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DIGITAL TRANSFORMATION SENTIMENT AND CAREER PROSPECT CONFIDENCE: THE MEDIATING ROLE OF PROACTIVE LEARNING

Le Bao Toan[1*], Duong Tuan Vu[1]

Abstract – *In the era of generative AI reshaping human capital structures, this study integrates conservation of resources theory and career construction theory to unravel the impact mechanism of digital transformation sentiment on students' career prospect confidence. Utilizing structural equation modeling on a survey sample of 368 business and management students from regional universities in the Mekong Delta, Vietnam, collected between January and February 2026, the research focuses on testing the mediating role of the proactive learning strategy. This specific geographic and disciplinary focus provides unique insights into the adaptive behaviors of students within an emerging regional digital hub. Empirical results confirm that digital transformation sentiment exerts a strong direct influence on career prospect confidence and serves as a 'psychological antecedent' that drives self-directed learning behaviors. Notably, the study demonstrates the existence of an indirect transmission mechanism: a strategic awareness of technological shifts activates a 'resource spiral' through a proactive learning strategy, thereby strengthening confidence in future career paths. These findings offer a novel perspective on transforming perception into competitive advantage, while suggesting strategic implications for higher education institutions in designing training ecosystems that place learner proactivity at the core.*

Keywords: business and management students, career prospect confidence, digital transformation sentiment, proactive learning strategy.

[1]Tra Vinh University, Vietnam

*Corresponding author: lbtoan@tvu.edu.vn

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I. INTRODUCTION

Digital transformation is no longer a peripheral concept but has evolved into a comprehensive strategic restructuring, propelled by the powerful convergence of artificial intelligence (AI), big data, and cloud computing. This shift creates a new survival environment where technology is not merely a supportive tool but a core element reshaping entire economic and social processes [1]. In this context, higher education faces an urgent imperative to equip learners with systemic adaptive responses to maximize personalized learning systems, thereby mitigating the risk of competency obsolescence in a volatile digital labor market [2].

Contemporary theoretical discourse acknowledges a pivotal shift toward learner-centered educational models, where maintaining and enhancing human capital value becomes a vital strategy [3]. Rather than focusing solely on static technical skills, recent studies emphasize the ability to master smart tools to assert individual value against the dominance of automated management algorithms [4]. Despite persisting infrastructural barriers and technical pressures, current trends move strongly toward applying modern methodologies such as problem-based learning and flipped classrooms to reactivate students' critical thinking and independent decision-making capabilities [5].

Moving into the 2024–2026 period, the explosion of Generative AI has shifted the focus from technological experimentation to core pedagogical application, transforming self-directed competence into a 'survival skill' [6]. When learners recognize the strategic utility of the digital ecosystem, their self-efficacy is bolstered, driving them to proactively construct learning pathways toward sustainable employment goals [7]. The intersection of technical intelligence and adaptive mindset enables learners not only to utilize tools but also to ‘conquer’ their career trajectories within an ecosystem characterized by structural changes [8].

Within the scope of this study, digital transformation sentiment (DTS) is defined as a multi-layered psychological construct reflecting students’ belief systems and attitudes toward the structural transformations of the labor market under the impact of technology. DTS extends beyond the recognition of disruptive technologies (such as AI, big data, or cloud); it encompasses the capacity for strategic evaluation of shifting professional forms and the ability to forecast the obsolescence of traditional skill values in the digital age. Inheriting these arguments, this study analyzes the interaction between DTS and proactive learning strategy (PLS) in shaping students’ career prospect confidence (CPC). By positioning learners as the subjects of a ‘resource spiral,’ the research aims to clarify the transmission mechanism: how the perception of the positive value of technological breakthroughs serves as a ‘behavioral nudge’ prompting students to restructure their competencies. Consequently, this work is expected to provide practical managerial implications for higher education institutions in building smart training ecosystems that help learners maintain a competitive edge in the global digital economy. The novelty of this study lies in shifting the focus from basic technology acceptance to decoding the psychological and behavioral transformation of students. While existing literature extensively documents the direct impact of digital literacy on employment, the internal mechanism converting technological sentiment into career confidence remains underexplored [1, 9]. This research distinguishes itself by empirically validating the ‘digital competence execution loop,’ where PLS serves as an essential transmission belt between DTS and CPC. By targeting business and management students in the Mekong Delta, a region representing an emerging digital labor market in a transition economy, the study provides unique contextual insights into how internal resource spirals activate when institutional support is still evolving. Centrally, the research illuminates how students transform technological awareness into proactive actions to build professional resilience and competitive advantage. These findings contribute directly to digital human capital theory, thereby providing a robust foundation for higher education institutions to restructure their training ecosystems toward a learner-centric approach.

II. LITERATURE REVIEW

A. *Theoretical framework*

This study synthesizes three theoretical pillars to explain the mechanism connecting technological perception, learning behavior, and career development in the digital era.

