International Journal of Research and Review
[Indexed, Peer-Reviewed Journal]
Volume 13; Issue: 5; May 2026
Website: www.ijrrjournal.com
Research Paper *E-ISSN: 2349-9788; P-ISSN: 2454-2237*

Long-term Orientation and Artificial Intelligence Adoption among Vietnamese Business Students Based on the Innovation Diffusion Theory: A Structural Equation Modelling Analysis

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DOI: https://doi.org/10.52403/ijrr.20260564

ABSTRACT

This study presents a quantitative investigation of undergraduate business students in Hanoi, Vietnam to understand the relationship between Long-term Orientation (LTO) and AI adoption on the basis of innovation diffusion theory. A survey of 368 students of various business and management specializations was conducted via on-line Google Form. Structural Equation Modelling (SEM) analysis was used to test hypotheses related to conceptual framework. The SEM analysis results revealed mixed support across the seven hypothesised relationships, with uniformly path coefficients warranting both theoretical reflection and contextual explanation. Critically, the positive effect of Long-term Orientation (LTO) on Behavioral Intention advances a culturally sensitive extension of innovation diffusion theory, affirming that adoption behaviour in high LTO societies is meaningfully shaped by cultural value systems alongside, and arguably beyond, innovation characteristics alone.

Keywords: Long-term Orientation; AI adoption; Innovation Diffusion Theory, Students, Vietnam

INTRODUCTION

The accelerating diffusion of Artificial Intelligence (AI) across global economic and educational landscapes has created an unprecedented imperative for academic institutions to understand technology adoption behaviors among their student populations. With AI investment projections approaching 6.3 trillion USD and approximately 25% of occupational roles susceptible to AI-driven displacement, AI competency has become an indispensable attribute of future-ready business professionals [1]. Within educational settings, AI is progressively reshaping pedagogical methodologies, knowledge acquisition processes, and academic productivity [2]. Therefore, AI renders the investigation of its behavioral and cultural determinants both theoretically urgent and practically consequential [3].

Extending this inquiry into the cultural domain, the present study draws upon The Innovation Diffusion Theory (IDT) discussed by Rogers [4] (2003). This is a robust and widely validated framework for examining how innovations are perceived and adopted across social systems through dimensions of relative advantage, compatibility, complexity, trialability, and observability [5]. While extant literature has increasingly applied the IDT to AI adoption in educational contexts, the moderating influence of Long-term Orientation (LTO), that is Hofstede's cultural dimension reflecting perseverance and future-oriented adaptive capacity, remains a conspicuous scholarly gap [6]. Vietnam constitutes a particularly pertinent research context, combining a pronounced long-term cultural ethos with a rapidly digitalizing higher education sector. Employing Structural Equation Modelling (SEM), this study investigates how LTO shapes AI adoption intentions among Vietnamese private university business students, offering both theoretical and practical contributions to this underexplored domain [7].

LITERATURE REVIEW

Long-term Orientation

Long-term Orientation (LTO), rooted in [8] Confucian dynamism theory, reflects individuals' propensity to prioritize perseverance, future-directed planning, and sustained effort over immediate gratification [9]. In technology adoption contexts, individuals exhibiting high LTO perceive emerging technologies not merely as convenience tools but as strategic investments yielding long-range competency development, or a temporal disposition that aligns naturally with IDT theory's emphasis on perceived long-term innovation utility [10]. Within educational settings specifically, LTO operates as a consequential non-cognitive attribute that meaningfully shapes learning engagement and academic outcomes [11]. Students with high LTO tend to pursue learning objectives with greater persistence and commitment, qualities empirically associated with grit and academic achievement [12]. According to Kiani et al [13] it can further establish a significant correlation between LTO and academic performance, while Maheshwari [14] demonstrated that delayed gratification preferences correlate strongly with both educational achievement and technology adoption. Critically, Cidral et al. [9,14] confirmed that LTO exerts a significant moderating effect on the relationship between e-learning usage and perceived net benefits. This, combined with the results from the studies of Massi et al [15], and Dwivedi et al [16] would provide compelling empirical justification for integrating this cultural dimension into AI adoption research within Vietnamese higher education [17].

Diffusion of Innovation Theory

The Innovation Diffusion Theory (IDT), originally propounded by Rogers (2003) [4], remains one of the most enduring frameworks for understanding how technological innovations are adopted across social systems, positing that innovations characterized by relative advantage, compatibility, low complexity, trialability, and observability achieve broader and more rapid diffusion [4]. What distinguishes IDT from purely technical acceptance models is its fundamentally humanistic orientation, and its recognition that adoption is shaped not merely by functional utility but by perception, social influence, and deeply held cultural values [20,21]. Over the past two decades, IDT has demonstrated remarkable explanatory versatility across educational technology contexts, consistently affirming that favorable innovation attributes positively shape student attitudes and behavioral intentions [5]. The recent emergence of AI-powered tools has further extended IDT's analytical reach, introducing both transformative pedagogical opportunities and fresh theoretical challenges [22]. Beyond generating human-like text, AI tools have demonstrated meaningful capacity to strengthen students' critical thinking and decision-making skills, while Natural Language Processing enables more personalized learning experiences. Nevertheless, as Assidi et al [23] rightly note, the complex interplay of factors shaping AI engagement, particularly among students, warrants considerably deeper investigation. The present study is situated squarely within this theoretical tradition, extending IDT's analytical boundaries into the culturally distinctive and empirically underexplored context of Vietnamese private university business education [22,24].

