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Acceptance of artificial intelligence and its effect on entrepreneurial intention in foreign trade students: a mirror analysis

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Abstract

Artificial intelligence (AI) has experienced a significant increase in its application in the educational field worldwide. This study aimed to analyze the acceptance of AI and its effect on the entrepreneurial intentions of international trade university students in Peru and Ecuador. With a quantitative approach and a non-experimental applied design, an online survey was administered to international trade students from Peru and Ecuador. Amos version 24 software was used to obtain model fit indices and perform gender-based invariance tests. Additionally, SmartPLS statistical software, based on the partial least squares (PLS) technique, was employed to test the hypotheses of the structural equation model (SEM). The measurement model presented acceptable fit indices. When calculating invariance, the configural, metric, and scalar models were satisfactory, although the residual model was not confirmed. It was found that hedonic motivation, habit, and performance expectations influenced international trade students' intention to use AI. Likewise, it was discovered that the intention to use AI tools has an effect on entrepreneurial intention. Gender and age did not moderate the effect of AI usage intention on entrepreneurial intention. The study provides empirical evidence on the acceptance of AI and its influence on students' entrepreneurial intentions, offering valuable information for educators, policymakers, and technology developers in the educational field.

Keywords: Artificial intelligence, Entrepreneurship, Acceptance of AI, College students, Foreign trade, Educational technology

Introduction

The application of artificial intelligence (AI) in education has significantly increased globally in recent years (Al-Hawawreh et al., 2023; Cleary et al., 2023). From virtual reality applications to the launch of AI-driven chatbots like ChatGPT, Claude, or Perplexity, these technologies have garnered significant attention in the educational sector due to recent advancements and their growing popularity (Vecchiarini & Somià, 2023). However, this dynamism presents a fundamental challenge: the effective integration of AI into educational systems, particularly in critical areas such as international trade (Yadav et al., 2023). Moreover, this challenge goes beyond mere technological adoption; it involves the understanding, acceptance, and application of AI by future professionals (Stevens & Stetson, 2023; Zhang et al., 2023a, 2023b).

Currently, there is a growing gap between advancements in AI and the ability of educational systems to adapt their curricula and pedagogical methods to these technologies (Greiner et al., 2023). This knowledge gap raises questions about how students are being prepared for a labor market that increasingly demands AI competencies and how this preparation influences their entrepreneurial predisposition (Kumar et al., 2023). Furthermore, the variability in the quality and focus of AI education across different regions and countries complicates the understanding of this phenomenon, as differences in available resources and educational policies significantly influence how students interact with and perceive AI (Salas-Pilco & Yang, 2022).

The intention to engage in entrepreneurship has attracted the attention of numerous researchers from different fields, who have focused on predicting the behavior of new venture creation (Batista-Canino et al., 2024; Kautonen et al., 2013), with intention being considered the best individual predictor of such behavior. Recent studies have explored various aspects of AI acceptance and its impact on entrepreneurial intentions. Nuseir et al. (2020) examined self-efficacy and entrepreneurial competence as antecedents of entrepreneurial intentions in the context of smart cities, finding that AI entrepreneurship education mediates the relationships between entrepreneurial competence, self-efficacy, and entrepreneurial intentions. Dabbous and Boustani (2023) investigated the influence of entrepreneurial education and AI development on entrepreneurial intentions, considering the mediating role of perceived behavioral control. They found that perceived behavioral control fully mediates the relationship between the performance expectancy of AI solutions and entrepreneurial education with entrepreneurial intention. Abaddi (2023) aimed to merge the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) to fill a research gap on the impact of GPT on the digital entrepreneurial intentions of students and technologically adept generations. The study's findings revealed the mediating power of GPT's perceived usefulness and ease of use, key components of TAM, paving the way for a future filled with unlimited possibilities in digital entrepreneurship.

Although these studies provide relevant information, gaps remain in understanding how AI acceptance influences entrepreneurial intentions, particularly in the context of international trade students in South American countries. This research addresses these gaps by aiming to analyze AI acceptance and its effect on the entrepreneurial intentions of international trade students in Peru and Ecuador. By focusing on this specific context, the study contributes to a more nuanced understanding of AI acceptance and its impact on entrepreneurial intentions. It also highlights the need to consider cultural and educational differences in the reception of emerging technologies and explores how leveraging AI's potential could be a crucial factor in fostering an entrepreneurial spirit.

The study is theoretically justified by the use of various technological adoption theories, such as the Theory of Reasoned Action, the Theory of Planned Behavior, and the Diffusion of Innovations Theory, providing a comprehensive analysis of how psychological, social, and technological factors influence the decision to adopt AI in entrepreneurship (Polisetty et al., 2023). Methodologically, the study employs a quantitative approach and contributes to the emerging field with a data collection instrument (with acceptable psychometric properties) to assess constructs such as perceived risk, hedonic motivation, performance expectancy, social influence, price value, effort expectancy, habit, and their influence on the intention to use AI tools and entrepreneurial intention. Future studies can utilize this instrument in other contexts, advancing the future research area on AI use among international trade students. Finally, from a practical and social perspective, the study is relevant due to its potential to generate policies and strategies that promote the effective integration of AI in the business sector, driving innovation, competitiveness, and economic growth. By addressing concerns such as data security and technological stress, this research could contribute to developing safer and more sustainable practices for implementing AI in entrepreneurship, benefiting both entrepreneurs and society at large.

