AIL and Entrepreneurial Intention: A Mediation Analysis of TPB-SCT Framework

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Abstract

This paper examines entrepreneurial intention (EI) among university students as an outcome of AIL, in relation to both the direct effect of AI literacy (AIL) as well as indirect influence via three cognitive-behavioural processes, namely AI-specific entrepreneurial self-efficacy (ESE), AI-enabled opportunity recognition (OR) and pragmatic thinking (PT). The model integrates the Theory of Planned Behaviour (TPB) and Social Cognitive Theory (SCT). A quantitative survey questionnaire was distributed to students at four universities (two public and two private), and 460 valid responses were collected from users of AI-enabled tools and platforms. Measurement and structural models were evaluated to test parallel mediation processes from AIL to EI via three mediators, and data were analysed using PLS-SEM. Results indicate a positive, statistically significant direct relationship between AIL and EI. In contrast, the indirect effects of AI in AI-specific ESE, AI-enabled OR, and PT are not statistically significant, which suggests that these processes have not yet developed strong mediating relationships between AIL and EI in the population sampled in the present study. Thus, AI-literate students tend to turn their AI knowledge and capabilities directly into EI instead of following the examined cognitive and behavioural routes. The study is limited by its cross-sectional study design and single-country context (Pakistan), which may limit generalizability. There is a need for future research to better understand mediators and boundary conditions. Educators and university administrations ought to create entrepreneurship programs that will enhance AIL and intentionally establish AI-ESE, OR, and PT, supported by hands-on learning experiences in which students use AI tools to solve problems in new venture creation. This research builds on AIL-EI literature by proposing a TPB-SCT-based parallel mediation model with limited mediation in an AI-intensive higher education setting and by promoting an agenda to address the link between AIL and EB in resource-constrained settings.

Keywords: Entrepreneurial Intention, Mediation Analysis, TPB-SCT Framework.

Introduction

AI has quickly infiltrated business, education, and daily life, transforming the way people seek information, make decisions, and generate value (Duong, 2025). Students are increasingly using AI-driven resources for ideation, analysis, and problem-solving in higher education, and there are serious concerns about how knowledge and skills related to AI can be applied to entrepreneurial motivation and behaviour (Duong, 2025). The ability to comprehend, assess, and successfully apply AI systems, often referred to as AIL, is becoming a crucial skill for future enterprises

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operating in a data- and algorithm-driven environment (Long and Magerko, 2020; Ng et al., 2021). Nevertheless, there is limited empirical evidence on the relationship between AIL and EI, especially among university students on the verge of entering dynamic, technology-intensive labour markets (Almatrafi et al., 2024; Duong, 2025).

EI has been known as one of the main proximal predictors of entrepreneurial behaviour, and the TPB highlights the importance of attitudes (AT), subjective norms (SN) and perceived behavioural control (PBC) in influencing EI (Ajzen, 1991, 2002). TPB has been utilised extensively to describe intentions in areas such as environmentally responsible consumption, technology adoption, and entrepreneurship (Amani et al., 2024; Bayona-Oré, 2024). Meanwhile, SCT highlights the mutually affecting relationships among personal aspects, behaviour, and environment, in which self-efficacy (SE) forms the core of human agency (Bandura, 1999; Bandura, 1986). SCT-based research on entrepreneurship reveals that greater ESE correlates with a stronger EI and higher persistence in the entrepreneurial activities (Lam et al., 2025; Newman et al., 2019).

Recent research has begun to incorporate digital and AI-related competencies into intention-based models, suggesting that technological capacities can reinforce SE, OR, and other cognitive mechanisms that promote EI (Ali et al., 2025; Amani et al., 2024; Duong, 2025). Nevertheless, much of the existing work addresses either general digital literacy or technology acceptance, and there is a gap in addressing the specific contribution of AIL and the psychological pathways by which it could affect students' EIs (Duong, 2025; Ng et al., 2021). Understanding these pathways is crucial for designing entrepreneurship education (EE) initiatives and for supporting AI not only as a tool but also as a catalyst for new venture creation in resource-constrained environments (Duong, 2025; Jain et al., 2025).