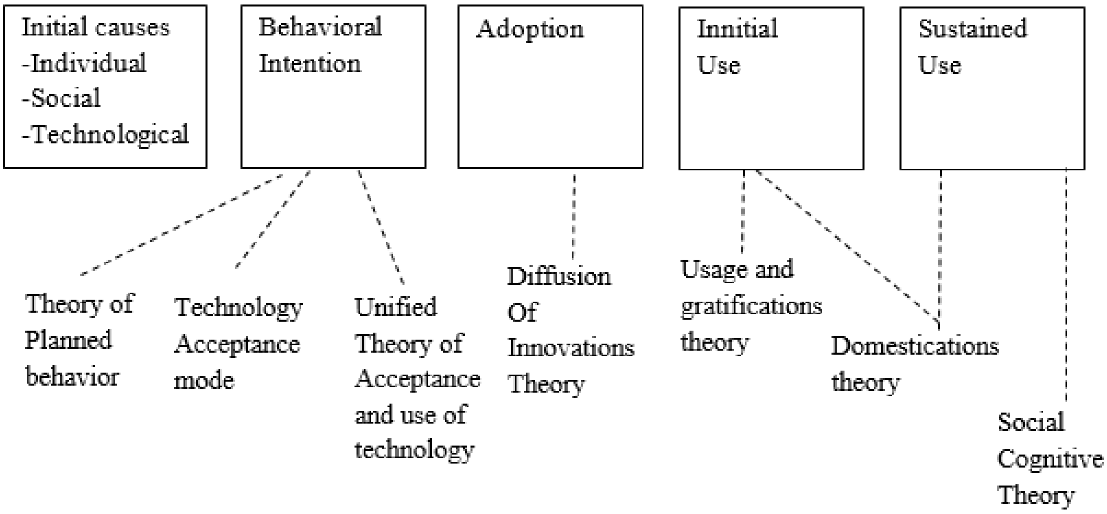

Figure 1: Acceptance of technology theories in their various phases
Sources: adapted from Dijk (2020)

As noted by van Dijk [25], innovation diffusion theory remains the most widely cited technology acceptance framework within AI-era scholarship. Rooted in a rich interdisciplinary tradition, its psychological foundation centers on the cognitive and evaluative processes through which individuals arrive at decisions to adopt or reject emerging technologies [5,26]. Unlike preceding theoretical models, where behavioural intention constitutes the primary dependent variable, this framework situates adoption itself as the central outcome of interest [27,28]. This framework positions technology adoption at the intersection of individual predisposition and social norms. It asserts that these internal and external factors are filtered through communication channels, which substantially define the scope and speed of the decision-making process [29]. Adoption is further mediated by individuals' subjective assessments of an innovation's defining technical properties. The acceptance of AI tools is mediated by four critical factors: functional superiority over legacy systems, alignment with established media practices, perceived ease of use, and contextual triability [26]. When these conditions are met, the barrier to integration is lowered, facilitating a more seamless transition from traditional to AI-augmented workflows [30].

Relative Advantage and AI Adoption

Within the framework of Diffusion of Innovation Theory, relative advantage denotes the perceived superiority of an innovation as measured by efficiency, utility, and competitive gain, over the methodologies it replaces [4,31]. In higher education, this construct specifically reflects the degree to which students perceive AI-driven tools as enhancing academic performance beyond conventional alternatives [5,32]. A critical divergence exists in these perceptions: early adopters prioritize AI's capacity to optimize information retrieval and complex decision-making, whereas late adopters often undervalue these benefits due to skepticism or lower self-efficacy [33]. This perceptual asymmetry is especially pronounced among business and management students, whose performance-oriented academic environments heighten their sensitivity to AI's productivity merits [26,34].

Compatibility and AI Adoption

Within the Innovation Diffusion Theory (IDT) framework, compatibility denotes the perceived alignment between an innovation and an adopter's existing values, past experiences, and practical requirements [36]. A pronounced divergence exists between early and late adopters; the former group typically exhibits digital fluency and progressive academic values that facilitate frictionless AI integration [38]. Conversely, "late movers" often perceive a misalignment between AI functionalities and their established study habits, disciplinary norms, or ethical frameworks [39]. For business students specifically, compatibility is contingent upon the tool's perceived relevance to analytical tasks and professional development, where the "fit" between technology and context is most decisive [38,39].

Complexity and AI Adoption

Complexity, within the Diffusion of Innovation Theory, refers to the degree to which an innovation is perceived as relatively difficult to understand and use [17;39]. While conventionally framed as an adoption barrier, complexity bears a more nuanced relationship with attitude toward AI adoption [40]. This type of AI adoption positions perceived difficulty not merely as an impediment but as a cognitively stimulating challenge capable of fostering curiosity, mastery motivation, and ultimately a favorable attitudinal disposition toward AI tools [15].

Trialability and AI Adoption

In Innovation Diffusion Theory, trialability is the degree to which an innovation can be tested on a limited basis before full commitment [4,26]. For students, this involves exploring AI tools in low-stakes academic settings, a process that fundamentally shapes their long-term adoption attitudes [19,40]. While initial limited access fosters ambiguity and hesitation [21], expanded exposure through curriculum integration or peer

In higher education, this construct reflects the degree to which students view AI tools as congruent with their academic routines and learning preferences - a perception that fundamentally dictates adoption and long-term integration [17,37].

experimentation replaces skepticism with experience-grounded confidence [5,41]. This shift is particularly decisive for business students, who utilize utility testing to validate AI's professional relevance [34,42].