Human capital theory and the shift toward digital capital

Human capital theory, pioneered by Schultz [10] and refined by Becker [11], asserts that investments in education and training create skills and knowledge with sustainable economic value for individuals. Amidst robust digital transformation, this concept has shifted toward ‘digital capital’. According to Pitzalis et al. [12], digital capital extends beyond mere device ownership; it is the capacity to leverage technology to create value.

In the research model, this theory serves as a foundation to explain the significance of DTS. When students accurately recognize the value of emerging technologies (such as AI, big data, and cloud), they are essentially re-evaluating their own human capital [1]. Accumulating digital competence is no longer an auxiliary skill but has become a strategic asset determining competitiveness and CPC in a labor market driven by algorithms and technology.

Conservation of resources theory and competency compensation mechanism

Conservation of resources (COR) theory establishes the premise that individuals constantly strive to maintain, protect, and build valuable resources to cope with environmental instability. In the generative AI era, rapid changes in job requirements pose a risk of eroding existing resources, such as career stability and traditional professional values [9, 13].

To react to these pressures, Li et al. [13] argued that individuals tend to mobilize internal psychological traits, typically proactivity, as strategic defensive resources. By activating 'resource spirals', students enhance their PLS to accumulate new resources (digital skills, technology certifications). This serves as a self-adjustment mechanism that helps learners transform digital challenges into motivation for competency restructuring, ensuring sustainable employability and strengthening future career prospects.

Connectivism and career construction theory

The essence of proactivity in modern education is shaped by Knowles' [14] perspective on self-directed learning. With the mass adoption of the Internet, Siemens [15] developed Connectivism, asserting that learning in the digital age is a process of establishing and exploiting flexible information nodes. This intersection is materialized through career construction theory [16], marking a shift from static career traits to a process of behavioral self-regulation. Central to this theory is 'career adaptability', a psychological resource encompassing concern, control, curiosity, and confidence [16].

In this study, these theories explain how students utilize a PLS as a tool to 'construct' and create a clear career development pathway. This process directly enhances their CPC, which refers specifically to an individual's psychological conviction in their capability to navigate and capitalize on evolving digital labor markets, thereby distinguishing it from general career optimism or decision self-efficacy. Consequently, this study synthesizes these three pillars into a 'resource-capability-result' logic. Within this framework, human capital theory defines the digital asset through DTS, which represents a student's cognitive and emotional perception toward technological shifts rather than general digital literacy. Concurrently, COR theory explains the motivation to activate a 'resource spiral' via self-directed learning behaviors, namely PLS. Finally, career construction theory transforms these proactive behaviors into tangible confidence, or CPC. This integration successfully bridges the research gap by moving from static technology adoption to a dynamic, learner-centric mechanism that decodes how psychological readiness converts into a competitive career advantage.

B. Literature review

Digital transformation sentiment

Within the scope of this study, DTS is defined as a multi-layered psychological construct reflecting students' belief systems and attitudes toward structural labor market shifts driven by technology. DTS extends beyond the mere recognition of disruptive technologies (such as AI, big data, or cloud); it encompasses strategic evaluation of shifting professional forms and the ability to forecast the obsolescence of traditional skillsets in the digital era. Researching digital perception has evolved from pure technical understanding to a comprehensive cognitive structure of strategic value. Matt et al. [17] established the foundation by asserting that this perception is linked to the ability to exploit technology for value recreation and resource alignment. By 2019, Vial [1] conceptualized this process through the convergence of the SMACIT technology suite – comprising social, mobile, analytics, cloud, and Internet of Things; this intersection creates inevitable 'transformation pressures', forcing individuals to redefine their competencies to adapt to digitalized environments. During the 2020–2024 period, this perception was extensively applied within higher education. Al-Fraihat [18] demonstrated that positive technological perception is reinforced when learners perceive optimization from support systems. Notably, Hutapea et al. [19] established the concept of 'digital psychology', a cognitive state that views technology as a performance optimization tool rather than a barrier. This cognitive synthesis has laid the groundwork for a shift toward learner-centered educational models, encouraging students to proactively acquire modern knowledge [20].

Proactive learning strategy

The foundation of proactive learning is rooted in social cognitive theory, where Bandura [21] asserted that self-efficacy is the core driver of self-regulated behaviors. Bateman et al. [22] expanded this concept into 'proactive personality', the tendency to seek opportunities and persevere in creating change despite environmental barriers.

In the digital age, Siemens [15] repositioned PLS through connectivism, viewing learners as agents managing information nodes to co-create knowledge. Savickas [16] considered this the highest manifestation of career adaptability. Recent studies indicate that PLS is no longer an auxiliary skill but a 'prerequisite' for success in e-learning spaces [13, 23]. In Vietnam, Bui et al. [24] specified PLS through digital self-study competence, regarding it as a launchpad for students to transform online interactions into substantive professional value.