Literature review

The acceptance of AI and the intention to undertake entrepreneurship intertwine within a theoretical foundation that considers multiple psychological, social, and technological factors (Polisetty et al., 2023). In this context, the perception of risk associated with AI plays a fundamental role, where concerns about security and privacy can negatively influence its adoption (Neyazi et al., 2023).

Simultaneously, performance expectancy, which assesses the perceived utility of AI in terms of efficiency and productivity, and effort expectancy, which reflects the ease of use and learning of AI, are crucial for fostering a positive attitude toward its integration in entrepreneurial projects. Social influence, reflecting the impact of peers' and mentors' opinions, and facilitating conditions, including the availability of resources and compatibility with existing technologies, are also significant determinants. Moreover, hedonic motivation, considering the pleasure derived from using AI, price value, assessing the cost–benefit relationship, and habit formation in the use of AI, are relevant aspects in the decision to adopt these technologies. Additionally, technological stress can act as a barrier, while the intention to use AI, entrepreneurial intention, and inclination toward innovation are indicators of a predisposition to incorporate AI in entrepreneurship.

Risk perception (RI) in adopting AI for entrepreneurship is grounded in the theory of risk aversion and decision-making under uncertainty (Puzić et al., 2019). Entrepreneurs assess potential negative outcomes associated with AI implementation, such as data vulnerability and security (Neyazi et al., 2023). This risk analysis is influenced by cognitive and emotional factors, where the assessment of AI safety and reliability becomes central. The literature suggests that risk perception can be exacerbated by a lack of familiarity and understanding of the technology, leading to a cautious or rejecting attitude toward adopting AI-based solutions (Allahham et al., 2024).

Performance expectancy (PE) aligns with expectancy-value theory, which posits that the likelihood of adopting new technology is directly related to the perceived expectation of its benefits (Kregel & Krynes, 2006). In the context of entrepreneurship, AI's performance expectancy refers to the belief that its use will bring significant improvements in terms of efficiency, productivity, and goal achievement (Ma & Huo, 2023). Studies in information technology management highlight that high performance expectancy can be a robust predictor of technological adoption, as well as who transmits the knowledge (Terblanche et al., 2023). This expectation is supported by evaluating how AI can contribute to process optimization, product and service innovation, and competitive advantage in the market.

Effort expectancy (EE) is based on the theory of perceived ease of use, which examines how the perception of ease or difficulty in learning and using AI affects acceptance in entrepreneurship (Malhan et al., 2023). The technological adoption literature suggests that the lower the perceived effort to use a technology is, the greater the likelihood of its adoption (Green, 2024). For AI, this involves assessing the user interface, learning curve, and integration with existing systems (Ebadi & Raygan, 2023). A low effort expectancy is associated with greater willingness to incorporate AI, as entrepreneurs tend to prefer technologies requiring less time and less resource investment for effective mastery and application.

Social influence (SI) is grounded in the theory of planned behavior and the diffusion of innovations theory. Social influence refers to the extent to which the perceptions and behaviors of significant individuals (such as colleagues, mentors, or opinion leaders) impact an entrepreneur's willingness to adopt AI (Mohr & Kühl, 2021). This social influence operates through subjective norms and perceived social pressure to conform to the expectations of the reference group (Chai et al., 2020). According to social conformity theory, entrepreneurs may be more likely to adopt AI if they perceive it as valued or adopted by their professional network (Gupta et al., 2021). This dimension is closely linked to the concept of social legitimacy in adopting new technologies, where approval from peers and industry experts plays a crucial role in the adoption decision (Chai et al., 2023).

Facilitating conditions (FC), based on the technology acceptance model and the unified theory of acceptance and use of technology (Saxena et al., 2023), refer to the entrepreneur's perception that the necessary organizational and technical infrastructure for effective use of AI is present (Zhao et al., 2023). This includes the availability of resources (such as funding, hardware, and software), technical knowledge, and AI compatibility with other technologies used in the company (Na et al., 2023). The technological adoption literature suggests that the presence of facilitating conditions reduces perceived barriers to implementing new technologies and can accelerate their adoption (Wang et al., 2023). Additionally, access to technical support and collaboration networks is considered a critical factor that can mitigate implementation difficulties and foster successful AI integration into business processes.

Hedonic motivation (HM) refers to the pleasure or satisfaction derived from using a technology. This dimension, founded on self-determination theory and intrinsic motivation models, suggests that enjoyment and fun associated with using AI can be significant motivators for entrepreneurs (Romero-Rodríguez et al., 2023; Strzelecki, 2023). Hedonic motivation is linked to user experience and the emotional design of technology (Tiwari et al., 2023). Research on psychology and consumer behavior indicates that when users find pleasure and satisfaction when interacting with a technology, their willingness to adopt and continue using it increases (Romero-Rodríguez et al., 2023). In the case of AI, aspects such as an intuitive interface, engaging interaction, and the ability to generate innovative and creative solutions can contribute to a positive hedonic user experience.

Based on economic decision-making theory and consumer behavior theory, price value (PV) analysis focuses on the cost–benefit evaluation entrepreneurs make when considering the adoption of AI (Chauvet et al., 2022). Price value perception relates to evaluating whether the perceived benefits of AI justify its cost. This analysis includes not only the monetary price, but also associated costs such as the implementation time and learning curve (Nadin, 2023). The behavioral economics literature suggests that technology adoption decisions are based not only on rational cost analyses, but also on subjective perceptions of value (Kadam et al., 2023). Therefore, perceiving a favorable quality–price relationship can be a determining factor in the decision to integrate AI into business processes.