Observability and AI Adoption

Under Innovation Diffusion Theory, observability is the degree to which an innovation's results are visible and communicable [7,43]. In academia, this entails students witnessing tangible AI utility via peer demonstrations or instructor endorsements, fostering socially mediated adoption attitudes [32,45]. While adoption initially depends on speculative narratives, increasing visibility through shared outputs and classroom integration generates the "social proof" necessary to normalize usage [7,10]. This shift is particularly influential for business students, who utilize peer benchmarking and outcome visibility as primary evaluative heuristics to validate the professional and academic efficacy of AI tools [24,40].

Attitude and Behavioral Intention to use AI

Attitude occupies a pivotal mediating role in AI adoption precisely because it serves as the evaluative bridge through which cognitive perceptions of an innovation are translated into motivational readiness to act [2,5]. No amount of institutional promotion or technological accessibility can reliably generate adoption behavior unless students first develop a fundamentally favorable evaluative stance [25]. That is, to make attitudinal cultivation an indispensable precondition for successful AI integration in higher education [31].

Behavioral intention, in turn, refers to the strength of an individual's conscious motivation and readiness to perform a specific behavior, or the deliberate adoption of AI tools in academic practice [46]. This intention is shaped by both intrinsic drivers such as intellectual curiosity and extrinsic influences including teacher-student interactions that model purposeful AI engagement and community endorsement that socially legitimizes adoption [47]. Students harboring positive attitudes demonstrably channel their favorable evaluations into stronger behavioral intentions and dedicated efforts to acquire AI competency [5,48].

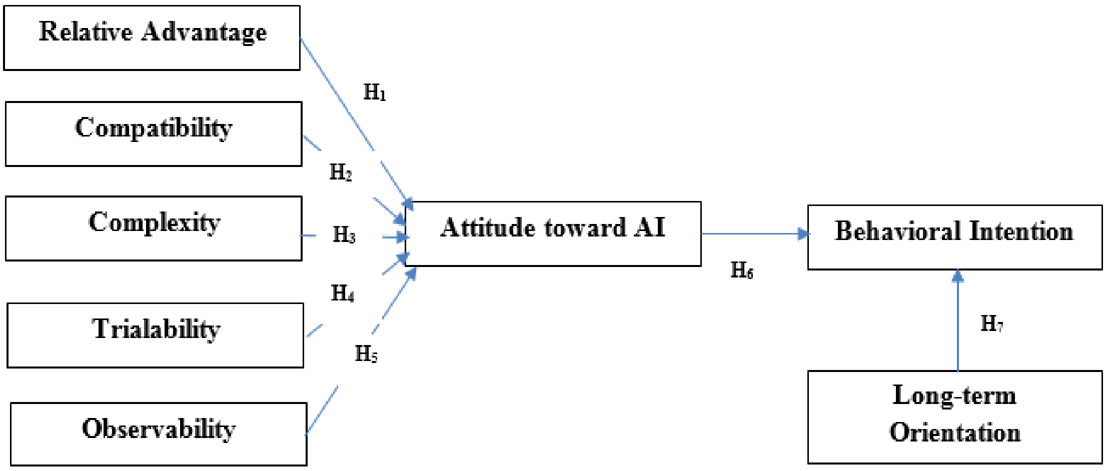

Figure 2: Conceptual Framework and Hypothesis
Sources: Authors' synthesis from literature

CONCEPTUAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

From this conceptual framework, the following hypotheses will be formulated and tested in this research as described in more detail below

H1: Relative advantage has a positive influence on AI adoption among students.

Multiple converging foundations substantiate a positive relationship between relative advantage and AI adoption intentions [5,22,35,41]. The IDT theory posits that stronger perceptions of an innovation's relative superiority directly elevate adoption likelihood which is a principle consistently validated across technology contexts ([4,17]. Empirically, students perceiving AI as outperforming existing learning tools demonstrate significantly higher adoption intentions [5], while cross-domain evidence from education, medicine, and banking further confirms its generalizability as a predictor of innovation uptake [5,18].

H2: Compatibility has a positive influence on AI adoption among students.

Several converging foundations support a positive relationship between compatibility and AI adoption intentions. IDT theory establishes that innovations perceived as congruent with users' values and prior practices are adopted at significantly higher rates [27,44], a proposition corroborated by a well-documented empirical correlation between compatibility and technology adoption across multiple contexts [23,50]. Furthermore, compatibility operates not merely at the functional but also at the normative level for students who perceive AI as ethically aligned with their institutional values and demonstrate stronger and more sustained adoption commitments [5;33].

H3: Complexity has a positive influence on attitude toward AI adoption among students.

Students who progressively overcome AI's perceived complexity frequently report a deepened sense of competence and intellectual engagement, transforming initial friction into a positive orientation toward the technology [20,36,51]. This is particularly evident among business and management students, whose training in analytically demanding environments renders them more resilient to technological complexity and more likely to develop favorable attitudes upon achieving functional proficiency [34]. Institutionally, structured onboarding and peer-assisted learning further accelerate the conversion of complexity-related apprehension into attitudinal openness [14,47]. When students perceive AI as complex yet conquerable, the resulting sense of accomplishment reinforces a positive evaluative stance for positioning complexity as a paradoxical driver of attitudinal favorability [44,45].

