Artificial Intelligence Literacy and Entrepreneurial Intentions Among University Students in Pakistan

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Abstract

The aim of this study is to examine the role of artificial intelligence (AI) literacy in predicting entrepreneurial intentions among university students in Pakistan. Based on social cognitive theory and the technology acceptance model, four AI-related dimensions were examined: AI Knowledge (AIK), AI Usage Competency (AIU), Perceived Usefulness of AI (PUA), and AI Self-Efficacy (AISE). A quantitative cross-sectional survey design was used, and data were collected from 400 university students through convenience sampling. The instrument consisted of 26 Likert-scale items adapted from established measures; a pilot test assessed wording clarity, and reliability analysis assessed internal consistency. Multiple regression analysis using IBM SPSS showed that all four dimensions significantly and positively predicted entrepreneurial intentions, accounting for 62.7% of the variance ($R^2 = .627$, $F(4, 395) = 167.582$, $p < .001$). AI Self-Efficacy emerged as the strongest predictor among the four variables included in the model ($\beta = .389$, $p < .001$), followed by AI Usage Competency ($\beta = .221$, $p < .001$), Perceived Usefulness of AI ($\beta = .197$, $p < .001$), and AI Knowledge ($\beta = .183$, $p < .001$). The results indicate that AI competence and confidence are positively associated with entrepreneurial intentions among university students. The findings support the careful integration of applied AI learning into entrepreneurship education while remaining subject to the limitations of a cross-sectional, self-report design.

Keywords: AI Self-Efficacy, AI Knowledge, Technology Acceptance, Entrepreneurial Intentions

Introduction

Artificial Intelligence (AI) technologies are reshaping innovation, value creation, and entrepreneurial activity. With the shift toward knowledge- and technology-based economies, the ability to understand and use AI tools has become an important skill for prospective entrepreneurs (Haefner et al., 2021; Nambisan, 2017). Recent evidence also links digital entrepreneurship knowledge and AI-related capabilities with students' entrepreneurial intentions and competencies (Wibowo et al., 2023; Duong, 2025). As incubators of entrepreneurial talent, universities are increasingly expected to equip students not only to understand technology but also to apply AI capabilities responsibly to entrepreneurial tasks.

Entrepreneurial intention, or a person's stated intention to start a business, is a proximal predictor of subsequent entrepreneurial activity (Ajzen, 1991; Bird, 1988). Prior research has examined individual, educational, and environmental antecedents of entrepreneurial intention (Krueger et al., 2000; Liñán & Fayolle, 2015). However, the rapidly developing relationship between AI literacy and entrepreneurial intention remains underexamined, especially among university students in Pakistan. Recent Pakistani evidence indicates that university students' AI literacy differs across academic disciplines, reinforcing the need for context-specific investigation (Butt et al., 2026).

This gap is important because AI can support opportunity recognition, market analysis, business planning, content development, and operational automation. Recent empirical work suggests that AI literacy may relate to e-entrepreneurial intention through psychological mechanisms such as entrepreneurial self-efficacy and identity aspiration rather than through a simple direct pathway (Duong, 2025). Nevertheless, evidence remains limited in Pakistan, where institutional access, disciplinary exposure, and digital capability may shape students' AI experiences differently.

To address this problem, the present study examines whether AI Knowledge, AI Usage Competency, Perceived Usefulness of AI, and AI Self-Efficacy predict entrepreneurial intentions among university students in Pakistan. Social cognitive theory (Bandura, 1986) explains the role of capability beliefs, while the Technology Acceptance Model (Davis, 1989) explains perceived usefulness. The Theory of Planned Behavior (Ajzen, 1991) is used only as a broader interpretive lens for intention formation; its core constructs—attitude, subjective norms, and perceived behavioral control—are not directly measured in the present model.

Accordingly, the study aims to test the predictive relationships between the four AI-related variables and entrepreneurial intentions and to compare their relative statistical contributions. Its contribution is to provide initial evidence from Pakistani university students and to identify AI Self-Efficacy as the strongest predictor among the four variables included in this model. The study does not claim causal proof; rather, it reports associations and prediction within a cross-sectional design.