Habit (HT), in the framework of habitual behavior theory and learning psychology, refers to the tendency to adopt automatic or routine behaviors concerning technology use (Baudisch et al., 2022). In the entrepreneurship context, if AI use becomes a habitual practice, its adoption is likely to be sustained over time. Habit formation is associated with repetition and familiarity, and the cognitive psychology literature suggests that once a behavior becomes a habit, resistance to change decreases and decision-making efficiency increases, from a simple task to a video game (Ketamo, 2011). In the case of AI, habituation may result from successful technology integration into daily entrepreneurial practices, leading to a perception of AI as an indispensable and natural tool in business management.

Based on technology stress theory and occupational psychology, technology use stress (STRESS) focuses on the anxiety and stress associated with adopting and using new technologies (Sheth et al., 2023). In the entrepreneurial realm, technological stress can arise from the perception that AI is complex, hard to understand or implement, and requires significant time and resource investment (Cabezas-Heredia et al., 2023). Research in this field indicates that technological stress can negatively impact mental and physical health, as well as productivity and job satisfaction (Appolis & Aderibigbe, 2023). Effective management of technological stress is, therefore, a critical component of the AI adoption process, and strategies to mitigate this stress include adequate training, technical support, and gradual adaptation of the technology to the user's needs.

Another important construct is the intention to use AI (BI), which is grounded in the theory of reasoned action and the theory of planned behavior, positing that behavioral intention is a significant predictor of actual action (Kandoth & Shekhar, 2022). In the entrepreneurship context, the intention to use AI reflects the degree to which an entrepreneur plans to incorporate this technology into her business processes (Jameel et al., 2023). This intention is influenced by attitudes toward the technology, perceived control over its use, and the subjective norms related to AI (Labrague et al., 2023). Research on the psychology of technological adoption has demonstrated that positive intentions toward a technology are a crucial step toward its effective adoption. Therefore, strengthening the intention to use AI among entrepreneurs may be key to its successful integration into entrepreneurship.

Entrepreneurial intention (ENTI) is related to the previous construct and focuses on the desire and planning to start and develop one's own business, potentially with the support of AI (Ainous, 2021). This intention can be viewed through the prism of self-efficacy theory and entrepreneurial motivation (Al-Mamary et al., 2020). The entrepreneurship literature suggests that self-efficacy, i.e., the belief in one's ability to execute behaviors necessary to achieve specific goals, is a critical factor in forming entrepreneurial intention (Prabandari & Chong, 2022). Additionally, perceiving that AI can be a valuable tool in achieving business success can strengthen this intention.

Finally, innovation (INNOVA) is closely linked to the diffusion of innovations theory and the concept of innovation orientation (Sjödin et al., 2023). In the entrepreneurial context, it refers to an individual's predisposition to adopt and experiment with new technologies, such as AI, to enhance their business (Marino et al., 2023). This orientation toward innovation involves a willingness to take calculated risks and openness to new ideas and practices (Babina et al., 2024) Studies in innovation management show that a strong innovation orientation is associated with a greater likelihood of early adoption of emerging technologies and a proactive approach to problem solving and market opportunity exploration.

Based on the above, the following research questions are formulated:

1. Is there a significant effect of performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HE), price value (PV), habit (HT), stress (STRESS), innovation (INNOVA), and risk (RI) on the intention to use artificial intelligence (AIUS)?
2. Is there a significant effect of the intention to use artificial intelligence (AIUS) on entrepreneurial intention (ENTI)?
3. Is there a moderating effect of age or gender on the relationship between the intention to use artificial intelligence and entrepreneurial intention (ENTI)?

Methods and materials

An empirical study was conducted to test the research hypotheses of the measurement model. The study's characteristics qualify as applied, exploratory research with a non-experimental, cross-sectional design.

Participants

This study involved 318 students from the field of foreign trade who were hailing from 10 universities in Peru and Ecuador. Participants were selected through nonprobabilistic accidental sampling, thus relying on the voluntary support of all participants in completing the survey.

Table 1 shows that 57.67% of the participants were female and 42.33% were male. Moreover, the majority of respondents (57.67%) were younger than the other ages (18 to 22 years). Students from public higher education institutions made up 51.99% of the sample, and all participants reported using artificial intelligence tools in their academic activities. As for the distribution by country, 50.28 Ecuadorian students and 49.72 Peruvian students participated.

Instruments

The data collection instrument used was based on the UTAUT2 model (Nikolopoulou et al., 2021; Venkatesh et al., 2012) and consisted of 12 constructs

Table 1 Demographic information of the participants ($n = 318$)

	n	%
Gender		
Male	149	42.33
Female	203	57.67
Age		
18–22	204	57.95
23–26	98	27.84
27–30	19	5.40
31 to more	31	8.81
Type of university		
Public	183	51.99
Private	169	48.01
Have you used artificial intelligence tools in your academic activities?		
Yes	352	100
No	0	0
Country		
Peru	175	49.72
Ecuador	177	50.28

aimed at measuring the intention to use AI and its effect on entrepreneurial intention. Unlike the original UTAUT, the UTAUT2 model is suitable for introductory or initial phases, such as assessing the impact of artificial intelligence and its adoption among foreign trade students. The entrepreneurial intention construct (ENTI) was adapted from Venkatesh et al., (2012).