H4: Trialability has a positive influence on attitude toward AI adoption among students

Several foundations support trialability's positive influence on adoption attitudes. IDT theory establishes that innovations permitting hands-on trial are adopted more favorably, as direct experience resolves uncertainty more effectively than secondhand information [46]. Empirically, trialability has been identified as a comparatively stronger adoption predictor than several co-existing IDT attributes [45], while cross-domain evidence further confirms that trial-based exposure consistently elevates adoption rates beyond purely technological contexts [50].

H5: Observability has a positive influence on attitude toward AI adoption among students.

These dynamics are well-grounded empirically. Results from [5] demonstrate that the visual accessibility of innovation benefits drove significantly higher acceptance rates - a finding that translates compellingly to AI adoption contexts [30]. Moreover, observability functions as a self-reinforcing social mechanism whereby visible adoption begets further adoption, independently amplifying technology acceptance rates over time [5,31].

H6: Student attitude positively influences behavioral intention toward AI adoption

Abdalla et al in their 2024 study [5] postulate that the institutional AI implementation succeeds most reliably when student attitudes are favorable and encounters systematic resistance when attitudinal dispositions remain negative for confirming attitude as the critical gateway variable governing whether behavioral intention materializes or stalls [2,34,35],. Encouragingly, students already exhibit broadly favorable attitudes toward AI, rendering the prevailing attitudinal climate conducive to strong adoption momentum [10].

H7: Long-term Orientation (LTO) has a positive influence on behavioral intention toward AI adoption among students.

This cultural orientation carries particular resonance in the Vietnamese context, where Confucian values historically govern academic and professional decision-making, rendering LTO a theoretically grounded and culturally sensitive predictor of AI adoption behavior [9,11,14]. Critically, LTO is hypothesized to exert a direct positive influence on behavioral intention independent of attitude - suggesting that culturally embedded temporal dispositions function as a motivational antecedent that transcends cognitive evaluation alone [49]. Empirically, individuals oriented toward the long term are demonstrably more likely to translate favorable AI evaluations into concrete adoption commitments, affirming LTO's unique explanatory contribution within the present structural equation model [52,42].

METHODS

Measurement and Questionnaire Back-Translation

All measurement variables were adapted from established literature and synthesized below:

Constructs	From studies
Relative Advantage	[5]; [22];[35];[41]
Compatibility	[5][23];[27];[44]
Complexity	[5][36];[51];[63]
Trialability	[5][30];[31];[36]
Observability	[5][30];[31];[57]
Long-term Orientation	[9]; [11];[62];[63]
Attitude toward AI	[2; 5;34; 35;42]
Behavioral Intention	[12; 34; 36]

Based on these measurements, field survey questionnaires would be developed to collect data for factor analysis to be performed with the aim to condense survey items into theoretically coherent constructs. This methodological approach was consistent with Hair et al.'s 2018 guidelines [53] and other scholars such as [42,48,60]. Responses were captured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (completely agree). The questionnaire, originally developed in English, underwent rigorous back-translation into Vietnamese following Behr's [42, 54] protocol - a methodological necessity given that most measurement instruments originate in Western contexts, where cross-cultural validity remains empirically underexplored [54,55,56]. Two independent bilingual researchers performed the forward and back-translation sequentially; pilot-testing with bilingual respondents confirmed response consistency across both language versions. Prior to formal data collection, a pilot study involving 15 student respondents was conducted to refine technical wording and ensure conceptual clarity, with participant feedback directly informing item-level revisions [55,60].

Survey and Sampling

Data were collected from undergraduate students at Peace University in Hanoi, Vietnam, between October 2025 and March 2026. Established in 2008 under Prime Ministerial Decision No. 244/QĐ-TTg, Peace University became a private institution affiliated with the Sovico–Vietjet Air conglomerate whose chair has been recognized among Fortune's inaugural list of Asia's 100 Most Powerful Women [58]. The university's diverse academic specializations rendered it a contextually appropriate sampling site. Convenience sampling was employed due to inherent time and budgetary constraints characteristic of academic survey research, whereby participants were selected based on availability and accessibility rather than probabilistic criteria. As digital natives with prior AI exposure, Hoa Binh (or Peace in English name) University students constitute a relevant and accessible population for SEM-based inquiry. Following Hair et al.'s [53] guideline of ten responses per measurement item, a minimum of 240 responses was required. However, this study ultimately obtained 368 valid responses, thereby, sufficiently exceeding Hair et al threshold [53,60].

Data Collection and Processing

A validated online questionnaire was distributed via Google Form which is accessible through hyperlink and QR code to eligible undergraduate business students at Peace University, Hanoi. Lecturers administered the survey anonymously during scheduled class sessions, while trained student researchers assisted with participant solicitation and data entry [60]. A pre-survey rehearsal was conducted to standardize procedures and ensure collection integrity. Of the 750-plus eligible undergraduates identified through the Department of Student Affairs, 368 fully completed responses were recorded, yielding a 51% response rate - an acceptable threshold for this scale of inquiry [53,59]. Raw data were migrated from Google Sheets into SPSS 22 for processing. Missing values were addressed through mean replacement to preserve database integrity, followed by normality testing to confirm analytical suitability [42,53]. Descriptive statistics profiled sample demographics, while exploratory factor analysis, with factor extraction fixed at one per construct, examined inter-item relationships across dependent and independent variables. The processed dataset was subsequently prepared for AMOS-based Structural Equation

Modeling (SEM) to formally test the study's hypotheses [60].