Career prospects in the digital era

Modern career prospects are defined as students' positive beliefs and expectations regarding their ability to achieve professional goals in a digitalized labor market. Savickas [16] asserted that CPC is based on 'adaptability' – a psychological resource helping individuals manage transitions from school to the market.

De Vos et al. [25] redefined the nature of CPC by establishing the concept of 'sustainable employability' instead of mere job stability. For the 2024–2026 period, digital creativity and collaboration have formally become decisive factors in individual positioning [26]. The role of micro-credentials is emphasized as a form of specialized competency validation, helping students maintain their human capital value despite technological fluctuations [8, 27].

Overview of research trends in Vietnam

In Vietnam, the digital transformation process in higher education has shifted from the stage of infrastructural digitalization to the restructuring of learning experiences and the shaping of strategic mindsets for students. The pioneering study by Duong et al. [28] established a critical theoretical foundation for the interaction mechanism between digital learning environments and the transformation of students' belief systems and entrepreneurial mindsets. Following this trajectory, Nguyen et al. [29] applied an extended technology acceptance model (TAM) to assert that the quality of a digital ecosystem transcends mere utility, directly impacting perceived value and activating value co-creation behaviors between students and educational institutions. Notably, in the Education 5.0 era, Nguyen et al. [30] elevated this discourse by positioning digital competence as a key internal resource, serving as a 'trigger variable' for intrinsic motivation that helps students overcome technical barriers to proactively engage in sustainable career development pathways.

In summary, this research inherits and adapts standardized scales from established literature: DTS is built upon the frameworks of Vial [1] and Al-Fraihat [18]; PLS is derived from Bateman et al. [22] and Bui et al. [24]; while CPC is based on Savickas [16]. Regarding methodology, the study adopts the two-stage partial least squares structural equation modeling (PLS-SEM) analytical procedure, evaluating the measurement model followed by the structural model, consistent with the rigorous statistical standards and thresholds proposed by Hair et al. [31] and Henseler et al. [32].

Identification of research gaps

Although the fundamental theoretical system for individual variables has been established, the profound fluctuations of the 2025–2026 period reveal three critical research gaps in existing models. First, there is a lack of an integrated structure regarding the competency transmission mechanism; most current studies remain confined to the TAM or pure academic outcomes [1, 18], leading to a disconnection in decoding the transformation from strategic awareness (DTS) into executive behavior (PLS) to create career outcomes (CPC). Second, the mediating role of PLS in the AI era remains ill-defined, as empirical validation of this 'bridge' role has not been thoroughly explored among economic students in dynamically transitioning regions. Third, there is a significant imbalance between research on technological platforms and behavioral adaptation practices. Specifically, the self-adjustment mechanism of learners in response to new professional pressures and standards remains a missing piece, leaving the picture of digital transformation in Vietnamese higher education incomplete.

C. Research hypothesis development

Digital transformation sentiment and career prospect confidence

Based on Vial's [1] digital human capital perspective, DTS is not merely a technical attitude but a profound understanding of value restructuring within a new ecosystem. This recognition serves as a 'cognitive catalyst' [18], fostering skill readiness and directly bolstering long-term CPC [9]. Particularly in Vietnam, a deep understanding of the digital economy enables learners to clarify career trajectories and mitigate automation-related uncertainty. Consequently, the following hypothesis is proposed:

H_1: Digital transformation sentiment has a positive impact on career prospect confidence.

Digital transformation sentiment and proactive learning strategy

From an adult education perspective, Knowles [14] established that self-directed behavior constitutes the core of sustainable learning. Within digital environments, this cognitive readiness effectively acts as a catalyst for executive behaviors. This alignment is further supported by Duong et al. [28], who emphasized that a positive technological perception compels individuals to proactively transform their mindset into specific actions to mitigate the risk of obsolescence. Consequently, when students clearly perceive the strategic benefits of digital platforms, they voluntarily establish goals and exhibit persistence in digital self-study [24]. Therefore, the study proposes:

H_2: Digital transformation sentiment has a positive impact on proactive learning strategy.

Proactive learning strategy and career prospect confidence

According to career construction theory, proactivity is the ultimate manifestation of adaptability [16]. In modern digital education, PLS has evolved from an auxiliary factor into a prerequisite for technological mastery [33]. Recent evidence from 2024–2025 emphasizes that PLS transforms learning behavior into a sustainable competitive advantage [34], fostering digital human capital and superior employability skills [26]. Ultimately, the synergy between executive competence and intrinsic belief fosters robust optimism regarding future career paths. Based on these theoretical arguments, it is hypothesized that:

H_3: Proactive learning strategy has a positive impact on career prospect confidence.