The survey was structured as an online questionnaire using Google Forms (https://forms.gle/bvCyXrdWwbGTcQac8; https://forms.gle/XiijC6pzjKBRSPbAA) and included items from the constructs, along with sociodemographic questions such as age, sex, type of university, and a filter question about the implementation of artificial intelligence as a teaching strategy. The survey also included a question to identify what types of AI participants had started to use. The second section contained 42 items with a 5-point Likert scale ranging from "strongly disagree" to "strongly agree". This scale was chosen for its relevance and adaptability in measuring attitudes [64], with 4 items for RI, 4 items for PE, 4 items for EE, 3 items for SI, 4 items for FC, 3 items for HM, 3 items for PV, 4 items for HT, 3 items for ST, 3 items for AIUS, 4 items for ENTI and 3 items for INNOVA. To avoid response biases, the items in the online survey were randomly distributed.

Before the survey was administered, 5 experts in the field reviewed the instrument to assess the relevance, clarity, representativeness, coherence, and consistency of all the items in relation to the geographical context of the study Peru and Ecuador. The items were translated by a specialist in English and Spanish. Additionally, a pilot test with 60 teachers was conducted to obtain representative reliability values. Following the final adaptation of the items, the survey was finalized.

Data collection and analysis method

The data were collected through an online survey of undergraduate university teachers from 10 public and private universities in Peru and Ecuador from October to December 2023. The average time to complete the form was 15 min. In total, 374 responses were collected, but only 352 responses were used; 22 responses were rejected if the students either opted not to participate or indicated not having used AI in their academic training.

Structural equation modeling (SEM) was performed via the partial least squares (PLS) technique using SmartPLS software. Reliability was assessed using Cronbach's alpha coefficient and composite reliability (CR), with values above 0.7 (Table 3). Convergent validity was evaluated through the average variance extracted (AVE), with values above 0.5 (Table 3). Discriminant validity was assessed following the criterion of Fornell and Larcker (1981) ensuring that the square root of the AVE of each construct was not greater than the correlations of all the other constructs with that specific construct. Subsequently, the descriptive statistics, standardized path coefficients, and p values of the research hypotheses were tested using SmartPLS.

For testing invariance, Amos software version 24 was used. The measurement model was estimated using maximum likelihood with Promax rotation. The comparative fit index (CFI = 0.940) was acceptable (Nunnally, 1994). Chi-square values assessing the discrepancy between observed and model-estimated data were acceptable ($X^2 = 1295.455$). A CMIN/DF = 1.928 indicated a good fit, as values between 1 and 3 are indicative of this. The root mean square error of approximation (RMSEA = 0.054) suggested a good fit to the population. PClose showed a value of Pclose = 0.064 > 0.05, reflecting a good fit.

Finally, measurement invariance was assessed using Amos version 24. Configural, metric, and scalar invariance were calculated, and the software computed fit statistics for subsamples, such as Chi-square, CFI, RMSEA, and Pclose.

Results

Table 2 presents the descriptive statistics of the study constructs. Central tendency and dispersion measures indicated that the mean values for all constructs were around the midpoint of the scale, with a reported mean of 0.000 and a uniform standard deviation of 1.000 for each construct, indicating standardized data with consistent variance across constructs.

The assessment of minimum and maximum values reveals that, despite standardization, there are variations in the range of responses. For example, the EE construct has the lowest minimum value (− 3.386), and the ST construct has the highest maximum value (3.071), indicating an asymmetric distribution of responses for these constructs. Moreover, the values vary from negative kurtosis in several constructs, such as the SI (− 1.677), suggesting a flatter distribution than normal, to high positive kurtosis in age (12.101) and HM (1.544), indicating a sharper distribution with heavier tails than a normal distribution. The Cramer–von Mises test was used to assess the goodness of fit to a normal distribution and given that all the reported p values were less than 0.001, the distributions of the constructs were

Table 2 Descriptive statistics of the study constructs

	Mean	Median	Min	Max	SD	Kurtosis	Skewness	Cramér–von Mises test statistic	Cramér–von Mises *p* value
AIUS	0.000	0.386	− 2.939	1.494	1.000	0.804	− 0.812	1.168	< 0.001
EE	0.000	0.316	− 3.386	1.550	1.000	0.954	− 0.768	0.752	< 0.001
ENTI	0.000	0.098	− 2.820	1.801	1.000	0.411	− 0.512	0.420	< 0.001
FC	0.000	0.202	− 3.396	1.667	1.000	1.071	− 0.710	0.885	< 0.001
HM	0.000	0.313	− 3.376	1.543	1.000	1.544	− 0.834	1.724	< 0.001
HT	0.000	0.054	− 2.778	1.718	1.000	0.449	− 0.556	0.439	< 0.001
INNOVA	0.000	0.270	− 2.981	1.353	1.000	− 0.795	− 0.610	2.094	< 0.001
PE	0.000	0.191	− 3.166	1.310	1.000	1.545	− 1.058	0.966	< 0.001
PV	0.000	0.000	− 2.544	1.811	1.000	0.200	− 0.474	1.329	< 0.001
RI	0.000	0.479	− 5.106	1.890	1.000	3.666	− 1.614	4.067	< 0.001
SI	0.000	0.286	− 2.549	1.649	1.000	− 0.117	− 0.422	0.906	< 0.001
ST	0.000	− 0.219	− 3.451	3.071	1.000	1.077	− 0.270	1.290	< 0.001

significantly different from a normal distribution in the study population, assuming a conventional 95% confidence level.

