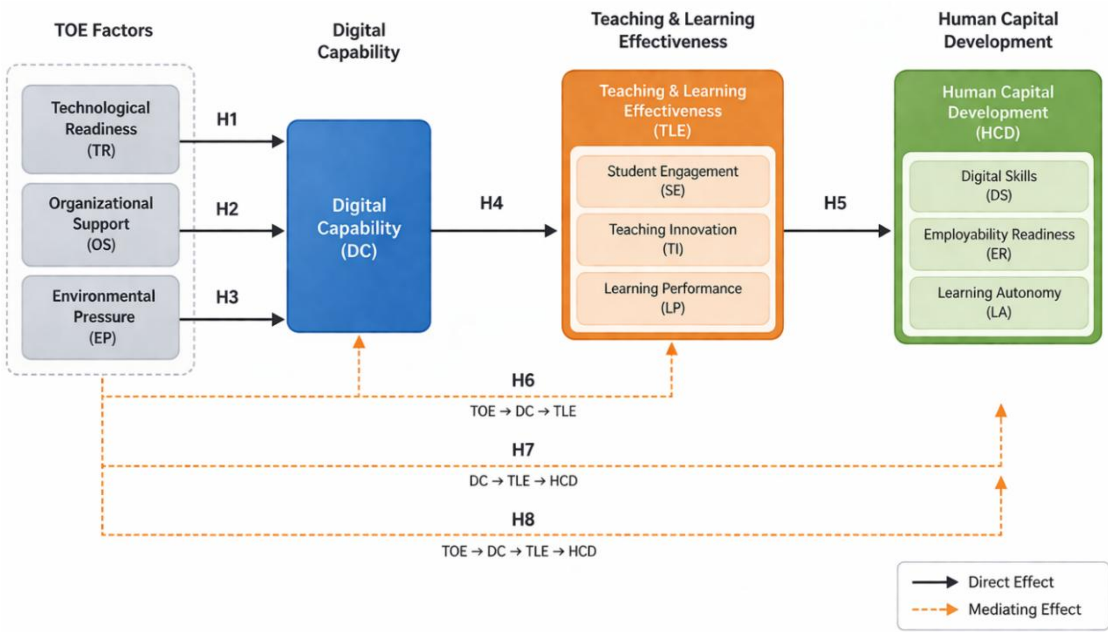

Figure 1. Proposed research model *(Source: Developed by the authors)*

The model illustrates the relationships among Technology–Organization–Environment (TOE) factors, digital capability, teaching and learning effectiveness, and human capital development. Digital capability serves as a key mediating mechanism linking contextual factors to educational outcomes, while teaching effectiveness further mediates the relationship between digital capability and human capital development.

4. RESEARCH METHODOLOGY

4.1. Research design and data collection

This study employs an exploratory sequential mixed-methods design to enhance both theoretical rigor and contextual relevance. The research was conducted in two phases: a qualitative phase to refine concepts, followed by a quantitative phase to test the proposed research model using empirical data.

In the first phase, semi-structured interviews were conducted with eight experts, including university lecturers, educational technology specialists, and educational administrators involved in digital transformation initiatives in higher education. These interviews aimed to assess the conceptual and contextual suitability of the proposed concepts and measurement scales, particularly those regarding technology readiness, organizational support, environmental pressure, digital competence, teaching and learning effectiveness, and human resource development. Expert feedback was used to finalize the questionnaire and ensure its applicability to the context of public higher education in Vietnam.

In the second phase, a structured questionnaire survey was conducted with students and lecturers from seven universities in Ho Chi Minh City. Surveying both groups aimed to gather complementary perspectives on digital competence and technology-integrated teaching and learning activities within the university environment. Students provided information primarily from the learner's perspective, while lecturers contributed insights from the teaching perspective. To ensure comparability between the two groups, the measurement scales were developed based on participants' perceptions and experiences regarding digital technology in teaching and learning activities. A convenience sampling method was employed due to factors related to accessing the target survey population. The questionnaire was administered online over an eight-week period. A total of 568 responses were initially collected. Following data screening and the exclusion of incomplete or invalid questionnaires, 528 valid responses were retained for final analysis, representing a valid response rate of approximately 93.0%.