Literature Review

Entrepreneurial Intentions: Conceptual Foundations

Entrepreneurial intention occupies a central position in entrepreneurship research as a proximal predictor of entrepreneurial behavior. The Theory of Planned Behavior (TPB) proposes that intention is shaped by attitude toward the behavior, subjective norms, and perceived behavioral control (Ajzen, 1991). In entrepreneurship research, these constructs help explain why people may be more willing to start a business when they hold favorable attitudes, perceive social support, and believe they can perform entrepreneurial tasks (Liñán & Chen, 2009). In this study, TPB provides contextual understanding of intention formation, but its three core constructs are not operationalized or tested.

Krueger et al. (2000) also showed that entrepreneurial intention can be influenced by perceived desirability of entrepreneurial action, perceived feasibility of entrepreneurial action, and individual competencies and the environment. In an academic environment, elements that have been identified as contextually conducive to entrepreneurial intentions are entrepreneurship education, peer network, role models and resources (Neck & Greene, 2011; Souitaris et al., 2007). In addition to the standard contextual variables of economics, a new context is added by the digital transformation of the economy: AI literacy, which can alter how technically-literate students see the desirability and feasibility of entrepreneurship.

AI Literacy and Related AI Beliefs

AI literacy refers to competencies needed to understand, evaluate, explain, and use AI systems effectively (Long & Magerko, 2020). Existing frameworks commonly emphasize cognitive, technical, practical, and ethical capabilities (Ng et al., 2021; Wang et al., 2023). The present model therefore treats AI Knowledge and AI Usage Competency as core literacy dimensions. Perceived Usefulness of AI, derived from TAM, and AI Self-Efficacy, derived from social cognitive theory, are treated as theoretically related AI beliefs rather than intrinsic literacy dimensions. The four variables are analyzed together because knowledge and usage skills may operate alongside usefulness perceptions and capability beliefs when students evaluate AI-enabled entrepreneurial activity.

AI Knowledge and Entrepreneurial Intentions.

AI Knowledge refers to a person's conceptual understanding of AI principles, algorithms, and applications (Ng et al., 2021). Understanding emerging technologies can increase awareness of their business potential and support the generation of new business ideas (Haefner et al., 2021). Knowledge of how AI can streamline processes, support prediction, or enable new products may help students recognize entrepreneurial opportunities. Therefore, the study proposes:

H1: AI Knowledge significantly and positively predicts Entrepreneurial Intentions among university students.

AI Usage Competency and Entrepreneurial Intentions

AI Usage Competency refers to the practical ability to use, troubleshoot, and adapt AI technologies for different tasks (Long & Magerko, 2020). Domain-relevant competencies may strengthen confidence and reduce perceived barriers to venture creation (Man et al., 2002). Students who can use AI for market analysis, customer segmentation, content creation, or operational automation may perceive entrepreneurship as more feasible. This reasoning yields:

H2: AI Usage Competency significantly and positively predicts Entrepreneurial Intentions among university students.

Perceived Usefulness of AI and Entrepreneurial Intentions

Perceived Usefulness of AI is when the user thinks that the use of AI will improve their performance and outcomes (Davis, 1989). Perceived usefulness is a consistent factor that has been found to be one of the major determinants of the intent to use technology and the resulting behaviors, with grounding in the Technology Acceptance Model (TAM) (Venkatesh et al., 2003). If the potential entrepreneurs believe that the AI tool is very useful in business planning, product development, or competitive analysis, their intentions to undertake entrepreneurial activities may increase. Building on the context of the entrepreneur, the present study proposes:

H3: Perceived Usefulness of AI significantly and positively predicts Entrepreneurial Intentions among university students.

The Relationship between AI Self-Efficacy and Entrepreneurial Intentions.

AI Self-Efficacy is the degree to which a person believes that he or she can effectively utilize AI technologies to complete certain tasks (Bandura, 1986; Compeau & Higgins, 1995). According to self-efficacy theory, people with high levels of self-efficacy are more likely to start and continue with difficult behaviors, such as entrepreneurial action (Zhao et al., 2005). In the AI context, students with a positive outlook on leveraging AI in business would be expected to display less risk aversion and greater perceived behavioral control over entrepreneurial outcomes, which would manifest in greater entrepreneurial intentions. The study proposes:

H4: AI Self-Efficacy is significantly and positively associated with Entrepreneurial Intentions among university students.