Model measurement results

Table 3 shows the Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) values for convergent validity. According to the criterion established by Hair (2009), all item factor loadings should exceed the value of 0.50. The study's results demonstrated that the factor loadings for all the items ranged between 0.729 and 0.983, satisfying this criterion. Cronbach's alpha and the CR were obtained to assess the reliability of the latent variable. According to the criteria of Nunnally (1994), values above 0.70 are considered adequate. As illustrated in Table 3, all the constructs exceeded this threshold. Finally, the AVE is used to determine convergent validity, and according to Teo and Noyes (2014), values above 0.50 are considered acceptable; all the constructs in the model exhibit values above this threshold.

The SEM discriminant validity analysis revealed a meticulously differentiated structure among the various constructs comprising the structural equation model. Following Fornell and Larcker (1981), for discriminant validity to be established, the square root of the AVE (numbers on the diagonal) must be greater than the correlations with other constructs (numbers off the diagonal in the same row and column). In Table 4, it is evident that the diagonal values are substantially greater than the correlations with other constructs.

Research hypothesis testing

The testing of the research hypotheses was conducted using the SEM approach and the partial least squares (PLS) technique. The goodness-of-fit indices of the research model (for which the research hypotheses were tested) were acceptable: $\chi^2 = 1708$, SRMR = 0.065, d_ULS = 1.457, d_G = 1.087, and NFI = 0.859.

Table 5 and Fig. 1 show the standardized path coefficients and other results. Four out of the 13 hypotheses were accepted. Path coefficients for the four verified

Table 3 Reliability and convergent validity of the measurement model

Constructs	Items	Outer loadings	*p* value
RISK (α = 0.922; AVE = 0.811; CR = 0.945)	RI1	0.885	< 0.001
	RI2	0.685	< 0.001
	RI3	0.771	< 0.001
	RI4	0.953	< 0.001
PERFORMANCE EXPECTANTY (α = 0.903; AVE = 0.776; CR = 0.945)	PE1	0.777	< 0.001
	PE2	0.870	< 0.001
	PE3	0.874	< 0.001
	PE4	0.945	< 0.001
EEFFORT EXPECTANCY (α = 0.881; AVE = 0.738; CR = 0.918)	EE1	0.832	< 0.001
	EE2	0.827	< 0.001
	EE3	0.816	< 0.001
	EE4	0.920	< 0.001
SOCIAL INFLUENCE (α = 0.907; AVE = 0.844; CR = 0.942)	SI1	0.836	< 0.001
	SI2	0.871	< 0.001
	SI3	0.983	< 0.001
FACILITATING CONDITIONS (α = 0.819; AVE = 0.649; CR = 0.881)	FC1	0.689	< 0.001
	FC2	0.855	< 0.001
	FC3	0.887	< 0.001
	FC4	0.729	< 0.001
HEDONIC MOTIVATION (α = 0.910; AVE = 0.848; CR = 0.943)	HM1	0.895	< 0.001
	HM2	0.873	< 0.001
	HM3	0.959	< 0.001
PRICE VALUE (α = 0.901; AVE = 0.835; CR = 0.938)	PV1	0.789	< 0.001
	PV2	0.956	< 0.001
	PV3	0.939	< 0.001
HABIT (α = 0.894; AVE = 0.758; CR = 0.926)	HT1	0.782	< 0.001
	HT2	0.919	< 0.001
	HT3	0.904	< 0.001
	HT4	0.838	< 0.001
STRESS (α = 0.796; AVE = 0.711; CR = 0.880)	ST1	0.789	< 0.001
	ST2	0.865	< 0.001
	ST3	0.987	< 0.001
AI USAGE INTENTION (α = 0.893; AVE = 0.823; CR = 0.933)	AIUS1	0.896	< 0.001
	AIUS2	0.895	< 0.001
	AIUS3	0.931	< 0.001
ENTREPRENEURSHIP INTENTION (α = 0.881; AVE = 0.737; CR = 0.918)	ENTI1	0.895	< 0.001
	ENTI2	0.837	< 0.001
	ENTI3	0.855	< 0.001
	ENTI4	0.845	< 0.001
INNOVATION (α = 0.974; AVE = 0.927; CR = 0.981)	INNOVA1	0.977	< 0.001
	INNOVA2	0.898	< 0.001
	INNOVA3	0.786	< 0.001

α: Cronbach's alpha, AVE: average variance extracted, CR: composite reliability

hypotheses ranged from 0.162 to 0.833. Additionally, the path from AIUS → ENTI had a high magnitude (T = 15.814), and the path from PE → AIUS had a minimal magnitude (T = 3.658) but was significant. Finally, the coefficient of determination values suggest that the RI, PE, EE, SI, FC, HM, PV, HT, stress, and invertase analysis