Building on TPB as the main lens for EI (Ajzen, 1991) and SCT as a secondary lens to personal cognitive mechanisms (Bandura, 1999), we tested in this study whether AIL affect EI directly and indirectly via SCT, with SCT as a consistent mediator. including AI-ESE, AI-enabled OR and PT. AI-ESE is well-defined as confidence in the ability to use AI tools to execute the key entrepreneurial tasks, AI-enabled OR refers to the perceived capability to recognise and assess entrepreneurial opportunities that involve AI, and PT is a flexible, resourceful and solution-oriented style of problem-solving in uncertain environments (Al Halbusi et al., 2024; Duong, 2025; Lam et al., 2025). Together, these mediators are conceptualised as personal cognitive mechanisms through which AIL could be interpreted as EI, in accordance with both SCT's emphasis on SE and cognition and the TPB's emphasis on intention as the immediate antecedent of behaviour (Ajzen, 1991; Bandura, 1999).

This study aims at three broad objectives. First, it investigates the direct impact of AIL on EI among university students in Pakistan, building on the recent studies on AI and digital literacy in EE and related fields of behaviour (Autio et al., 2018; Ip, 2024). Second, it is a test of a parallel mediation model in which AI-ESE, AI-enabled OR, and PT serve as consistent mediators between AIL and EI (Ali et al., 2025; Almatrafi et al., 2024; Cardon et al., 2023). Third, it draws implications for future studies of entrepreneurial bricolage (EB), which can be defined as the creative recombining of available resources to exploit opportunities under constraints, and we propose EB as an interesting avenue to unpack the ways in which AI-literate students may pursue venture creation (Aaouid et al., 2024; Lanivich et al., 2026).

To achieve these aims, the study analyses data from university students and uses PLS-SEM with SmartPLS4, as in recent management research, extending TPB with additional constructs for technology-intensive contexts (Greiner et al., 2023; Jain et al., 2025). To assess the questionnaire's appropriateness, a pilot study (n=39) was conducted to evaluate its content and construct validity.

In the major survey, 460 valid cases were analysed. By combining AIL and a TPB-SCT framework, and highlighting the (limited) mediating role of AI-ESE, AI-enabled OR and PT, the study contributes to the new wave of research at the juncture of AIL and EI, and provides practical insights for universities to foster AI-enabled entrepreneurship (Duong, 2025; Jain et al., 2025; Ng et al., 2021).

Literature Review and Hypotheses Development

TPB and EI

The TPB framework considers intention as the immediate antecedent of behaviour, determined by AT toward behaviour, SN and PBC (Ajzen, 1991). AT shows how much an individual rates acting or failing to act on a behaviour; SN describes the supposed pressure to act or not act on a behaviour; and PBC shows how easy or difficult an individual believes acting on a behaviour is, based on available resources and opportunities (Ajzen, 1991, 2002). TPB has been widely used to explain intentions across diverse fields, such as environmentally responsible consumption, technology adoption, and entrepreneurial behaviour (Duong, 2025; Jain et al., 2025).

TPB offers a powerful model of EI in entrepreneurship studies and is often complemented by other SE-focused theories, including SCT, to explain how individual thinking drives EI (Liñan and Fayolle, 2015; Newman et al., 2019). Prior studies indicate that positive entrepreneurial AT, positive SN, and increased PBC are positively associated with student EI across a variety of cultural and educational contexts (Al Halbusi et al., 2024; Almatrafi et al., 2024; Amani et al., 2024). Extension and integration of TPB-SCT increases the explanatory power of the model and is also consistent with recent studies, where TPB has been extended with new constructs, including environmental concern in green banking (Jain et al., 2025), perceived innovation support in digital entrepreneurship (Lam et al., 2025; Miah et al., 2025). Within the same stream, the current work builds on an intention-based model by incorporating AIL as a prerequisite to EI and by examining its indirect impact through SCT-congruent cognitive and behavioural processes.

SCT and AI-Entrepreneurship

SCT elucidates human functioning as the result of triadic reciprocal interconnection among personal factors, behaviour and environment (Bandura, 1999; Bandura, 1986). A key construct of SCT is SE, defined as people's beliefs in their abilities to organise and carry out courses of action needed to achieve specified kinds of performance (Bandura, 1999). Research on entrepreneurship has repeatedly shown that increased ESE is associated with higher EI and greater persistence in venture-related activities (Newman et al., 2019; Zhao et al., 2005). Learning experiences, mastery, vicarious observation, and social persuasion all influence the SE, which, in turn, affects how individuals think, feel, motivate themselves, and act (Bandura, 1999).