Research Methodology

Research Design

This research is a quantitative approach with a cross-sectional survey design. The positivist philosophical approach is used in line with the aim of testing theoretically formulated hypotheses using empirical data (Creswell & Creswell, 2018). The cross-sectional design allows measuring AI literacy and entrepreneurial intentions simultaneously on a sample of students with diverse characteristics that can be used for statistical analysis of hypothesized relationships.

Population and Sample

The target population comprised undergraduate and postgraduate students enrolled at universities in Pakistan. A sample of 400 students was recruited through convenience sampling, a pragmatic non-probability method commonly used in survey research (Saunders et al., 2019). The accessible records did not retain university names, public/private status, city or province, academic discipline, program level, or an institution-level sampling frame; therefore, institutional distribution and the number of undergraduate versus postgraduate respondents cannot be reported. No formal a priori power analysis was conducted. These omissions and the use of convenience sampling limit representativeness and generalizability beyond the participating respondents.

Measurement Instrument

Data were gathered using a structured self-administered questionnaire containing 26 items across five constructs: AI Knowledge (5 items), AI Usage Competency (5 items), Perceived Usefulness of AI (5 items), AI Self-Efficacy (5 items), and Entrepreneurial Intentions (6 items). Items were rated on a five-point Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree). AI Knowledge and AI Usage Competency items were adapted from Ng et al. (2021); Perceived Usefulness items from Davis (1989) and Venkatesh et al. (2003); AI Self-Efficacy items from Compeau and Higgins (1995); and Entrepreneurial Intentions items from Liñán and Chen (2009). A pilot test with 30 students assessed wording clarity and led to minor revisions. Cronbach's alpha assessed internal consistency; it did not establish construct validity. Content validity beyond adaptation and pilot review, factor structure, convergent validity, and discriminant validity were not tested and should be addressed through expert review and EFA/CFA in future research.

Data Analysis

IBM SPSS Statistics (Version 26) was used for data analysis. First, Cronbach's alpha assessed internal consistency. Second, means and standard deviations described the constructs. Third, Pearson correlations assessed bivariate associations. Fourth, standard multiple regression tested the combined and individual predictive contributions of AI Knowledge, AI Usage Competency, Perceived Usefulness of AI, and AI Self-Efficacy to Entrepreneurial Intentions. Fifth, variance inflation factors (VIFs) assessed multicollinearity. Normality of residuals, linearity, homoscedasticity, independence of errors, influential cases, and common method bias were not statistically assessed in the available analysis; this restricts the strength of inference and is acknowledged as a limitation. Statistical significance was evaluated at $p < .05$ (two-tailed).

Analysis And Interpretation

The demographic profile of the respondents is shown below:

The convenience sample included 400 university students. Of these, 214 (53.5%) were male and 186 (46.5%) were female. Most respondents were aged 18–22 years (n = 240, 60.0%), followed by 23–27 years (n = 126, 31.5%) and 28 years or above (n = 34, 8.5%). These figures describe the respondents only; because convenience sampling was used and institutional and disciplinary

distributions were unavailable, they should not be interpreted as evidence that the sample represents all university students in Pakistan.

Table 1

Demographic Profile of the Sample (N = 400)

Variable	Frequency (n)	Percentage (%)
Gender		
Male	214	53.5
Female	186	46.5
Age Group		
18–22 years	240	60.0
23–27 years	126	31.5
28 years and above	34	8.5
Total	400	100.0

Reliability Analysis

Cronbach's alpha coefficients were calculated to assess internal consistency. All five constructs exceeded the commonly used threshold of $\alpha \geq .70$ (Nunnally, 1978): Entrepreneurial Intentions ($\alpha = .901$), AI Self-Efficacy ($\alpha = .889$), AI Usage Competency ($\alpha = .867$), AI Knowledge ($\alpha = .842$), and Perceived Usefulness of AI ($\alpha = .823$). These coefficients indicate satisfactory internal consistency but do not, by themselves, establish content or construct validity.