The mediating role of the proactive learning strategy

The mediating mechanism of PLS is rooted in Connectivism [15] and career adaptation strategies. De Vos et al. [25] asserted that proactivity serves as an 'execution loop', helping to preserve and enhance individual value amidst market fluctuations. In the current context, PLS facilitates the shift from psychological readiness (DTS) to actual career outcomes by enhancing learning performance [19]. Accumulating micro-credentials through self-study is the primary method through which PLS realizes career potential from initial perceptions [27]. This process restructures competence, fostering robust confidence in career prospects. Accordingly, the final hypothesis is formulated:

H_4: Proactive learning strategy plays a mediating role in the relationship between digital transformation sentiment and career prospect confidence.

In summary, by systematizing the theoretical pillars of human capital, conservation of resources, and career construction, this study establishes a comprehensive analytical framework for the impact of technological perception on students' career prospects. The system of four hypotheses (H_1 to H_4) focuses on decoding the role of DTS as a cognitive antecedent and PLS as a core behavioral transmission mechanism to build CPC. The structural relationships and path directions among these variables are visualized in the proposed research model in Figure 1.

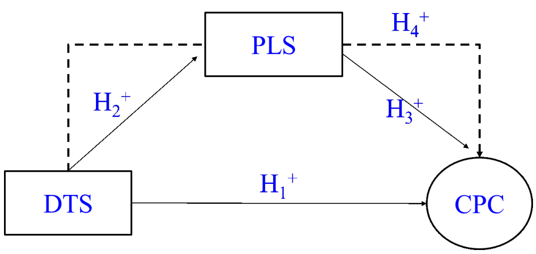

Fig. 1: Proposed research model

III. RESEARCH METHODOLOGY

A. Research design and measurement instruments

This study employs a quantitative approach with descriptive and inferential research designs. The primary objective is to test hypotheses regarding the impact mechanisms among DTS, PLS, and CPC. Primary data were collected via a cross-sectional survey using self-administered online questionnaires. Utilizing digital platforms for data collection not only optimizes access to the target population but also minimizes social desirability bias caused by direct interviewer-respondent interaction, thereby ensuring data objectivity and integrity.

The latent variables in the model are quantified using a 5-point Likert scale, ranging from 1 (Strongly disagree) to 5 (Strongly agree). These scales were adapted and refined from prior studies [1, 16, 18, 22, 24] to fit the higher education context, ensuring that learners' psychological states and behaviors are standardized into statistical indicators for structural equation modeling (SEM).

B. Sampling method and sample size determination

The study specifically targets Business and Management students as they represent the cohort most immediately impacted by the digital restructuring of professional services and corporate governance. Furthermore, the focus on Vinh Long Province provides a representative case study of emerging labor markets in the Mekong Delta, where the gap between global digital standards and local institutional support necessitates higher individual proactivity. This study employed a convenience sampling method, specifically targeting Business and Management students in the Mekong Delta region. To ensure data reliability, respondents were approached through official faculty Zalo groups and student emails. The survey was conducted immediately following Digital Business or IT-related sessions; this specific context ensured that respondents had a heightened awareness of technological shifts, thereby enhancing the accuracy of their reflections on DTS and PLS constructs. To ensure statistical power, the sample size was determined by integrating two rigorous standards. First, based on a finite population of N = 2,058 (according to the 2024 Annual Reports of Tra Vinh University and Cuu Long University), the Krejcie et al. [35] formula required a minimum of 322 observations (5% margin of error, 95% confidence level). Second, following Hair et al. [31], a 5:1 ratio for the 15 observed variables necessitated 75 to 150 units. Consequently, the final sample exceeds both thresholds, ensuring representativeness for inferential analysis.

The actual collection yielded 368 valid responses, significantly exceeding the aforementioned minimum thresholds. This sample size not only satisfies the 'ten-times rule' for predictor variables in the PLS-SEM model but also provides sufficient degrees of freedom for the path coefficients (beta) and coefficients of determination (R^2) to achieve high stability and generalizability.

C. Study site and data representativeness

Data collection and processing were completed between January and February 2026. The empirical data were gathered from economics students in Vinh Long Province, specifically focusing on

Tra Vinh University and Cuu Long University – the two largest providers of Business and Management training in the region [36]. The total population was verified through the 2024 Annual Reports of these institutions, providing a baseline to validate the representativeness of the actual sample (Table 1). While the population frame was derived from these 2024 annual reports to establish the baseline for sample distribution, the primary survey data were collected in early 2026 (Table 3) to ensure that the findings reflect contemporary digital perspectives. Although a minor proportional shift between the actual sample and the population exists (approximately 10% deviation), the absolute sample size at each unit satisfies the necessary representativeness thresholds. This distribution ensures that the model findings remain robust and are not biased by the unique characteristics of a single institution.

Table 1: Sample composition relative to the total population

Institution	Population (N)	(%)	Sample (n)	(%)
Tra Vinh University	1,486	72.2%	229	62.2%
Cuu Long University	572	27.8%	139	37.8%
Total	**2,058**	**100%**	**368**	**100%**

Although there is a slight shift in proportions between the actual sample and the theoretical population (approximately 10% deviation), the absolute sample size at each unit reached the necessary representativeness threshold. This distribution reflects the diversity of the training environment, thereby enhancing the convergent validity of the findings and ensuring the model is not biased by the characteristics of a single institution.