Background statistics.

Table 1 presents the demographic composition of the sample. A total of 368 valid responses were retained for analysis, comprising 235 male respondents (63.9%) and 133 female respondents (36.1%). In terms of academic specialization, Business Administration constituted the largest proportion (52%), followed by Banking (27%) and E-Commerce and Law (21%). Regarding ethnic background, the Kinh majority accounted for 343 respondents (93.2%), while ethnic minority groups represented 25 respondents (6.8%). The distribution of academic year indicated that first-year students comprised the largest cohort (53%), followed by second-year (24%) and third-year students (23%), suggesting a sample predominantly composed of early-stage undergraduates with relatively formative technology adoption experiences [56]. Collectively, the demographic characteristics of the sample demonstrate sufficient diversity and structural adequacy, satisfying the representativeness requirements necessary for reliable Structural Equation Modelling analysis in accordance with [53].

Table 1 Sample's demographic characteristics

Gender	**N**	**%**	**Years of study**	**N**	**%**
Female	235	64	First year	189	53
Male	133	36	Second Year	91	24
Total	368	100	Third Years	88	23
Fields of study	**N**	**%**	Total	368	100
Business Administration	190	52	**Ethnicity**	**N**	**%**
Banking	100	27	Non-Kinh	25	7
Laws & E-commerce	78	21	Kinh	343	93
Total	368	100	Total	368	100

Sources: Data processing of student survey with SPSS 22

Exploratory factor analysis (EFA), with a fixed factor solution per construct, was conducted using SPSS 22 to reduce the 16 questionnaire items into coherent variable sets [53,56]. Normality was confirmed via the Kolmogorov-Smirnov test ($p < 0.001$). As presented in Table 2, all constructs exceeded the minimum KMO threshold of 0.6, and Bartlett's Test of Sphericity reached statistical significance ($p < 0.001$), affirming dataset adequacy. Factor loadings for all items surpassed the 0.6 threshold, exceeding the minimum acceptable criterion of 0.5 According to Swierczek and Ha [60] and Tyupa [56] thereby validating all four constructs for subsequent advanced analyses [53]

Table 2 Exploratory Factor Analysis and Reliability Test Results

Factor Items	**Factor Loadings**	**KMO and Bartlett's Test**	**Cronbach's Alpha and *(Eighen Value)***
RLA1. AI contributes to building students' capabilities.	0.88	0.733 and 513.6; df=3 p<0.001	0.862 ***(2.35)*** 78 % of variance
RLA2. I can save time and efforts by using AI	0.89		
RLA3. AI helps me to be more effective	0.87		
COM1. AI is compatible with my current situation	0.92	0.744 and 634.4; df=3 p<0.001	0.890 ***(2.46)*** 82 % of variance
COM2. I spent so much time and effort in AI.	0.89		
COM3. I am afraid of misuse of AI.	0.91		
CPL1. Using AI does NOT require technical skills	0.89	0.745 and 640.4; df=3 p<0.001	0.890 ***(2.44)***

CPL2. Interacting with AI would NOT confuse me	0.914		80 % of variance
CPL3. AI is clear and understandable	0.910		
TRA1. I learned about AI before others	0.91	0.747 and 623.1; df=3 p<0.001	0.889 (2.44) 81 % of variance
TRA2. I want to try AI before effective adoption	0.89		
TRA3. My university regulates the use of AI	0.908		
OBV1. AI is visible around my university	0.884	0.738 and 654.1; df=3 p<0.001	0.892 ***(2.45)*** 82 % of variance
OBV2. If I use AI, other classmates will observe me	0.912		
OBV3. I am more likely to use AI when seeing my friends do it	0.924		
ATD1. Using AI would be a positive decision	0.88	0.739 and 553.1; df=3 p<0.001	0.872 ***(2.3)*** 80 % of variance
ATD2. I have a positive impression of using AI for studies	0.894		
ATD3. I would feel excited to use AI for my studies	0.902		
LTO1. I like to use AI in my studies to achieve long-term goals	0.801	0.693 and 237.2; df=3 p<0.001	0.760 ***(2.03)*** 68 % of variance
LTO2. I prefer to use AI for my life-long study	0.836		
LTO3. I think about saving money for the future AI use	0.830		
BHV1. I would be willing to use AI now and, in the future,	0.897	0.719 and 549.5; df=3 p<0.001	0.861 ***(2.36)*** 79 % of variance
BHV2. I intend to use AI as soon as possible	0.852		
BHV3. I intend to use AI for my better academic performance	0.913		

Source: Author synthesis from data analysis results

The EFA results in Table 2 provide robust empirical justification for proceeding to Structural Equation Modelling (SEM), demonstrating strong construct validity and internal consistency across all eight constructs. All factor loadings exceeded the 0.70 threshold [53], ranging from 0.801 (LTO1) to 0.924 (OBV3), confirming convergent validity at the item level. Cronbach's Alpha coefficients ranged from 0.760 (LTO) to 0.892 (Observability), uniformly surpassing the 0.70 acceptability criterion [37,54], confirming satisfactory internal consistency. Collectively, these psychometric properties validate the instrument's suitability for credible latent variable modelling and hypothesis testing within the subsequent SEM framework [59].