Table 4 Discriminant validity of the measurement model

	RI	PE	EE	SI	FC	HM	PV	HT	ST	AIUS	ENTI	INNOVA
RI	**(0.901)**											
PE	0.096	**(0.881)**										
EE	0.078	0.572	**(0.859)**									
SI	0.075	0.614	0.571	**(0.919)**								
FC	0.048	0.535	0.703	0.655	**(0.805)**							
HM	0.050	0.654	0.643	0.630	0.709	**(0.921)**						
PV	0.021	0.434	0.493	0.511	0.605	0.577	**(0.914)**					
HT	0.040	0.591	0.581	0.699	0.631	0.690	0.640	**(0.871)**				
ST	0.027	0.031	0.030	0.026	0.052	0.085	0.001	0.007	**(0.843)**			
AIUS	0.054	0.655	0.591	0.639	0.598	0.704	0.497	0.805	0.002	**(0.907)**		
ENTI	0.016	0.607	0.611	0.669	0.629	0.722	0.571	0.837	0.019	0.813	**(0.858)**	
INNOVA	0.156	0.162	0.156	0.106	0.118	0.107	0.178	0.139	0.340	0.130	0.089	**(0.963)**

Bold values indicate the square roots of the average variances extracted (AVE) from the diagonal, which must be greater than the off-diagonal correlations

Table 5 Testing of research hypotheses

Constructs	2.50%	97.50%	SD	T statistics (|O/STDEV|)	P-value	Path	Decision
AIUS → ENTI	0.720	0.927	0.053	15.814	0.000***	0.833***	Accepted
EE → AIUS	− 0.014	0.159	0.044	1.605	0.108	0.070	Rejected
FC → AIUS	− 0.116	0.105	0.057	0.288	0.774	− 0.016	Rejected
HM → AIUS	0.072	0.308	0.060	3.241	0.001**	0.195**	Accepted
HT → AIUS	0.394	0.701	0.079	7.057	0.000***	0.561***	Accepted
INNOVA → AIUS	− 0.088	0.046	0.035	0.706	0.480	− 0.024	Rejected
PE → AIUS	0.083	0.254	0.044	3.658	0.000**	0.162**	Accepted
PV → AIUS	− 0.175	0.019	0.050	1.684	0.092	− 0.084	Rejected
RI → AIUS	− 0.054	0.073	0.032	0.365	0.715	0.012	Rejected
SI → AIUS	− 0.062	0.162	0.057	1.000	0.317	0.057	Rejected
Stress → AIUS	− 0.066	0.055	0.031	0.101	0.920	− 0.003	Rejected
Age × AIUS → ENTI	− 0.032	0.090	0.031	0.757	0.449	0.023	Rejected
Gender × AIUS → ENTI	− 0.160	0.122	0.072	0.321	0.748	− 0.023	Rejected

Path: Coefficient Path; SD: Standard deviation

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

(INNOVA) explain 74% of the variation in the AIUS. The AIUS explains 67% of the variation in the ENTI.

Model invariance tests

The results, recorded in Table 6, encompass various structural models with the purpose of determining if the acceptance of artificial intelligence operates equivalently in subgroups based on gender. The configural model, serving as the reference model, was established with a value of $\chi^2/\mathrm{df} = 1.50$, CFI = 0.950, RMSEA = 0.045, and PClose = 0.100, indicating satisfactory fit. The acceptance of the configural model suggests that the evaluated items reflect the same construct in both gender groups, providing a solid starting point for measurement invariance.

Progressing towards metric invariance, the factor loadings were equalized between men and women. The results maintained a good fit ($\chi^2/\mathrm{df} = 1.52$, CFI = 0.948, RMSEA = 0.047), supporting the assumption that the relationship between the items and the underlying construct is comparable in both groups. This finding allows for moving towards more complex analyses involving correlations and regressions between genders.

When addressing scalar invariance, it was observed that both the factor loadings and the item intercepts were uniform across groups, as denoted by CFI = 0.946 and RMSEA = 0.049. The acceptance of this model affirms that the means of the latent constructs are comparable, which is essential for subsequent comparisons in the average scores of the constructs.

However, upon exploring residual invariance, which posits equality in the variances and covariances of measurement errors, an inadequate fit was found ($\chi^2 = 1.64$, CFI = 0.926, RMSEA = 0.064), and it was rejected due to a significant change in the CFI relative to the scalar model. This evidence indicates discrepancies in response