From an SCT perspective, AIL can be seen as a domain-specific capability which affects personal cognitive factors such as SE beliefs, OR and PT, which affect EI. As students develop conceptual knowledge and experiences with AI tools, they may develop stronger beliefs about their ability to use AI in entrepreneurial tasks, increased sensitivity to AI-enabled opportunities and more pragmatic approaches to experimentation under uncertainty (Duong, 2025; Ng et al., 2021). In this paper, SCT is used to complement TPB by providing justification for including AI-ESE, AI-enabled OR and PT as personal cognitive mechanisms through which AIL might affect students' EI.

AIL and EI

AIL is typically defined as a combination of knowledge, skills, and AT that help individuals understand how AI systems operate, critically assess their outputs, and use them effectively and responsibly (Long & Magerko, 2020; Ng et al., 2021). In higher education, AIL is emerging as curricula increasingly incorporate tools with AI capabilities for learning, problem-solving, and creative work, which could determine students' confidence and willingness to use AI in professional and entrepreneurial settings (Al Halbusi et al., 2024; Autio et al., 2018). Empirical research across related fields suggests that digital and AI-related literacy is positively associated with behavioural intentions to adopt AI-based technologies and to participate in tasks that support AI (Almatrafi et al., 2024; Greiner et al., 2023).

Within entrepreneurial environments, recent studies suggest that AIL may positively impact students' beliefs in the feasibility and desirability of AI-enabled enterprises by increasing students' knowledge of AI capabilities, limits and areas of application (Duong, 2025; Muhammad et al., 2023). AI-literate students may be more prepared to recognise AI as a scalable resource, and automated routines and data-driven business models that can be used to enhance their entrepreneurial motivation to pursue business in AI-rich environments (Liang et al., 2025; Miah et al., 2025). Consistent with TPB, such improved perceptions can translate into higher levels of EIs, as AIL influences underlying beliefs about the outcomes, social acceptance, and the controllability of entrepreneurial action enabled by AI (Ajzen, 1991, 2002).

H1: AIL has a positive and significant effect on EI.

AI-ESE

ESE is the belief that an individual can successfully execute tasks and roles involved in new venture creation (Bandura, 1999; Zhao et al., 2005). Higher ESE has been consistently associated with higher EI and a greater chance of engaging in entrepreneurial behaviour, as people who feel more able are more willing to invest effort and persevere in the face of obstacles (Newman et al., 2019; Zhao et al., 2005). In the educational setting, entrepreneurship programs that improve SE tend to report substantial gains in students' EI, underscoring SE's role as a psychological mechanism in the development of intentions (Amani et al., 2024; Linan & Fayolle, 2015). From an SCT perspective, ESE is a central personal factor through which learning experiences influence motivation and behaviour (Bandura, 1999).

The increasing integration of AI tools into entrepreneurial tasks suggests the relevance of AI-ESE, defined here as students' confidence in using AI systems to implement core entrepreneurial activities such as idea generation, market analysis, and business model development (Almatrafi et al., 2024; Duong, 2025). AIL is likely to reinforce AI-ESE by giving students conceptual understanding and hands-on experience that mitigate perceived complexity and uncertainty about AI for use in venture contexts (Long & Magerko, 2020; Ng et al., 2021). In turn, students who feel efficacious in applying AI to entrepreneurial tasks may be more likely to form EIs, because they see AI-enabled entrepreneurship as more feasible and within their control, consistent with both SCT and TPB (Ajzen, 1991; Bandura, 1999).

H2: AI-ESE mediates the relationship between AIL and EI.

AI-Enabled OR

OR refers to the cognitive processes by which people recognise and assess situations as potential business opportunities (Filser et al., 2023; Linan & Fayolle, 2015). Prior research demonstrates that EE can improve students' opportunity recognition, and these skills mediate the link between education and EI (Fayolle & Gailly, 2015). A multilevel model of EE also concludes that OR partly mediates the relationship between education and EI, providing evidence for OR as a proximal factor in the development of intention (Cardon et al., 2023; Miah et al., 2025). Within SCT, such evaluative cognitions represent personal factors that are influenced by experiential and observational learning (Bandura, 1997).