Table 3 Correlation Matrix to be used for SEM analysis

Variables in the model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
(1) Relative. Advantage	1							
(2) Compatibility	0.047	1						
(3) Complexibility	0.116*	0.027	1					
(4) Trialability	-0.029	0.049	0.028	1				
(5) Observability	0.082	0.069	0.070	0.030	1			
(6) Attitude.toward.AI	-0.016	0.019	-0.061	-0.002	0.053	1		
(5) Longterm. Orientation	0.022	0.038	-0.003	0.074	-0.067	-0.042	1	
(8) Behavioral. Intent	0.133*	0.128*	0.078	0.07	0.112*	0.074	0.054	1
Mean	3.9	3.9	3.9	3.9	3.8	3.8	3.4	3.6
Standard Deviation	0.9	0.8	0.8	0.9	0.8	0.8	0.7	0.6

Source: Author synthesis from data analysis results

Table 3 presents the correlation matrix serving as a foundational diagnostic tool within this study's SEM framework. The predominantly low-to-moderate inter-construct correlations (r=-0.067 to 0.133) confirm satisfactory discriminant validity and the absence of multicollinearity, satisfying a critical prerequisite for reliable SEM parameter estimation [5,54]. Notably, statistically significant correlations of Relative Advantage (r=0.133*), Compatibility (r=0.128*), and Observability (r = 0.112*) with Behavioral Intention provide preliminary bivariate support for the hypothesized IDT-based structural relationships. Additionally, the near-zero correlation between Long-term Orientation and Attitude (r=-0.042) corroborates LTO's role as a direct antecedent of Behavioral Intention, bypassing attitudinal mediation. Collectively, these findings substantiate the structural integrity and construct independence necessary for credible SEM analysis [53;60].

RESULT AND DISCUSSION

Model Fit Assessment and Construct Reliability

Model fit was evaluated using multiple indices recommended by Hair et al. (2018). Results indicate acceptable fit: $\chi^2(121) = 213.364$, $p < 0.001$, CMIN/DF = 1.763, well within the ≤ 3.0 threshold (Byrne, 2010). RMSEA = 0.05 confirms close population fit, while incremental indices such as CFI = 0.971, IFI = 0.971, TLI = 0.963, and NFI = 0.936, all substantially exceeded the 0.90 benchmark [2,52,53], collectively confirming that the hypothesized model adequately represents the observed data [6;37].

Standardized factor loadings across all five IDT constructs confirm satisfactory indicator reliability. Loadings ranged from 0.74 (Triability) to 0.91 (Observability), uniformly exceeding the 0.70 threshold (Hair et al. [53]. Compatibility demonstrated the strongest convergent validity (0.83–0.88), while Observability exhibited the most consistent loadings (0.80–0.91), confirming that all indicators reliably reflect their intended latent constructs [9; 35;37].

Structural Path Analysis

Structural path coefficients from the five IDT constructs to student Attitude toward AI adoption revealed that Triability ($\beta = 0.09$) and Complexity ($\beta=0.07$) were the most influential predictors, while Observability ($\beta=0.06$), Compatibility ($\beta=-0.03$), and Relative Advantage ($\beta=-0.02$) produced negligible coefficients. The negative paths from Compatibility and Relative Advantage suggest that, within the Vietnamese private university context, perceptions of AI's functional superiority and practice compatibility do not significantly shape attitudinal formation which likely reflects the nascent AI literacy among the sampled population, where experimentation capacity and operational complexity concerns predominate [15]. The Attitude-to-Behavioral Intention path ($\beta=0.08$) confirmed a positive directional relationship, consistent with IDT theory and Abdalla et al [5] proposition that attitudinal dispositions mediate innovation adoption decisions.

Long-term Orientation demonstrated a positive direct path to Behavioral Intention ($\beta=0.06$), suggesting that future-oriented cultural values incrementally strengthen AI adoption intentions among Vietnamese students [8,37]. Nevertheless, near-zero R^2 values for both Attitude and Behavioral Intention indicate that additional psychological, institutional, and contextual determinants warrant investigation in future research [12,17].