D. Proposed research model and operationalization

Integrating human capital, conservation of resources, and career construction theories, this study proposes a structural model to examine how digital perception shapes career prospects through the mediating role of proactive learning. The specific research hypotheses are synthesized in Table 2.

Table 2: Summary of research hypotheses

Hypotheses	Relationship	Core theoretical basis
H_1	DTS → CPC (+)	Human capital theory [1, 11]
H_2	DTS → PLS (+)	Adult education theory [14]
H_3	PLS → CPC (+)	Career adaptability theory [16]
H_4	DTS → PLS → CPC	Digital self-study competency loop [24]

Note: (+) denotes a positive impact

Operationalization of constructs and measurement scales

The constructs in the model were operationalized through scales adapted from reputable international literature [1, 16, 18, 22] and refined via a back-translation process to ensure contextual compatibility with Vietnamese higher education. Specifically, DTS was measured using five items (after screening) based on the frameworks of Vial [1] and Al-Fraihat [18], reflecting students' strategic understanding of technological value. Similarly, PLS comprised five items developed from [22] 'proactive personality' construct and the digital self-study competence identified by Bui et al. [24]. Finally, CPC was quantified through five items inherited from the self-efficacy and career adaptability scales of [9]. All observed variables utilized a 5-point Likert scale to provide a consistent database for inferential statistical analysis.

E. Data analysis method

First, descriptive statistics are employed to summarize the sample characteristics (e.g., institution, gender, and major) using frequencies and percentages. Concurrently, parameters such as mean and standard deviation are calculated for the observed variables. This step identifies general evaluation trends among students and examines data distribution prior to advanced testing.

Subsequently, the study utilizes PLS-SEM via SmartPLS software. This technique is particularly advantageous for prediction-oriented models and does not impose strict requirements on normal data distribution [31]. The analytical process is conducted in two stages: measurement model evaluation tests the validity and reliability of the scales using outer loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and discriminant validity via Heterotrait-Monotrait (HTMT) and Fornell-Larcker criteria; Structural model evaluation tests the research hypotheses by examining path coefficients (beta), t-values (using the Bootstrapping technique), coefficients of determination (R^2), and effect sizes (f^2). All statistical outputs, including path coefficients and validity metrics, were generated and processed using SmartPLS 3.0 software based on the collected primary dataset.

IV. RESULTS AND DISCUSSION

A. Descriptive statistical characteristics of the sample

Prior to testing the structural model, a demographic analysis of the respondents was conducted to verify the representativeness and coverage of the data. The demographic distribution of the 368 valid participants, surveyed in early 2026 across institutions, majors, and academic years, is summarized in Table 3.

Table 3: Summary of sample demographics (n = 368)

Criteria	Classification	Frequency	Percent (%)	Cum. (%)
Institution	Tra Vinh University	229	62.2	62.2
	Cuu Long University	139	37.8	100.0
Major	Accounting	114	31.0	31.0
	Office Administration	71	19.3	50.3
	E-commerce	66	17.9	68.2
	Finance – Banking	61	16.6	84.8
	Business Administration	56	15.2	100.0
Academic year	First-year	143	38.9	38.9
	Second-year	108	29.3	68.2
	Third-year	72	19.6	87.8
	Fourth-year	45	12.2	100.0
Total		**368**	**100.0**	

The research sample (n = 368) exhibits a balanced and diverse structure, providing a robust foundation for subsequent structural model testing. Data were primarily sourced from Tra Vinh University (62.2%) and Cuu Long University (37.8%), ensuring objective variance in pedagogical environments. Regarding disciplinary distribution, the cohort is led by Accounting (31.0%), Office Administration (19.3%), and E-commerce (17.9%), fields at the forefront of digital transformation where technology-professional convergence is most pronounced. Furthermore, a 'rejuvenation' trend is evident, with first- and second-year students comprising over 68% of the sample. While seniors represent only 12.2% due to internship commitments, the inclusion of all academic levels effectively captures the perceptual shift along the educational trajectory, from initial curiosity to employment-oriented perspectives. Collectively, these demographic characteristics (detailed in Table 3) ensure both the scale and diversity required for reliable inferential analysis.

B. Measurement model evaluation

The measurement model was assessed for reliability and validity using outer loadings, Cronbach's alpha, CR, and AVE. The statistical results for the construct reliability and convergent validity of the three latent variables are summarized in Table 4.