Among the 528 valid participants, 429 were students (81.3%) and 99 were faculty members (18.8%). Females constituted 59.8% (n = 316) of the sample, while males accounted for 40.2% (n = 212). Participating students ranged in age from 18 to 21 and were enrolled across all four years of their undergraduate programs. Participating faculty members ranged in age from 25 to 59. Participants were recruited from seven universities in Ho Chi Minh City, ensuring institutional diversity within the study context.

The final sample of 528 observations was subsequently used to evaluate the measurement and structural models using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method.

Table 1. Descriptive statistics of respondents' demographics (N = 528)

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	212	40.2
	Female	316	59.8
Role	Student	429	81.3
	Lecturer	99	18.8
Student: Year of study (n=429)	Year 1	99	23.1
	Year 2	109	25.4
	Year 3	96	22.4
	Year 4	125	29.1
Lecturer: Age (n=99)	≤30	24	24.2
	31–40	37	37.4
	41–50	27	27.3
	>50	11	11.1

Source: Authors' compilation based on survey data

The respondents represent diverse academic disciplines and varying levels of experience in using digital technologies in learning. This diversity enhances the generalizability of the findings within the context of Vietnamese public universities.

4.2. Measurement instruments

All constructs in this study were measured using multi-item scales adapted from prior validated studies, with minor modifications to fit the context of higher education and AI-enhanced learning. The questionnaire was originally developed in English and translated into Vietnamese using a back-translation procedure to ensure semantic equivalence. All items were measured on a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). Technological readiness, organizational support, and environmental pressure were adapted from established TOE-based studies [9], [8]. Digital capability was measured based on digital competence frameworks [12]. Teaching and learning effectiveness was operationalized using constructs from prior e-learning and educational effectiveness research

[3], [22], [4]. Human capital development was measured using indicators related to digital skills, learning autonomy, and employability readiness [16], [2].

A pilot test was conducted with 30 students to assess the clarity and reliability of the measurement instrument before the main data collection. A summary of the constructs, measurement items, and their sources is presented in Table 2.

Table 2. Measurement Scales

Construct	Measurement items	Source
Technological Readiness (TR)	TR1. High-speed internet and learning management systems are consistently available at the university. TR2. The university provides adequate hardware, software, and AI tools for teaching and learning activities. TR3. The university's digital infrastructure adequately supports advanced teaching and learning activities.	[6]; [9]; [8]
Organizational Support (OS)	OS1. University leaders actively support the adoption of digital and AI-enabled education. OS2. The university provides regular training on new digital and AI-based tools. OS3. The university provides clear policies and accessible technical support for digital technology use	[10]; [15]
Environmental Pressure (EP)	EP1. Competitive pressure among universities encourages digital transformation in teaching and learning. EP2. Government policies and regulations encourage universities to enhance digital capabilities. EP3. The labor market increasingly expects graduates and lecturers to possess digital and AI-related competencies	[8]; [9]
Digital Capability (DC)	DC1. I can effectively use AI tools, such as generative AI, for my learning or teaching tasks. DC2. I can integrate different digital tools into my learning or teaching routines. DC3. I can solve basic technical problems when using digital platforms.	[23]; [24]; [12]
Teaching & Learning Effectiveness (TLE)	1. Student Engagement (SE) Code: SE1–SE3 SE1: Digital tools increase students' engagement in learning activities. SE2: Interactive technologies make learning more interesting. SE3: Students participate more actively when using digital tools. 2. Teaching Innovation (TI) Code: TI1–TI3 TI1: Digital tools enable more innovative teaching methods. TI2: AI tools help create more creative learning materials. TI3: Teaching approaches become more flexible with digital tools. 3. Learning Performance (LP) Code: LP1–LP3 LP1: Digital tools help improve understanding of complex topics. LP2: Learning outcomes improve when digital tools are used. LP3: Digital tools enhance learning efficiency.	[3]; [4]

Human Capital Development (HCD)	1. Digital Skills (DS) Code: DS1–DS3 DS1: I have developed strong digital skills through my learning experience. DS2: I can effectively use digital tools in academic or work contexts. DS3: My ability to use technology has improved significantly. 2. Employability Readiness (ER) Code: ER1–ER3 ER1: I feel prepared for the digital labor market. ER2: My skills meet current job market requirements. ER3: I am confident in applying digital tools in future jobs. 3. Learning Autonomy (LA) Code: LA1–LA3 LA1: I can learn new technologies independently. LA2: I take initiative in improving my skills. LA3: I can adapt quickly to new technological changes.	[16]; [2]

Source: Developed by the authors

Human capital development was operationalized through three dimensions, including digital skills, learning autonomy, and employability readiness.