In AI-intensive environments, the OR increasingly focuses on understanding how AI technologies can be used to solve problems, create new services, or reconfigure value chains (Duong, 2025; Xie & Wang, 2025). AI-literate students may be better able to scan for AI-enabled opportunities, assess the technology's feasibility, and consider the potential for data-driven competitive advantages, while demonstrating superior AI-OR (Basu et al., 2022; Ng et al., 2021). Students who feel that more opportunities lie ahead and are attainable by AI are, in turn, more likely to develop EIs, consistent with opportunity-based and cognition-based views of entrepreneurship (Fields, 2024; Linan & Fayolle, 2015).

H3: AI-OR mediates the relationship between AIL and EI.

Pragmatic Thinking

PT is characterised by a problem-solving orientation, marked by flexibility, resourcefulness, and an orientation towards workable, context-sensitive solutions rather than idealised designs (Newman et al., 2019). In entrepreneurial contexts, such a pragmatic orientation has been linked to action, experimentation, and learning under uncertainty and is conceptually related to "effectual" and bricolage-based approaches to venture creation (Audretsch et al., 2019; Autio et al., 2018). SCT posits that such thinking strategies are shaped by experience, SE, and environmental feedback, which in turn influence how individuals respond to challenges and opportunities (Bandura, 1999). Students with better PT are more likely to pursue entrepreneurial initiatives by innovatively integrating available resources and adapting plans in response to new information, which may promote EI in dynamic settings (Almatrafi et al., 2024; Basu et al., 2022).

AIL may help students practice PT by introducing them to AI tools for rapid prototyping, iterative testing, and data-driven decision-making, and by encouraging them to try good-enough solutions rather than perfection (Duong, 2025; Ng et al., 2021). As students become more comfortable with using AI to explore options, simulate outcomes and change strategies, they may develop a more pragmatic orientation towards entrepreneurship, concerned with what is feasible with available AI and non-AI resources (Camelo-Ordaz et al., 2020; Ip, 2024). In turn, pragmatic thinkers may be

more likely to develop EI because they see fewer barriers and more pathways for implementing action toward venture creation (Almatrafi et al., 2024).
H4: PT mediates the relationship between AIL and EI.

Summary of the Mediation Model

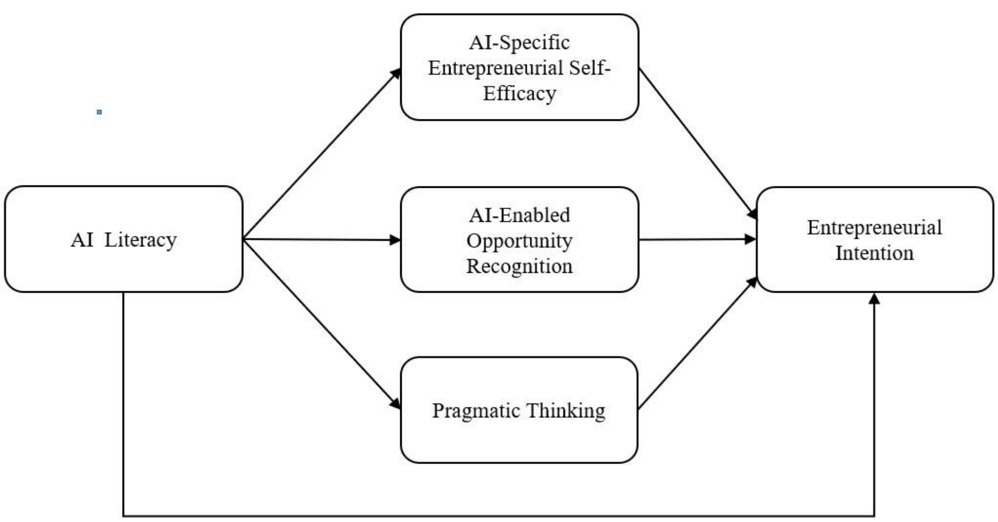
Drawing on TPB and SCT and building upon previous research work that enhances the usefulness of intention-based models with further psychological and contextual constructs (Ajzen, 1991; Bandura, 1999; Jain et al., 2025), the present study suggests a parallel mediation model in which AIL affects EI both directly and indirectly through AI-ESE, AI-enabled OR and PT. This structure is consistent with recent recommendations to test multiple mediators simultaneously to assess the relative contributions of different mechanisms (Polisetty et al., 2024).