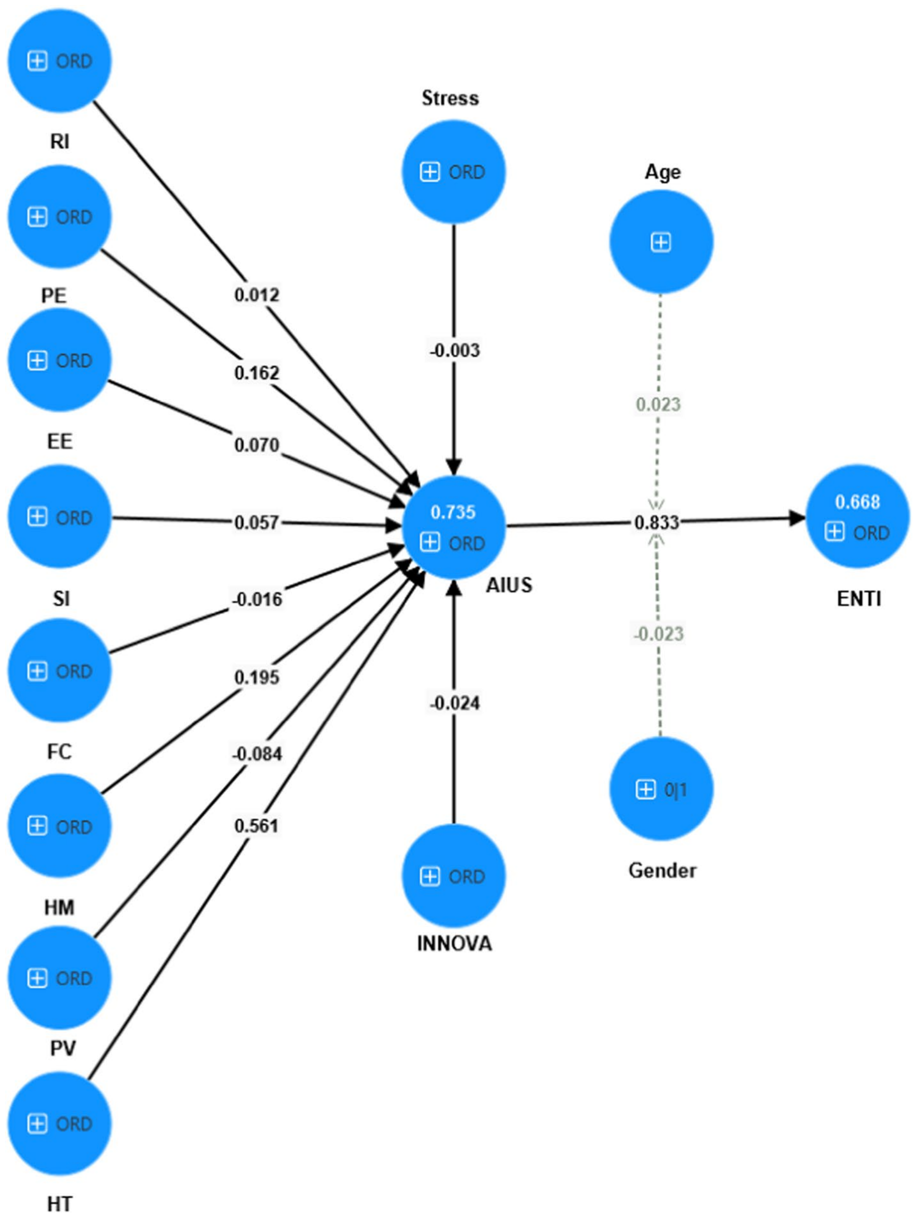

Fig. 1 Standardized path coefficients from the research model

Table 6 Tests of measurement invariance

Model	X2/df	CFI	RMSEA	PClose	Decision
All groups	1.49	0.948	0.041	0.095	–
Male	1.50	0.952	0.050	0.108	–
Female	1.506	0.954	0.049	0.110	–
M1: configural invariance	1.50	0.950	0.045	0.100	Accepted
M2: metric invariance	1.52	0.948	0.047	0.095	Accepted
M3: scalar invariance	1.54	0.946	0.049	0.090	Accepted
M4: residual invariance	1.64	0.926	0.064	0.060	Rejected

consistency and possible differences in the reliability of measurements between men and women.

In conclusion, having confirmed configural, metric, and scalar invariance (although not residual) provides favorable evidence, facilitating valid inferences for analyzing the acceptance of artificial intelligence and its effect on entrepreneurial intention.

Discussion

This research analyzed the acceptance of artificial intelligence (AI) and its impact on entrepreneurial intentions among foreign trade students in Peru and Ecuador. The SEM results were consolidated, revealing acceptable goodness-of-fit indices. The model's coefficient of determination revealed that RI, PE, EE, SI, FC, HM, PV, HT, stress, and INNOVA accounted for 74% of the variance in the AIUS, while the AIUS explained 67% of the variance in the ENTI.

Regarding the first research question, the study's findings confirm that Hedonic Motivation (HM) positively influences AIUS among foreign trade students. These results align with those reported by Karjaluoto et al., (2019), Khalilzadeh et al., (2017), demonstrating a positive association between hedonic motivation and the intention to use technology. Additionally, the study showed that habit (HT) significantly predicts AIUS in students' use of AI, corresponding with the findings in Kim and Lee (2022), Lee and Wong (2016), Nikolopoulou et al., (2021) that demonstrated the influence of habit on the intention to use technologies among users.

Hedonic motivation underscores the importance of enjoyment in technological adoption, while habit emphasizes the impact of familiarity with technology. These findings are crucial for designing educational technologies and implementing academic programs, suggesting that they should focus on both functional and enjoyable aspects to foster effective adoption of AI in education.

Additionally, the study confirms that Performance Expectancy (PE) positively influences AIUS, aligning with the findings of Khechine et al., (2020), Romero-Rodríguez et al., (2023), Elyta and Muhammad (2021) that showed that effort expectancy influences the behavioral intention to adopt technology. However, the study also revealed that EE, FC, PV, SI, INNOVA, STRESS, and RI did not significantly influence AIUS, which aligns with the findings of other contexts where these relationships were also not confirmed (Hamzah et al., 2023; Nikolopoulou et al., 2020; Romero-Rodríguez et al., 2023).