4.3. Data analysis technique: PLS-SEM

The proposed research model was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) [25], [26] with SmartPLS software. PLS-SEM was selected due to its suitability for complex models involving multiple constructs and mediating relationships. In addition, it does not require strict assumptions about data normality and is appropriate for exploratory and prediction-oriented research.

The data analysis followed a two-step approach, including the assessment of the measurement model and the structural model. First, the measurement model was evaluated in terms of reliability and validity. Indicator reliability was confirmed as all outer loadings exceeded the recommended threshold of 0.70. Internal consistency was assessed using Cronbach's alpha and composite reliability, both exceeding 0.70. Convergent validity was established through average variance extracted (AVE) values above 0.50. Discriminant validity was evaluated using the Fornell–Larcker criterion [27] and the heterotrait–monotrait ratio (HTMT) [28], with all values below the recommended threshold of 0.85. Second, the structural model was assessed by examining path coefficients and their significance using bootstrapping with 5,000 resamples. The coefficient of determination (R^2) was used to evaluate the explanatory power of the model, while effect size (f^2) assessed the relative impact of exogenous constructs. Predictive relevance (Q^2) was examined using the blindfolding procedure.

In addition, mediation analysis was conducted to test indirect effects. Both specific indirect effects and sequential mediation paths were evaluated to better understand the underlying mechanisms of the model.

4.4. Common method bias

To address potential common method bias, both procedural and statistical remedies were applied. Procedurally, respondents were assured of anonymity and confidentiality to reduce evaluation apprehension. Statistically, Harman's single-factor test was conducted. The results indicate that no single factor accounted for the majority of the variance, suggesting that common method bias is not a serious concern in this study.

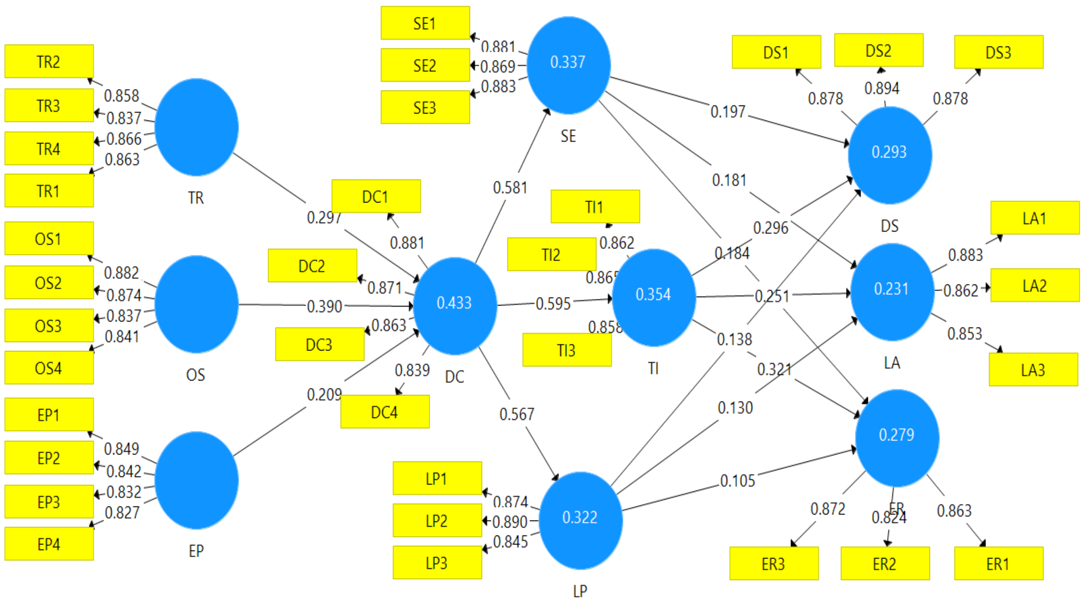

Figure 2. Results of the Structural Model (PLS-SEM Analysis)