Methodology

Research Framework

The study is based on TPB and SCT, which together highlight the roles of beliefs, PBC and SE in shaping behavioural intentions (Ajzen, 1991; Bandura, 1999). In this study, AIL is modelled as an exogenous construct that affects the level of EI in university students, and indirectly through three parallel mediators: AI-ESE, AI-enabled OR, and PT. This is based on recommendations to test more than one mediator at a time to capture unique cognitive-behavioural mechanisms within a cohesive structural model (Hair & Alamer, 2022; Kline, 2023; MacKinnon et al., 2023). The framework aligns with recent management research that extends TPB by adding additional antecedents and mediators to explain behavioural intentions in technology-intensive settings (Jain et al., 2025).

Figure 1: Hypothesized research model



Measurement Scale

Data was gathered through the use of a structured questionnaire consisting of two sections (respondent demographics and latent construct measures). The demographic section included gender, age, program level, and type of university, and the second section comprised multi-item

Likert-type scales for AIL, EI, AI-ESE, AI-enabled OR, and AI-enabled PT. All constructs were measured on a five-point Likert scale (from 1 ("strongly disagree") to 5 ("strongly agree")), the same type of scale that has also been used in previous TPB-based and technology adoption research in management (Jain et al., 2026) and in EE research (Linan & Fayolle, 2015).

The AIL scale was used to capture students' self-assessed knowledge, understanding, and effective use of AI tools and applications within academic and problem-solving contexts, and was adapted from existing AI and digital literacy tools for higher education settings (Long & Magerko, 2020). EI was assessed using items measuring students' plans and willingness to start a new venture in the future, developed from popular scales used in EI studies (Linan & Chen, 2009). AI-ESE items reflected the confidence of students in the use of AI tools for fundamental entrepreneurial activities such as idea generation, market analysis and business planning, an extension of existing ESE measures to an AI-enabled context (McGee et al., 2009). AI-enabled OR was measured using items assessing perceived ability to identify and evaluate AI-based entrepreneurial opportunities, derived from OR scales used in EE studies (Ozgen and Baron, 2007; Singh et al., 1999). PT was operationalised with items drawn from Dewey's (1998) pragmatist approach to inquiry and an operationalisation of PT in the context of entrepreneurship research by Urban and Kujinga (2017) that captures the reality of making decisions that are consequence-focused (for example, "I make decisions based on a clear assessment of facts and outcomes").

All multi-item scales were tested for reliability (internal consistency) and convergent validity. Cronbach's alpha values were 0.791 (AIL) to 0.901 (EI), and composite reliability values were greater than the recommended threshold value of 0.70 for all constructs. Average variance extracted (AVE) values exceeded 0.50 and demonstrated adequate convergent validity (Hair & Alamer, 2022). These findings confirm the measurement model's reliability and validity for subsequent structural analysis.

Sampling and Data Collection

The research adopted a cross-sectional survey research design that utilised all university students who had used AI-enabled tools and platforms in their studies. A purposive (criterion-based) sampling was used to ensure the relevant participants in the research questions were covered (Etikan et al., 2017), with the sample including students of two public and two private universities, which are similar in terms of program portfolio and exposure to digital technologies, as purposive approaches have been employed in the previous literature when the target population has particular characteristics (Jain et al., 2025). Self-administered questionnaires were used to collect data, with the maximum number of individuals reached and questionnaires completed face-to-face, which is the standard practice in research on behavioural and technology acceptance and adoption (Jain et al., 2025; MacKenzie and Podsakoff, 2012; Podsakoff et al., 2012).

460 (valid responses) is a larger sample than is recommended as a minimum in partial least squares structural equation modelling, such as the "10-times rule" and model-complexity guidelines (Hair and Alamer, 2022). Ethical considerations were followed by notifying participants that the research was voluntary, offering confidentiality and anonymity, and ensuring that the data would be used only for research (Podsakoff et al., 2012).

Analytical Method

Data were analysed using partial least squares structural equation modelling (PLS-SEM), which is suitable for predictive, variance-based modelling and for examining complex relationships between latent variables in behavioural research (Hair & Alamer, 2022). PLS-SEM is particularly suitable when the purpose of the analysis is to explain variance in key endogenous constructs, the model involves multiple mediators, and the data are likely to fail the multivariate normality assumptions (MacKenzie & Podsakoff, 2012).