Regarding the second research question, the study confirms that AIUS significantly affects ENTI among foreign trade students. This relationship demonstrates that a greater intention to use AI increases the intention to embark on entrepreneurial ventures, similar to findings in other contexts showing the relationship between the intention to use and the behavioral intention to adopt a technology (Nikolopoulou et al., 2021; Singh et al., 2020).

Finally, regarding the third question, the findings suggest that neither gender nor age moderates the relationship between AIUS and ENTI, indicating that neither factor significantly buffers the relationship between AIUS and ENTI among foreign trade students.

Overall, the study results provide empirical evidence on different constructs of the UTAUT2 model adapted in the context of AI tool acceptance in higher education.

Additionally, this research contributes to the debate on the positive impact of AI tools on students' entrepreneurial intentions, offering evidence that supports the relationship between these two factors.

It is important to highlight that the main conclusions of the study are compared with the results of research conducted in various contexts, such as Malaysia (Karjaluoto et al., 2019; Lee & Wong, 2016), the restaurant industry (Khalilzadeh et al., 2017), the educational field in Greece (Nikolopoulou et al., 2021) and Korea (Kim & Lee, 2022), and the mobile financial services sector (Singh et al., 2020). This comparison provides a broad and enriching context for discussing the article's results, allowing the conclusions to be placed within a global research landscape on AI acceptance and entrepreneurial intentions. This comparative approach strengthens the relevance and applicability of the study's findings, as they can be contrasted with trends and patterns observed in different settings and sectors.

Implications, limitations, and future studies

This study has several limitations that could lead to future research. A significant limitation is the use of a nonprobabilistic sampling method, which potentially introduces selection bias. Participants, mainly from specific educational institutions in Peru and Ecuador, might not be representative of the broader student population interested in foreign trade and entrepreneurship. This limitation restricts the generalization of the findings to other educational and geographical contexts.

Another major limitation is the cross-sectional design of the study, which provides a snapshot of attitudes and perceptions at a specific time. This approach limits the understanding of how perceptions and attitudes toward AI and entrepreneurship might evolve over time. Moreover, the study focuses on specific variables related to AI acceptance and entrepreneurial intention, potentially excluding other influential factors such as the economic environment or educational policies.

For future research implications, this study highlights the need for more representative and probabilistic sampling approaches to enhance the generalizability of the findings. Future research could benefit from broader and more diverse samples, including students from different regions and educational contexts. This approach would allow for a better understanding of how AI acceptance varies in different cultural and educational environments.

Longitudinal studies could be valuable for tracking how attitudes and perceptions toward AI and entrepreneurship evolve over time. This would provide a deeper understanding of the long-term dynamics of AI adoption and its impact on students' entrepreneurial aspirations.

Expanding the scope of research to include a more detailed analysis of how variables such as the economic environment, educational policies, and cultural differences influence AI acceptance and entrepreneurial intention would not only enrich the understanding of the topic, but also provide valuable insights for designing policies and educational programs aiming to effectively integrate AI in foreign trade education and foster entrepreneurship among students.

Conclusions

This study reveals key findings on how students perceive and adopt AI in the context of foreign trade.

First, the use of SEM in this specific context of foreign trade and entrepreneurship represents a notable methodological adaptation. By presenting acceptable goodness-of-fit indices, this study not only validates the applicability of SEM in this field, but also sets a precedent for future research exploring complex relationships between variables in similar areas. This methodological approach could be replicated or adapted in future studies to examine other dimensions of technology and education.

Second, the significant influence of HM and PE on AI acceptance is highlighted. Students show a greater inclination to use AI when they perceive inherent enjoyment (HM) and believe that the technology will improve their performance (PE). These factors align with previous studies, reaffirming the importance of intrinsic motivations and efficacy expectations in technological adoption.

Furthermore, the study revealed that habit (HT) is a key predictor of AI use intention. This finding suggested that familiarity and comfort with technology are crucial for its adoption among students. Routine and previous experience with similar technologies can, therefore, facilitate greater integration of AI in academic and professional activities.

Another notable aspect is the direct and significant impact of AI use intention (AIUS) on students' entrepreneurial intention (ENTI). This relationship proposes that students willing to adopt AI also show a greater propensity for entrepreneurship. This finding is particularly relevant, as it underlines AI's potential to not only enhance students' technical skills, but also inspire and foster their entrepreneurial aspirations.

Additionally, the study concludes that neither gender nor age plays a statistically significant moderating role in the relationship between AI use intention (AIUS) and entrepreneurial intention (ENTI). This finding indicates that the disposition toward adopting AI and entrepreneurial aspirations is consistent across different genders and age groups, suggesting widespread acceptance of AI among students, regardless of these demographic variables.

In conclusion, the study's findings provide a detailed understanding of AI acceptance and its influence on foreign trade students' entrepreneurial intentions, offering valuable insights for educators, policymakers, and technology developers in the educational field.

Abbreviations

AI	Artificial intelligence
TAM	Technology acceptance model
TPB	Theory of planned behavior
UTAUT2	Unified theory of adoption and use of technology
SEM	Structural equation modeling
PLS	Partial least squares
CR	Composite reliability
AVE	Average variance extracted

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The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate
The study was approved by the Ethics Committee of the Technical University of Machala (code no. 259/2022). Informed consent was obtained from all participants included in the study; if participants were under 18 years of age, parents or legal guardians provided informed consent. Likewise, the intervention was conducted in accordance with the Declaration of Helsinki.

Consent for publication
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