Table 4: Results for construct reliability and convergent validity

Construct	Items	Loadings	Alpha	rho_A	CR	AVE
CPC	CPC1-CPC5	0.776 – 0.865	0.874	0.880	0.909	0.666
DTS	DTS1-DTS6*	0.750 – 0.812	0.840	0.846	0.886	0.609
PLS	PLS1-PLS5	0.754 – 0.855	0.876	0.881	0.910	0.669

Note: DTS3 was excluded during screening

As shown in Table 4, all outer loadings exceed the 0.70 threshold with absolute significance ($t > 18.408$, $p < 0.001$). Internal consistency is robust, as Cronbach's alpha and CR values significantly surpass the 0.70 benchmark. Convergent validity is confirmed by AVE values (0.609–0.669), exceeding the 0.50 requirement [37].

C. Discriminant validity

Discriminant validity was evaluated using the Fornell-Larcker criterion and the HTMT ratio to ensure each construct is unique. The comparative results between inter-construct correlations and HTMT ratios are presented in Table 5.

Table 5: Discriminant validity results (Fornell-Larcker vs. HTMT)

Construct	CPC	DTS	PLS
CPC	**0.816**	*0.858*	*0.639*
DTS	0.744	**0.780**	*0.587*
PLS	0.562	0.511	**0.818**

Note: Bold values on the diagonal are the square root of AVE; values below the diagonal are correlations; italicized values above the diagonal are HTMT ratios

The results confirm that the square root of the AVE for each construct (bold) is higher than its correlations with the others. Additionally, all HTMT ratios are below the 0.90 threshold [38, 39], proving that the constructs (DTS, PLS, CPC) are distinct and represent unique conceptual phenomena [32].

D. Multicollinearity assessment

Before evaluating the structural relationships, the study examined the variance inflation factor (VIF) to detect potential multicollinearity issues within the inner model. According to Hair et al. [31], multicollinearity is considered problematic when VIF values exceed 5.0.

The empirical results indicate that all inner VIF values are well within the acceptable threshold. Specifically, for the paths predicting CPC, both DTS and PLS yielded a VIF of 1.354. Furthermore, the path from DTS to PLS showed an ideal VIF of 1.000. These low values confirm the absence of multicollinearity among the latent constructs, ensuring that the subsequent path coefficients (beta) accurately reflect the true predictive power of each factor without being inflated by collinearity bias.

E. Explanatory power and effect size assessment

The model's predictive capability and the individual contribution of each exogenous construct were evaluated using the coefficient of determination (R^2) and effect size (f^2). Table 6 outlines the integrated outcomes computed for these statistical indicators.

Table 6: Integrated results of R^2 and f^2

Construct	R^2	Adj. R^2	Predictor	f^2	Impact level
CPC	0.598	0.596	DTS	0.705	Large
			PLS	0.110	Small to Medium
PLS	0.261	0.259	DTS	0.354	Large

Regarding explanatory power, the model explains 59.8% of the variance in CPC (R^2 = 0.598), which, according to Chin [40], represents a substantial predictive capacity for students' career prospects. For PLS, DTS explains 26.1% of its variance (R^2 = 0.261), a moderate level given that proactive learning is often influenced by various external psychological and environmental factors.

Analysis of effect sizes (f^2) based on Cohen's [41] criteria reveals that DTS plays a decisive role, exerting a 'Large' effect on both CPC (0.705) and PLS (0.354). In contrast, the effect of PLS on CPC (0.110) is categorized as 'Small to Medium'. These findings highlight that while both factors are significant, improving DTS serves as a more powerful catalyst for enhancing students' career confidence compared to focusing solely on learning strategies.

F. Research hypothesis testing

The study employed the Bootstrapping technique with 5,000 resamples to test the statistical significance of the path coefficients within the structural model. A detailed synthesis of these empirical metrics is provided in Table 7.

Table 7: Summary of hypothesis testing results

Path	β	M	SD	t	P	Decision
Direct effects						
H_1: DTS → CPC	0.619	0.617	0.058	10.736	0.000	Supported
H_2: DTS → PLS	0.511	0.514	0.045	11.398	0.000	Supported
H_3: PLS → CPC	0.245	0.248	0.050	4.922	0.000	Supported
Indirect effects						
H_4: DTS → PLS → CPC	0.125	0.128	0.029	4.341	0.000	Supported

Empirical results from the bootstrapping procedure with 5,000 subsamples indicate that all direct relationships in the research model achieved very high statistical significance ($p < 0.001$).

Specifically, DTS exerts the most potent driving force on CPC with a standardized path coefficient of 0.619 (t = 10.736), confirming its core importance in explaining the variance of CPC. Simultaneously, the linkage between DTS and PLS also reached a significant impact value (0.511, t = 11.398), demonstrating a tight synergy between these two constructs. Finally, the impact of PLS on CPC, while lower in magnitude (0.245, t = 4.922), maintains robust scientific significance, contributing to the overall impact mechanism within the model.