The analysis was done in two phases. First, the measurement model was evaluated using inspection of indicator loadings, Cronbach's alpha, composite reliability, AVE, and discriminant validity criteria (Hair & Alamer, 2022). Second, to evaluate the structural model, path coefficients, coefficient of determination (R2), effect sizes (f2) and predictive relevance (Q2) were estimated, and the significance of direct and indirect effects was tested for significance using bootstrapping with a large number of resamples (Etikan et al., 2017). Mediation was evaluated according to procedures established for parallel multiple mediator models, and indirect effects were evaluated using bias-corrected bootstrap confidence intervals (Kline, 2023; Kock & Hadaya, 2018).

To mitigate the potential threat of common-method bias, procedural and statistical solutions were implemented. Procedurally, respondents were assured of anonymity, and there were no right or wrong answers, which reduces evaluation apprehension and social desirability (Podsakoff et al., 2003). Statistically, Harman's single-factor test and variance inflation factor (VIF) diagnostics were applied; the single factor explained less than 50% variance, and all inner values of VIF were less than the recommended cut-off of 3.3, which indicates that common method bias was not likely to cause serious concern (Kock & Hadaya, 2018; Podsakoff et al., 2012).

Results

Measurement Model Assessment

Internal consistency, reliability and convergent and discriminant validity were the initial measures evaluated in the measurement model. All the reflective indicators had normal loadings of more than 0.68, and most were higher than the recommended 0.70, indicating that the items were well capturing the corresponding latent construct. Cronbach alpha scores were between 0.791 AIL and 0.901 EI, and the value of composite reliability was greater than 0.79, which was above the 0.70 mark, and it verified the internal consistency. The AVEs for all constructs were greater than 0.50, indicating good convergent validity (Hair and Alamer, 2022).

The assessment of multicollinearity was conducted using variance inflation factors (VIFs), which were well below the conservative cut-off of 3.3 for all indicators, indicating no multicollinearity (Kock and Hadaya, 2018). The Fornell-Larcker criterion and cross-loadings were used to examine discriminant validity; in both cases, the square root of a construct's AVE was higher than its correlations with other constructs, and items loaded higher on this construct than on other constructs, confirming discriminant validity (Hair and Alamer, 2022). Combined, these findings suggest that the measurement model is valid and reliable, providing sufficient grounds to assess the structural relations among AIL, the three mediators, and EI.

Table 1: Assessment of Measurement Model

Construct	Indicator	Outer Loadings	VIF	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
AIL	AIL1	0.752	1.538	0.791	0.794	0.545
	AIL2	0.736	1.506			
	AIL3	0.739	1.517			
	AIL4	0.679	1.368			
	AIL5	0.781	1.63			

EI	EI1	0.762	1.724	0.901	0.902	0.718
	EI2	0.881	3.06			
	EI3	0.882	3.095			
	EI4	0.853	2.636			
	EI5	0.851	2.514			
ESE	ESE1	0.782	1.772	0.845	0.85	0.564
	ESE2	0.767	1.756			
	ESE3	0.743	1.583			
	ESE4	0.772	1.794			
	ESE5	0.743	1.64			
	ESE6	0.694	1.519			
OR	OR1	0.768	1.597	0.811	0.813	0.57
	OR2	0.784	1.799			
	OR3	0.767	1.627			
	OR4	0.736	1.548			
	OR5	0.717	1.418			
PT	PT1	0.769	1.643	0.814	0.815	0.573
	PT2	0.750	1.595			
	PT3	0.761	1.566			
	PT4	0.755	1.617			
	PT5	0.750	1.616			

Structural Model Assessment

It was examined by looking at path coefficients, effect sizes, explained variance and predictive relevance. The coefficient of determination (R2) for EI was found to be 0.352 showing that AIL and the mediators explain about 35.2% variance of EI, which is classified as a moderate level of explanation in behavioural research (Hair & Alamer, 2022). The Stone-Geisser Q2 value for EI was 0.246 which indicates satisfactory predictive relevance for the model.