Source: Export from Smart PLS

5. RESULTS OF PLS-SEM ANALYSIS

5.1. Measurement model assessment

Table 3. Results of construct reliability and convergent validity

Construct	Outer Loadings (OL)	Cronbach's alpha	rho_A	Composite reliability	AVE	VIF
DC	0.839 – 0.881	0.887	0.889	0.922	0.746	2.122 – 2.518
DS	0.878 – 0.894	0.860	0.865	0.914	0.780	2.156 – 2.187
EP	0.827 – 0.849	0.858	0.860	0.904	0.701	1.928 – 2.122
ER	0.824 – 0.872	0.814	0.822	0.889	0.729	1.687 – 1.908
LA	0.853 – 0.883	0.834	0.836	0.900	0.750	1.840 – 2.037
LP	0.845 – 0.890	0.839	0.844	0.903	0.757	1.874 – 2.218
OS	0.837 – 0. 882	0.881	0.883	0.918	0.738	2.065 – 2.570
SE	0. 869 – 0.883	0.851	0.851	0.909	0.770	2.014 – 2.152
TI	0.858 – 0.862	0.827	0.828	0.896	0.743	1.827 – 1.950
TR	0.837 – 0.866	0.878	0.880	0.916	0.733	2.062 – 2.226

(Source: SMART-PLS3 analysis)

As shown in Table 3, all constructs meet the required thresholds for reliability and validity. Indicator loadings, Cronbach's alpha, and CR values all exceed 0.70, while AVE values surpass 0.50, confirming strong internal consistency and convergent validity. Additionally, VIF values remain below 5, indicating no multicollinearity issues.

Discriminant validity is confirmed using both the Fornell–Larcker criterion and the HTMT ratio. The square root of AVE for each construct exceeds its correlations with other constructs. In addition, all HTMT values are below the recommended threshold of 0.85. These results indicate that the constructs are empirically distinct.

Overall, the measurement model meets all required criteria and provides a solid foundation for the structural model analysis.

Table 4. HTMT results (Discriminant validity Assessment)

	DC	DS	EP	ER	LA	LP	OS	SE	TI	TR
DC	0.864									
DS	0.540	0.883								
EP	0.385	0.136	0.837							
ER	0.515	0.600	0.188	0.854						
LA	0.503	0.605	0.165	0.576	0.866					
LP	0.567	0.423	0.255	0.398	0.380	0.870				
OS	0.539	0.329	0.248	0.300	0.264	0.337	0.859			
SE	0.581	0.451	0.232	0.434	0.404	0.577	0.302	0.878		
TI	0.595	0.492	0.211	0.491	0.433	0.582	0.292	0.590	0.862	
TR	0.480	0.241	0.270	0.256	0.330	0.325	0.326	0.330	0.318	0.856

(Source: SMART-PLS3 analysis)

5.2. Structural model and hypotheses testing

The structural model was assessed using path coefficients, coefficients of determination (R^2), and model fit indicators obtained from SmartPLS. As shown in Table 5, the model demonstrates an acceptable fit, with SRMR (standardized root mean square residual) and NFI (normed fit index) values falling within recommended ranges (SRMR < 0.10; NFI > 0.80). Overall, these results suggest that the proposed model fits the data reasonably well.

Table 5. Model Fit Assessment

	Saturated Model	Estimated Model
SRMR	0.038	0.097
d_ULS	0.846	5.572
d_G	0.474	0.634
Chi-Square	1527.182	1826.881
NFI	0.857	0.829

(Source: SMART-PLS3 analysis)

The structural relationships were evaluated using bootstrapping results. The findings show that all TOE factors have significant positive effects on digital capability. Technological readiness ($\beta = 0.297$, $p < 0.001$), organizational support ($\beta = 0.390$, $p < 0.001$), and environmental pressure ($\beta = 0.209$, $p < 0.001$) all significantly contribute to the development of digital capability, supporting H1–H3. Among these factors, organizational support has the strongest effect.

Digital capability, in turn, has a strong positive impact on teaching and learning effectiveness across its dimensions. The effects are significant for student engagement ($\beta = 0.581$, $p < 0.001$), teaching innovation ($\beta = 0.595$, $p < 0.001$), and learning performance ($\beta = 0.567$, $p < 0.001$), supporting H4.

Teaching and learning effectiveness significantly influence human capital development. Among its dimensions, teaching innovation shows the strongest effect ($\beta = 0.251–0.321$, $p < 0.001$), followed by student engagement ($\beta = 0.181–0.197$, $p < 0.001$) and learning performance ($\beta = 0.105–0.138$, $p < 0.05$). These results support H5.