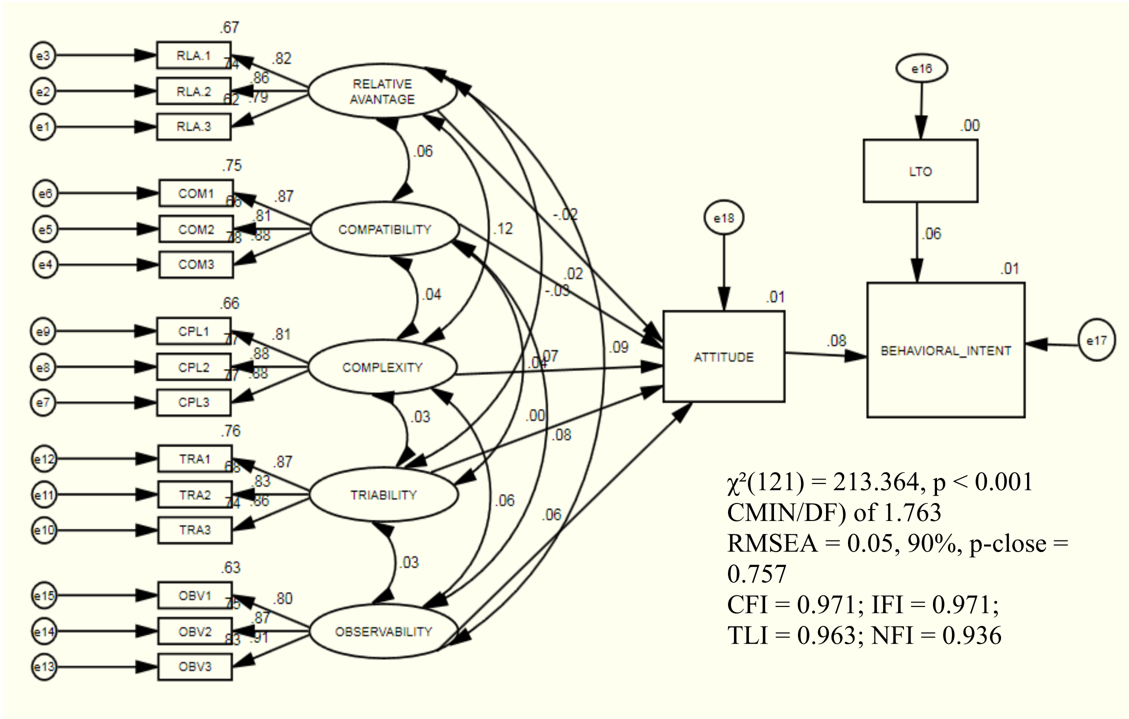

Figure 2: Structural Equation Modelling (SEM) Analysis
Sources: SEM analysis results from AMOS

Taken collectively, the structural equation modelling results provide partial empirical support for the hypothesized relationships [49]. The IDT innovation attributes demonstrate differential predictive relevance, with Triability and Observability emerging as the most substantively meaningful predictors of student attitude [63]. LTO exhibits a consistent positive association with Behavioral Intention, reinforcing its theoretical relevance as a cultural moderator within the Vietnamese higher education context [20,36]. The strong model fit indices confirm the structural validity of the proposed framework, while the modest explained variance in the endogenous constructs points to productive opportunities for theoretical extension, particularly through the incorporation of additional cultural, institutional, and motivational variables in future scholarly inquiry [14].

Table 4 Synthesis of hypothesis test results

Variables	Path	Variable	Coefficients	Hypothesis test results
Attitude	<---	Relative Advantage	-0.019*	Rejected
Attitude	<---	Compatibility	0.02*	Supported
Attitude	<---	Complexity	-0.067*	Rejected
Attitude	<---	Triability	0.001	Supported
Attitude	<---	Observability	0.063*	Supported
Behavioral Intention	<---	Attitude	0.083*	Supported
Behavioral Intention	<---	(LTO)	0.058*	Supported

Sources: Synthesized by author from SEM analysis using AMO

The standardized regression coefficients reveal that Complexity (β=−0.067) and Observability (β = 0.063) exert the most substantial opposing effects on Attitude toward AI, whereas Compatibility (β=0.02) and Relative Advantage (β=−0.019) contribute marginally. Notably, Triability (β=0.001), while statistically supported, registers a negligible practical effect on Attitude, suggesting that mere trial accessibility alone is insufficient to meaningfully shape attitudinal dispositions toward AI among Vietnamese business students. Subsequently, Attitude (β=0.083) and Long-Term Orientation (β = 0.058) emerged as significant positive antecedents of Behavioral Intention, affirming that attitudinal formation and cultural disposition constitute primary determinants of AI adoption intentions among Vietnamese business students. Importantly, the rejection of Relative Advantage (β =-0.019) and Complexity (β=-0.067) as hypothesized positive antecedents indicates that students' perceptions of AI's functional superiority remain insufficiently consolidated, while operational difficulty continues to constitute a substantive attitudinal barrier **[5]**.

These findings carry meaningful pedagogical implications: mitigating perceived complexity through scaffolded digital literacy interventions while enhancing AI observability within instructional environments represent the most actionable strategies for cultivating favorable adoption attitudes **[44,45,62].** The complete absence of direct pathways from any IDT attribute to Behavioral Intention further confirms that Attitude functions as a full mediator within this structural model, consistent with **[4,47]** foundational propositions. Furthermore, the positive influence of Long-Term Orientation suggests that students who conceptualize AI proficiency as a strategic, future-oriented competency are better positioned to develop technological self-efficacy and entrepreneurial capability within Vietnam's increasingly digitalized economic landscape **[45,62]**. Collectively, Table 4 synthesizes seven hypothesized structural relationships, of which five are empirically supported, reinforcing the theoretical robustness of the integrated IDT–LTO framework and its contextual applicability to Vietnamese higher education settings **[17].**

Total, direct and indirect effects in SEM analysis

Table 4 presents the decomposed total, direct, and indirect effects of all predictor constructs on Attitude and Behavioral Intention. Regarding total effects on Attitude, Complexity registers the largest absolute magnitude (β=-0.072), confirming its dominant suppressive role among IDT attributes, while Observability produces the strongest positive total effect (β=0.066), followed by Compatibility (β = 0.021). Relative Advantage (β=-0.021) and Triability (β=0.001) exert negligible total influences. Concerning total effects on Behavioral Intention, Attitude (β=0.054) and LTO (β=0.047) emerge as the most substantively meaningful predictors.

The direct effects decomposition confirms that all IDT attributes influence Behavioral Intention exclusively through Attitude, with no direct IDT-to-Behavioral-Intention pathways observed, thereby validating Attitude's full mediating role within the proposed structural model. Complexity demonstrates the strongest direct effect on Attitude (β=-0.072), while Observability exerts the most influential positive direct effect (β=0.066). Both LTO (β =0.047) and Attitude (β=0.054) register meaningful positive direct effects on Behavioral Intention exclusively, confirming LTO's theoretically distinctive function as an autonomous cultural antecedent operating independently of attitudinal mediation. These findings, therefore, confirm what has been found in the study of Sharma **[63]**.