The direct effect of AIL on EI was positive and statistically significant ($\beta = 0.135$, $t = 2.400$, $p = 0.016$, $f^2 = 0.016$), which supports H1 and shows that higher AIL is positively related to stronger EI among university students. In contrast, the indirect effects of AIL on EI through the three mediators were not found to be statistically significant at conventional levels. The indirect path through AI-ESE (H2) had a coefficient of 0.075 ($t = 1.787$, $p = 0.074$), the path through AI-OR (H3) had a coefficient of 0.054 ($t = 1.822$, $p = 0.069$) and the path through PT (H4) had a coefficient of 0.054 ($t = 1.525$, $p = 0.127$). These results show that, in this sample, AIL affects EI primarily through a direct path, rather than through the AI-cognitive and behavioural mechanisms tested.

Taken together, the findings show a pattern of increased EI in AI-literate students but weaker and statistically nonsignificant hypothesized mediating effects of AI-ESE, AI-OR and PT. This suggests that although AIL is an important predictor of EI, the psychological channels in which AI related competencies translate into entrepreneurial motivation remain only partially addressed by the mediators studied in this research, which leaves space for other mechanisms and boundary conditions that can be examined in further research.

Table 2: Assessment of Structural Model

Hypothesis	Path	Beta	t-value	p-value	f2	R2	Q2	Decision
H1	AIL -> EI	0.135	2.4	0.016	0.016	0.352	0.246	Supported
H2	AIL -> ESE -> EI	0.075	1.787	0.074				Not Supported
H2	AIL -> OR -> EI	0.054	1.822	0.069				Not Supported
H2	AIL -> PT -> EI	0.054	1.525	0.127				Not Supported

Discussion

The results thus show a positive, statistically significant direct relationship between AIL and EI, indicating that students who report higher levels of AIL are more likely to consider launching a new venture. This reinforces the view that technology-related competencies, and the AIL in particular, contribute to improving perceived feasibility and desirability of entrepreneurship in digital and AI-intensive environments (Duong, 2025; Ng et al., 2021). In other words, as students become better able to understand and use AI, they may see entrepreneurial activity as being more in their reach and reflective of emerging opportunity landscapes.

By contrast, the hypothesised indirect effects of AIL on EI via AI-ESE, AI-OR, and PT are not statistically significant, although the paths through the latter two are close to conventional significance thresholds. This pattern indicates that, within the present sample, AIL makes a more direct contribution to EI than the three SCT-consistent mediators modelled. One interpretation is that AIL may already embed a complex bundle of beliefs about the attractiveness, usefulness and controllability of AI-enabled entrepreneurship such that its influence on intention is only partly channelled through specific efficacy or opportunity-related cognitions. Another possibility is that there are other unmeasured variables, including entrepreneurial passion, perceived usefulness of AI in business settings, prior entrepreneurial exposure or perceived institutional support, that are more proximal mediators between the AIL-intention relationship than the mechanisms measured here (Cardon et al., 2023; Jain et al., 2025; Lam et al., 2025).

From a theoretical standpoint, the non-significant mediation effects are consistent with current debates in the TPB and entrepreneurship literatures regarding the conditions under which extended models are of explanatory value (i.e., when and under what circumstances they add value beyond the core intention predictors; Ajzen, 1991). The results indicate that including AI-ESE, AI-OR, and PT in the model does not significantly increase the model's explanatory power for EI in this context, despite the theoretical appeal and empirical importance of these constructs in other contexts. This is consistent with recent evidence in green banking and sustainability research, where extended TPB models sometimes yield non-significant paths while still providing valuable insights into boundary conditions and contextual nuances (Jain et al., 2025). Similarly, the study suggests that the importance of specific cognitive mechanisms also depends on a student's maturity in using AI tools, the types of tools they use, how the institutional environment supports their use, and how entrepreneurship is promoted there.

Looking at the results through an SCT lens, the findings also suggest that the personal factors through which AIL is translated into EI are not fully accounted for through the three mechanisms discussed. SCT emphasises the role of SE, outcome expectations, observational learning, and self-regulatory processes in influencing behaviour, and it seems plausible that AIL influences EI through combinations of these factors rather than through AI-ESE, AI-OR, or PT alone. For example, students who often see successful AI ventures or have high positive expectations for AI's effects on venture performance may form EIs despite their PT style or specific OR skills still being in development. Future research could thus extend the present model by adding additional constructs from SCT and by investigating interactions between AIL and contextual supports, such as innovative ecosystems.