A noteworthy highlight of these findings lies in the analysis of indirect effects. The data reveal a significant transmission mechanism from DTS to CPC through the mediating variable PLS, with an impact coefficient of 0.125 ($p = 0.000$, $t = 4.341$). According to the evaluation criteria of Baron et al. [42], as well as the updates by Preacher et al. [43], since both the direct effect (DTS to CPC) and the indirect effect are statistically significant, this model establishes a partial mediation role for PLS. This implies that DTS not only directly influences CPC but is also amplified through the presence of PLS, creating a multi-dimensional and systematic impact ecosystem.

The consistency between the outer loadings and t-statistics (ranging from 17.781 to 57.223) further evidences the high convergence and reliability of the component scales. The fact that all p-values reached 0.000 allows for the rejection of the null hypotheses (H0) and the acceptance of all research hypotheses with a confidence level exceeding 99.9%. Collectively, these indicators confirm that the research model possesses high practical value, accurately reflecting the behavioral dynamics of the subjects within the study context. This provides a solid foundation for subsequent managerial recommendations.

For a visual representation of the impact intensities and validation values between the latent constructs in the model, the bootstrapping analysis results from SmartPLS are illustrated in detail in Figure 2.

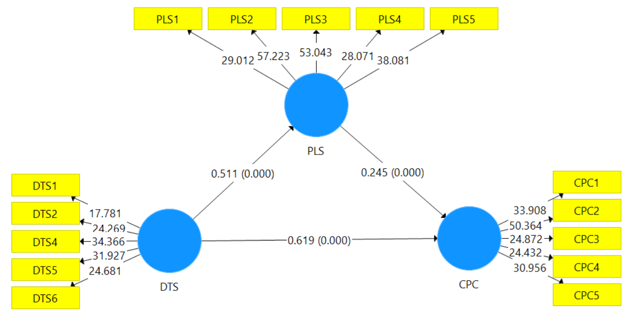

Fig. 2: Final structural model results

G. Discussion

The structural equation modeling results provide robust support for all proposed hypotheses, revealing a multi-layered mechanism that transforms perception into proactive behavior and, ultimately, into career confidence.

As conceptualized in COR theory, the findings confirm the existence of a 'resource spiral'. Specifically, the significant positive impact of DTS on PLS (beta = 0.511, $t = 11.398$, $p < 0.001$) suggests that digital perception acts as a critical psychological antecedent. This resource does not remain static but triggers a strategic investment in a proactive learning strategy, which in turn significantly strengthens CPC (beta = 0.245, $t = 4.922$, $p < 0.001$). Notably, the indirect effect of DTS on CPC through the mediation of PLS was also confirmed (beta = 0.125, $t = 4.341$, $p < 0.001$). While prior studies in developed contexts primarily emphasize formal institutional support and structural digital transformation as the 'main conditions' for development [1, 33], this research highlights a nuanced shift. In the specific context of emerging economies like Vietnam, the 'spiral' is driven more by the individual's internal ability to transform technological awareness into self-directed developmental actions. This confirms the proposition that proactivity is the highest manifestation of adaptability [16], serving as a vital bridge between digital sentiment and future career success in the generative AI era.

The decisive antecedent role of digital trans-

formation sentiment

Empirical evidence demonstrates that DTS operates as the most robust direct predictor of CPC (beta = 0.619, $p < 0.001$). This is entirely consistent with human capital theory [11] and the modern perspectives [1]. When students possess a profound awareness of the strategic value of technology, they essentially undergo a process of 're-evaluating' their own capabilities. The high impact coefficient (0.619) reflects that in the digital era, career confidence no longer stems from static degrees but from the ability to identify technological opportunities. This result aligns with Zhu et al. [9], asserting that digital perception acts as a psychological filter that helps individuals neutralize uncertainty and establish positive expectations for their professional future.

Simultaneously, DTS significantly drives PLS (beta = 0.511, $p < 0.001$). From the perspective of adult education theory [14], the perceived utility of technology serves as an 'activator' for self-directed behaviors. When students understand that SMACIT technologies are survival factors, they proactively mobilize internal resources to master knowledge rather than remaining passive recipients.

Proactive learning strategy: from adaptive behavior to competitive advantage

The relationship between PLS and CPC (beta = 0.245, $p < 0.001$) reinforces the tenets of career construction theory [16]. This path coefficient indicates that proactivity in learning functions as an executive 'psychological resource,' transforming potential knowledge into actual competitive advantage. Although the direct impact intensity of PLS is lower than that of DTS, its robust statistical significance ($t = 4.922$) confirms that proactive behavior is the primary tool for students to maintain sustainable employability, as noted by De Vos et al. [25]. This finding is consistent with recent evidence from the Vietnamese higher education sector, where Nguyen et al. [30] observed that internal digital motivation outweighs external technical pressure in long-term career orientation. Furthermore, the results extend the arguments of Bui et al. [24], suggesting that in regional universities like those in the Mekong Delta, digital self-study competence is not just a technical skill but a critical psychological bridge to professional confidence. This is particularly relevant in the Vietnamese context, where digital self-study competence is becoming a new benchmark for career readiness [24].