Table 6 presents the explanatory power of the structural model. Digital capability achieves an R^2 value of 0.433, indicating that TOE factors explain a substantial portion of its variance. The dimensions of teaching and learning effectiveness show R^2 values ranging from 0.322 to 0.354, while the dimensions of human capital development range from 0.231 to 0.293. These results indicate moderate explanatory power, which is consistent with expectations in behavioral and educational research.

Table 6. Explanatory Power of the Structural Model (R^2)

	R Square	R Square Adjusted
DC	0.433	0.430
DS	0.293	0.288
ER	0.279	0.275
LA	0.231	0.226
LP	0.322	0.321
SE	0.337	0.336
TI	0.354	0.353

(Source: SMART-PLS3 analysis)

Table 7. Structural model results and hypothesis testing

Hypothesis	Path	β (standardized)	p-value	Result
H1	TR → DC	0.297	<0.001	Supported
H2	OS → DC	0.390	<0.001	Supported
H3	EP → DC	0.207	<0.001	Supported
H4a	DC → SE	0.581	<0.001	Supported
H4b	DC → TI	0.595	<0.001	Supported
H4c	DC → LP	0.567	<0.001	Supported
H5a	SE → DS	0.197	<0.001	Supported
H5b	SE → ER	0.184	<0.001	Supported
H5c	SE → LA	0.181	<0.001	Supported
H5d	TI → DS	0.296	<0.001	Supported
H5e	TI → ER	0.321	<0.001	Supported
H5f	TI → LA	0.251	<0.001	Supported
H5g	LP → DS	0.138	<0.001	Supported
H5h	LP → ER	0.105	<0.001	Supported
H5i	LP → LA	0.130	<0.001	Supported

(Source: SMART-PLS3 analysis)

The summary of these findings confirms that all primary hypotheses are supported, setting the stage for a deeper look into the mediation mechanisms.

5.3. Mediation analysis

To better understand how these variables work together, we performed a mediation analysis using bootstrapping for indirect effects. The results reveal a clear chain of impact. First, digital capability acts as a vital bridge, connecting institutional TOE factors to teaching effectiveness (supporting H6). Furthermore, teaching effectiveness itself serves as the key mechanism that translates these digital skills into long-term human capital development (supporting H7).

Most importantly, the data confirms a sequential mediation process (H8). This shows that digital transformation follows a multi-stage path: institutional readiness builds capability, capability improves teaching, and better teaching finally creates human capital. Notably, we found no significant direct link between digital capability and human capital development. This 'full mediation' structure is a major finding; it suggests that digital tools only create real value when they are actively used to improve pedagogical practices.

5.4. Summary of findings

Overall, the findings strongly support the proposed research model. TOE factors play a significant role in shaping digital capability. In turn, digital capability improves teaching and learning effectiveness.

The results also show that human capital development is mainly driven by teaching and learning effectiveness. This suggests that digital capability alone is not enough. Its impact becomes meaningful only when it is translated into effective teaching practices. More importantly, the findings reveal a clear multi-stage process. TOE factors influence digital capability. Digital capability enhances teaching and learning effectiveness. These improvements then lead to better human capital outcomes.

Taken together, the results highlight the importance of a capability-driven approach to digital transformation in higher education. Digital capability acts as a bridge. It connects institutional conditions with teaching practices. Through this process, it ultimately contributes to human capital development.

6. DISCUSSION AND THEORETICAL CONTRIBUTIONS

6.1. Discussion of key findings

The results confirm a full mediation model, suggesting that technological and organizational factors do not automatically lead to better teaching outcomes. Instead, they must be converted into 'Digital Capability' first. This aligns with the Dynamic Capabilities View [7], emphasizing that resources alone are insufficient; it is the ability to integrate and reconfigure these resources that drives performance. In the context of Ho Chi Minh City's universities, simply providing high-speed internet or software is not enough if users (lecturers and students) cannot effectively use them for educational purposes. Furthermore, our findings echo several key points from previous literature but also offer new insights. For instance, the strong impact of organizational support on digital capability aligns with the work of Zhu et al. [19], who argued that top-down support is vital for any technology adoption. However, our study goes a step further by specifically highlighting AI readiness. While traditional studies focused on basic IT systems, we find that modern digital capability is heavily shaped by how universities integrate AI tools—a point that is becoming increasingly central to the field [18].