In summary, this research contributes to the emerging AI-entrepreneurship literature in three ways. First, it provides empirical evidence that AIL is an important predictor of EI among university students, thereby expanding TPB-based models of intention by incorporating a domain-specific technological competence. Second, it provides a systematic test of three SCT-consistent mediators and uncovers that, at least in this context, AI-ESE, AI-OR and PT are not strong channels through which AIL affects EI, which is important to publish and reflect on non-significant mediation results. Third, the findings open a fruitful agenda for exploring alternative mechanisms and boundary conditions, e.g., entrepreneurial passion and the perceived usefulness of AI and EB, that may better explain how AI-literate students turn their technological capabilities into long-term EIs.

Conclusion

The study also advances theory in three ways. First, it normalises AIL within the context of an intention-based approach and shows that AIL is a significant predictor of EI, thereby extending prior research on digital literacy and EE to the field of AI competencies (Amani et al., 2024; Duong, 2025). This strengthens the argument that models of intention need to account for technology-related capabilities to support entrepreneurial decisions in AI-rich environments (Al Halbusi et al., 2024). Second, by testing a parallel mediation model with AI-ESE, AI-OR and PT, the study has provided evidence that these theoretically-grounded constructs do not significantly mediate the relationship between AIL and EI in the current sample, which underscores the importance of publishing on and reflecting on the results of non-significant mediation tests (Jain et al., 2025).

Third, the results pave the way for integrating entrepreneurial bricolage (EB) into future models of the relationship between AIL and EI. Bricolage is a mechanism through which entrepreneurs make do by recombining available resources to meet new problems and opportunities under constraints (Aaouid et al., 2024). Given that AI tools can be flexibly repurposed and combined with other resources, it may be that AI-literate students are especially well-placed to engage in bricolage, leading us to suggest that constructs that capture bricolage behaviour or mindset may provide a more powerful explanation of how AIL affects EI and, subsequently, action than the mediators that are considered here.

Practical Implications

For university and college institutions and educators, the findings highlight the need to improve AIL among students as a component of entrepreneurship learning and broader curriculum development. Because the AIL is positively correlated with EI, incorporating AI-driven modules, practical training with AI tools, and project-based learning on AI-enabled business concepts may contribute to the development of EIs among students (Cardon et al., 2023; Chalmers et al., 2020; Duong, 2025). Meanwhile, the absence of effective mediation using AI-ESE, AI-OR and PT does not imply that only AIL is needed, but programs ought to actively develop those complementary competencies utilising experiential activities, mentoring and reflection on AI-based opportunity identification and problem-solving (Almatrafi et al., 2024; Chen et al., 2025; Lam et al., 2025).

Policy makers and university leaders can foster AI-empowered entrepreneurship by creating environments where students can work with AI and access data, as well as regulatory, ethical, and commercialisation guidance for AI-based businesses (Bhuiyan and Sciences, 2024; Jain et al., 2025). More can be done to transform AIL into tangible entrepreneurial initiatives by establishing incubation programs and innovation laboratories where people can engage in bricolage-like activities with AI and non-AI resources, especially in resource-starved settings where they simply have to make do with what they have on hand (Aaouid et al., 2024).

Limitations and Directions for Future Research

The study also has several limitations that offer avenues for future research. First, a cross-sectional design does not allow causal inferences; longitudinal or experimental designs would be more suitable for describing the effects of AIL changes and associated cognitions on EI and behaviour over time (Ali et al., 2025; Almatrafi et al., 2024). Second, the sample is based on 4 national universities and this can be a limitation because it is not very representative of the overall population; further research can be conducted to replicate and expand the model to other countries, types of institutions and groups of disciplines so as to establish the strength of the results (Al Halbusi et al., 2024; Newman et al., 2019).

Third, the analysis is conducted on three specific mediators, yet despite the theoretical basis, they are not the only possible mechanisms linking AIL and EI. The further study is to consider other mediators, including AI attitudes, the perceived usefulness of AI in entrepreneurship, entrepreneurial passion, entrepreneurial resilience, and moderators, including cultural values and prior entrepreneurial experience (Bayona-Ore, 2024; Chen et al., 2024). To sum up, expanding on the theme of EB, future studies might establish and experiment with models whereby bricolage behaviour or mindset mediates or moderates the correlation between AIL and entrepreneurial results to understand how AI-literate students creatively mobilise and recombine resources to create ventures in a deeper manner (Aaouid et al., 2024; Lanivich et al., 2026).

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