The mediating mechanism: the digital competence execution loop

The most critical finding is the partial mediating role of PLS in the relationship between DTS and CPC, showing a significant indirect effect of 0.125 ($p < 0.001$). This result substantiates the 'resource caravan' mechanism within COR theory, where positive perception generates initial psychological energy that requires the proactive execution filter of PLS to reach sustainable career confidence. Simply recognizing technological importance is insufficient for long-term competitive advantage. PLS amplifies the impact of perception by fostering mastery of skills through microcredentials and self-learning competencies [27]. The confirmation of the mediating role of PLS is theoretically significant as it validates the 'resource caravan' concept in the generative AI era. This finding implies that DTS does not automatically lead to career confidence; rather, it requires a behavioral catalyst. This study provides a significant contribution by identifying that for business students, the 'active investment' in learning is the bridge that prevents technological awareness from turning into digital anxiety, thus providing a more nuanced understanding of career construction in the 4.0 labor market. This indirect effect confirms the model's capacity to explain the student's psychological journey from shifting perceptions to behavioral changes and ultimately achieving stable career confidence in a digitalized era.

In a broader context, comparing these findings with existing literature reveals a significant alignment with the systematic review by Vial [1], confirming that digital sentiment is a foundational precursor to strategic agility. However, a nuanced divergence emerges when compared to global reviews that heavily emphasize external institutional support (e.g., Al-Fraihat [18]). While international models often prioritize the 'digital ecosystem' as the primary driver, the results in the Vietnamese context, consistent with the 'Education 5.0' perspective of Nguyen et al. [30], position digital competence and PLS as the more decisive internal triggers. this suggests that for students in transition economies, the 'resource spiral' is not just a passive reaction to infrastructure but a proactive 'digital psychology' [19] that converts technological pressure into career confidence. This distinction reinforces the necessity of moving toward learner-centered models where individual behavioral agility precedes formal structural transformation [24].

V. MANAGERIAL IMPLICATIONS AND CONCLUSION

A. Managerial implications

Based on the empirical findings and discussions above, the study proposes several key managerial implications to enhance students' confidence in career prospects in the digital transformation era.

For higher education institutions

'Perception-first' strategy

Given that DTS has the strongest impact (beta = 0.619), educational administrators should prioritize communication and mindset-oriented activities on the digital economy from the first year. Universities should go beyond providing technical infrastructure; they must organize seminars on career trends influenced by AI and big data to help students clearly perceive the utility and necessity of integrating technology into their professional expertise.

Designing an environment that triggers proactivity

Since the PLS plays a vital mediating role, training programs should shift from 'transmissive teaching' to 'challenge-based learning'. Integrating micro-credentials into the formal curriculum will encourage students to proactively engage in self-directed study to accumulate specialized digital competencies, thereby fostering career confidence.

Personalizing development roadmaps

Developing AI-driven career coaching systems can help students identify their individual skill gaps compared to market demands. This personalized insight acts as a catalyst, activating proactive learning behaviors to bridge resource deficiencies.

For economics and business students

Proactive human capital restructuring

Students must recognize that technology is not a barrier but a tool for optimizing professional performance. Maintaining a proactive mindset in seeking digital learning resources and building online professional networks is key to ensuring sustainable employability.

Leveraging the execution loop

Students should embrace the principle of 'lifelong learning' through directed self-study. Career prospect confidence is only attainable when learners translate positive perceptions into concrete actions, such as mastering data analytics tools or smart management platforms within the business industry.

For businesses and recruitment partners

Through a strategy of co-creating value, enterprises should actively collaborate with universities to establish digital labs or virtual internship programs. Early exposure to the reality of digital transformation within corporate environments will reinforce students' awareness and drive career adaptability behaviors while they are still in school.

B. Conclusion

This study was conducted to decode the impact mechanism of technological perception on students' career prospects amidst comprehensive digital transformation. Empirical results using the PLS-SEM model confirm the decisive antecedent role of DTS in driving both PLS and CPC. Notably, the study elucidates the partial mediation role of PLS, asserting that positive technological awareness can only be fully transformed into sustainable career value when executed through proactive, self-directed learning behaviors. These findings contribute a novel perspective to human capital theory and career construction theory, emphasizing that in the AI era, behavioral adaptability serves as the vital 'bridge' enabling individuals to master digital knowledge capital.

C. Limitations and future research directions

Despite achieving its objectives, this study possesses certain limitations that suggest avenues for further exploration. First, as the sample was restricted to Business students at specific institutions, future research should expand the scope to diverse disciplines and geographical regions to enhance generalizability. Second, while this model focused on positive perceptions, integrating inhibitory factors such as digital anxiety or perceived technological sentiment threat would provide a more multi-dimensional view of learners' psychology. Finally, the reliance on cross-sectional data limits the assessment of behavioral changes over time; therefore, longitudinal studies or educational experiments are recommended to provide more robust evidence of shifts in career adaptability following intensive digital training.

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