Table 2

Reliability Analysis — Cronbach's Alpha Coefficients

Construct	No. of Items	Cronbach's α
AI Knowledge (AIK)	5	.842
AI Usage Competency (AIU)	5	.867
Perceived Usefulness of AI (PUA)	5	.823
AI Self-Efficacy (AISE)	5	.889
Entrepreneurial Intentions (EI)	6	.901

Descriptive Statistics

The means and standard deviations of all the study constructs were reported in Table 3. The mean score of the students on Perceived Usefulness of AI ($M = 4.01$, $SD = .681$) was the highest, indicating that students generally consider AI tools to be useful. The mean score for Entrepreneurial Intentions was also relatively high ($M = 3.94$, $SD = .759$) representing a fairly

positive entrepreneurial attitude among the sample population. AI Knowledge (M = 3.89, SD = .701), AI Self-Efficacy (M = 3.82, SD = .733), and AI Usage Competency (M = 3.77, SD = .746) presented comparably high means. The moderate standard deviations for all constructs indicate good variability and that the scales were adequate to measure individual differences within the sample.

Table 3

Descriptive Statistics for Study Variables (N = 400)

Variable	Mean (M)	SD
AI Knowledge (AIK)	3.89	.701
AI Usage Competency (AIU)	3.77	.746
Perceived Usefulness of AI (PUA)	4.01	.681
AI Self-Efficacy (AISE)	3.82	.733
Entrepreneurial Intentions (EI)	3.94	.759

Correlation Analysis

Pearson bivariate correlations were calculated to determine the direction and magnitude of the relationships between the variables of interest in this study (Table 4). The results showed that Entrepreneurial Intentions was significantly positively correlated with AI Self-Efficacy ($r = .718$, $p < .01$), AI Usage Competency ($r = .648$, $p < .01$), Perceived Usefulness of AI ($r = .621$, $p < .01$), and AI Knowledge ($r = .566$, $p < .01$). Of the predictors, the inter-correlations ranged from $r = .587$ to $r = .693$, which corresponds to moderate to moderately high correlation. The inter-correlation coefficients suggest that there is a shared variance in the dimensions of AI literacy; however, the correlations were not greater than the threshold commonly used for identifying concerns with the presence of multicollinearity ($r > .85$; Field, 2018).

Table 4

Pearson Correlation Matrix for Study Variables (N = 400)

Variable	1	2	3	4	5
1. AIK	—				
2. AIU	.612**	—			
3. PUA	.587**	.655**	—		
4. AISE	.601**	.693**	.624**	—	
5. EI	.566**	.648**	.621**	.718**	—

*Note. AIK = AI Knowledge; AIU = AI Usage Competency; PUA = Perceived Usefulness of AI; AISE = AI Self-Efficacy; EI = Entrepreneurial Intentions. **p < .01 (two-tailed).*

Multiple Regression Analysis

We used a standard multiple regression analysis to analyze the data with Entrepreneurial Intentions as the criterion variable and AI Knowledge, AI Usage Competency, Perceived Usefulness of AI and AI Self-Efficacy as simultaneous predictors. Before interpretation, multicollinearity was evaluated using the VIF measures which ranged from 2.01 to 2.71 (Table 6), and were not problematic as they are below the commonly recommended threshold of 5 or 10 (Hair et al., 2019).

The overall regression model was statistically significant, $F(4, 395) = 167.582$, $p < .001$, with $R = .792$. The four predictors jointly accounted for 62.7% of the variance in Entrepreneurial Intentions ($R^2 = .627$, adjusted $R^2 = .623$, SE = .421). This substantial explained variance should be interpreted cautiously because all variables were self-reported at one time and some constructs may be conceptually related.

Table 5
Multiple Regression Model Summary

Model	R	R^2	Adjusted R^2	SE of Estimate
Full model	.792	.627	.623	.421

The ANOVA indicated that the regression model was statistically significant, $F(4, 395) = 167.582$, $p < .001$, with a regression sum of squares of 118.442 and a residual sum of squares of 70.008 (Table 6).

Table 6
Analysis of Variance (ANOVA) for the Regression Model

Source	SS	df	MS	F	p
Regression	118.442	4	29.611	167.582	< .001
Residual	70.008	395	.177		
Total	188.450	399			

The individual regression coefficients are given in Table 7. AI Self-Efficacy emerged as the strongest predictor of Entrepreneurial Intentions ($\beta = .389$, $t = 8.944$, $p < .001$), followed by AI Usage Competency ($\beta = .221$, $t = 5.117$, $p < .001$), Perceived Usefulness of AI ($\beta = .197$, $t = 4.668$, $p < .001$), and AI Knowledge ($\beta = .183$, $t = 4.212$, $p < .001$). All of the predictors contributed to the prediction of Entrepreneurial Intentions in a statistically significant manner and independently. The values of VIF ranged from 2.01 (AI Knowledge) to 2.71 (AI Self-Efficacy) showing lack of multicollinearity.