The indirect effects reveal that only Complexity (β=-0.004), Observability (β= 0.004), and Compatibility (β=0.001) transmit meaningful mediated pathways to Behavioral Intention through Attitude, while Triability and LTO register zero indirect effects. Collectively, these decomposed effects affirm the model's structural integrity and underscore Complexity and Observability as the most practically consequential intervention targets for promoting AI adoption among Vietnamese business students. The findings of this study also coincide with those of several scholars such as Tran **[45]** and Tien **[42]** Sharma **[63].**

Table 4. Summary of Total, Direct, and Indirect Effects

Predictor	Total Effects		Direct Effects		Indirect Effects	
	→ Attitude	→ Behav. Intent	→ Attitude	→ Behav. Intent	→ Attitude	→ Behav. Intent
Triability	0.001	0.000	0.001	0.000	0.000	0.000
Complexity	**-0.072**	**-0.004**	**-0.072**	0.000	0.000	**-0.004**
Compatibility	**0.021**	0.001	**0.021**	0.000	0.000	0.001
Relative Advantage	**-0.021**	**-0.001**	**-0.021**	0.000	0.000	**-0.001**
Observability	**0.066**	**0.004**	**0.066**	0.000	0.000	**0.004**
LTO	0.000	**0.047**	0.000	**0.047**	0.000	0.000
Attitude	0.000	**0.054**	0.000	**0.054**	0.000	0.000

Sources: Synthesized by author from SEM analysis using AMOS

CONCLUSION AND POLICY IMPLICATIONS

Conclusions

This study examined the determinants of AI adoption intentions among Vietnamese undergraduate business students by integrating Innovation Diffusion Theory (IDT) with Long-Term Orientation (LTO) within a Structural Equation Modelling framework. The findings yield three principal theoretical conclusions.

First, Complexity and Observability emerged as the most consequential IDT attributes influencing Attitude toward AI, affirming that reducing perceived operational difficulty while maximizing AI visibility within instructional environments constitutes the most actionable pedagogical strategy for cultivating favorable adoption attitudes. This conclusion confirms the study results of such scholars as Zeng and Huang [47]; Venaik et al [62].

Second, Attitude (β = 0.083) demonstrated the strongest direct effect on Behavioral Intention, reinforcing the theoretical centrality of attitudinal formation in technology adoption. Institutions cannot rely exclusively on perceived utility to drive adoption, or the affective and evaluative dimensions of students' AI orientations demand deliberate pedagogical cultivation through faculty modeling, peer observational learning, and community-level endorsement of AI's academic legitimacy. This conclusion also coincides with that of Tang et al [38] and Patnaik et al [39].

Third, LTO's significant direct effect on Behavioral Intention (β=0.058) constitutes this study's most distinctive theoretical contribution, demonstrating that culturally embedded temporal dispositions independently influence adoption motivation beyond attitudinal pathways. Consistent with Raman et al [5,22,27], students exhibiting strong LTO perceive AI proficiency as a strategically valuable long-term competency, rendering LTO an indispensable cultural antecedent within IDT-based adoption frameworks applied to Confucian-influenced educational contexts.

Collectively, these findings reposition AI adoption as a cultural, attitudinal, and experiential phenomenon, urging contextually sensitive and humanistically intentional approaches to AI integration within Vietnamese higher education [41,48].

Policy Implications for Educational Management

The structural findings carry substantive policy implications for Vietnamese higher education administrators and institutional policymakers. The significant influence of Complexity and Observability on Attitude suggests that universities should systematically institutionalize structured AI experimentation opportunities within formal curricula [17,35]. This includes dedicated AI literacy programs, pilot learning environments, and supervised hands-on workshops, enabling students to evaluate AI tools within academically scaffolded and ethically governed settings [9,10].

The results of this study coincide with those of [7,8,36] study. That is, LTO's positive influence on Behavioral Intention implies that culturally congruent policy framing with the aim to position AI competency as a strategic, career-sustaining investment, rather than a short-term academic convenience, is likely to yield more durable adoption behaviors among Vietnamese students [36,44,49]. Educational authorities are therefore encouraged to co-develop nationally coordinated AI governance frameworks aligned with UNESCO's Recommendation on the Ethics of AI (2021), establishing enforceable yet pedagogically enabling regulatory standards that safeguard academic integrity while promoting responsible and equitable AI integration across Vietnam's higher education sector [14,42].

While this study may have interesting implications for policy makers and practitioners, it is fair to acknowledge several limitations. The convenience sampling approach and single institution focus restrict broader generalizability. Additionally, reliance on self-reported perceptions positions findings as exploratory rather than definitive. Future research should employ probability sampling across diverse Vietnamese institutions, integrate mixed-methods approaches, and extend the theoretical framework toward cross-national ASEAN comparative analyses.

Declaration by Authors

Acknowledgement: None

Source of Funding: None

Conflict of Interest: No conflicts of interest declared.

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How to cite this article: Thai Thanh Ha, Le Dung Kien. Long-term orientation and artificial intelligence adoption among Vietnamese business students based on the innovation diffusion theory: a structural equation modelling analysis. *International Journal of Research and Review*. 2026; 13(5): 661-678. DOI: *https://doi.org/10.52403/ijrr.20260564*

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