Interestingly, our 'full mediation' result slightly differs from some technology acceptance models, such as Teo [15] and Venkatesh [29], which often show that infrastructure can directly improve teaching outcomes. In our case, especially within the context of Ho Chi Minh City, infrastructure alone does nothing unless it is 'activated' by the user's capability. This confirms the Dynamic Capabilities View: it is not the resources you have, but how you use them that matters. This shift in perspective is crucial for developing countries where high-tech tools are often available but not fully utilized.

This study examines how digital capability connects institutional conditions to teaching and learning effectiveness, and ultimately to human capital development in public universities. The findings offer several important insights.

First, technological, organizational, and environmental factors all shape digital capability. This is consistent with the TOE framework. Among them, organizational support stands out as the most influential factor. This result highlights the role of leadership, policies, and training. Digital transformation is not only about technology. It is mainly an organizational issue. Even with good infrastructure, weak institutional support can limit capability development.

Second, digital capability has a strong effect on teaching and learning effectiveness. This confirms that capability matters more than technology itself. What universities do with technology is more important than simply adopting it. Institutions that integrate digital tools into teaching are more likely to improve student engagement, support innovative teaching, and enhance learning outcomes.

Third, teaching and learning effectiveness plays a central role in human capital development. The results suggest that digital capability alone is not enough. Its impact becomes meaningful only when it is translated into effective teaching practices. Through improved pedagogy, students develop not only knowledge, but also skills such as autonomy, adaptability, and employability readiness.

Finally, the mediation analysis reveals a clear multi-stage process. Institutional conditions influence digital capability. Digital capability improves teaching and learning effectiveness. These improvements then lead to better human capital outcomes. This confirms that digital transformation in higher education is a capability-driven process. Value is created through a sequence of interconnected steps, not through isolated effects.

6.2. Theoretical contributions

This study makes several contributions to the literature on digital transformation, higher education, and human capital development.

First, it extends the TOE framework by introducing digital capability as a key mechanism. Prior research often focused on direct relationships. This study shows that contextual factors operate through capability development. This provides a clearer explanation of how transformation actually happens.

Second, the study connects digital transformation with human capital development. Many studies focus only on technology or learning outcomes. This research goes further by linking capability and teaching effectiveness to long-term student development. This is important in the digital economy, where graduates need both knowledge and digital skills.

Third, the study proposes and validates a multi-stage transformation process. The results support a sequential mediation model. This shows that outcomes emerge through a chain of processes. This perspective adds depth to capability-based theory and offers a more complete view of value creation in higher education.

Finally, the study provides evidence from an emerging economy. Research in this context is still limited. The findings show how institutional conditions shape capability development in a developing education system. This offers insights that may differ from those in more developed countries

6.3. Implications for future research

The findings suggest several directions for future research. First, future studies can include moderating variables such as digital learning culture or institutional readiness. These factors may help explain differences across institutions. Second, longitudinal research could provide deeper insights into how digital capability develops over time. Third, comparative studies across countries or different types of universities would help test the generalizability of the model.

7. CONCLUSION

7.1. Key findings

This study examines the role of digital capability in shaping teaching and learning effectiveness and human capital development in public universities. The findings confirm that digital transformation is not merely a technological issue, but a capability-driven process [7], [6].

Digital capability plays a central role in improving teaching and learning effectiveness [3], [4]. However, its impact on human capital development is not direct. Instead, it operates through teaching and learning effectiveness as a key mediating mechanism. These results highlight a multi-stage process in which institutional conditions influence digital capability, which then enhances teaching practices and leads to improved human capital outcomes [16], [2], [17].

7.2. Practical implications

The findings offer several important implications for university leaders and policymakers. First, investments in digital infrastructure alone are not sufficient [7]. Universities need to focus on developing digital capability, including training, organizational support, and effective integration of technology into teaching [19]. Second, improving teaching and learning practices should be a priority. Digital tools must be used to enhance student engagement, support innovative teaching, and improve learning performance [15]. Without effective pedagogical use, digital transformation is unlikely to produce meaningful outcomes.

7.3. Limitations and Future research

This study has several limitations. First, the data were collected from public universities in a single city, which may limit generalizability. Second, the cross-sectional design does not capture changes over time.

Future research may extend this study by incorporating additional contextual variables, conducting longitudinal analyses, and comparing results across different countries or institutional settings.

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