Table 7
Standardized Regression Coefficients and Multicollinearity Statistics

Predictor	β	t	p	VIF
AI Knowledge (AIK)	.183	4.212	< .001	2.01
AI Usage Competency (AIU)	.221	5.117	< .001	2.44
Perceived Usefulness of AI (PUA)	.197	4.668	< .001	2.18
AI Self-Efficacy (AISE)	.389	8.944	< .001	2.71

Note. Dependent variable: Entrepreneurial Intentions. β = standardized regression coefficient; VIF = Variance Inflation Factor. $R^2 = .627$, adjusted $R^2 = .623$, $F(4, 395) = 167.582$, $p < .001$.

Hypotheses Testing Summary

The regression results presented in Table 8 supported all four hypotheses. Each predictor showed a statistically significant positive relationship with Entrepreneurial Intentions; these findings support predictive associations rather than causal effects.

Table 8
Summary of Hypotheses Testing Results

H	Hypothesis Statement	β	Decision
H1	AI Knowledge → Entrepreneurial Intentions	.183**	Supported
H2	AI Usage Competency → Entrepreneurial Intentions	.221**	Supported
H3	Perceived Usefulness of AI → Entrepreneurial Intentions	.197**	Supported
H4	AI Self-Efficacy → Entrepreneurial Intentions	.389**	Supported

Discussion and Conclusion

Discussion

This study examined whether four AI-related variables predicted entrepreneurial intentions among university students. All four hypotheses were supported by the data: AI Knowledge, AI Usage Competency, Perceived Usefulness of AI, and AI Self-Efficacy each made a positive, statistically significant contribution in the regression model. Together, the predictors accounted for 62.7% of the variance in entrepreneurial intentions. Given the cross-sectional self-report design and conceptual overlap among the predictors, this result should be interpreted as substantial predictive association rather than evidence of causal influence.

AI Self-Efficacy as the Dominant Predictor

AI Self-Efficacy had the largest standardized coefficient among the four predictors (β = .389). This pattern is consistent with social cognitive theory, which emphasizes capability beliefs in motivated behavior (Bandura, 1986), and with recent evidence that AI literacy may relate to e-entrepreneurial intention through self-efficacy and identity-based mechanisms (Duong, 2025). Students who believe they can use AI tools effectively may also perceive fewer barriers to entrepreneurship. However, reverse directionality is plausible: students already interested in entrepreneurship may engage more with AI and consequently report greater confidence. The self-reported measure may also reflect general technological confidence rather than demonstrated AI competence.

AI Usage Competency and Practical Entrepreneurial Agency

AI Usage Competency had the second-largest standardized coefficient (β = .221), consistent with competency-based views of entrepreneurship (Man et al., 2002). Students who report being able to use AI platforms for business tasks may perceive lower barriers to venture creation. Digital technologies can enable low-cost experimentation and rapid iteration (Nambisan, 2017), yet access to infrastructure, training, and discipline-specific opportunities may condition this relationship in Pakistan. Because competency was self-reported, future research should include performance-based measures.

The two pathways to perceived usefulness and attitude are:

Perceived Usefulness of AI positively predicted entrepreneurial intentions (β = .197), consistent with TAM's proposition that perceived usefulness relates to technology-oriented intentions (Davis, 1989; Venkatesh et al., 2003). Students who see AI as useful for business planning, data-informed decisions, and customer engagement may view AI-enabled entrepreneurship more favorably. Nevertheless, perceived usefulness is an acceptance belief rather than a core AI literacy skill, and the present result supports applying TAM as an interpretive framework rather than claiming that the theory has been extended or fully tested.

Cognitive foundation of AI Knowledge.

Although AI Knowledge was the smallest predictor, it still had a significant and positive impact on entrepreneurial intentions (β = .183). The result is consistent with the general literature on knowledge-based opportunity recognition (Shane, 2000) that suggests that people with more complex and detailed knowledge structures are more likely to be able to recognize new entrepreneurial opportunities. An understanding of AI concepts like machine learning, NLP, and predictive analytics could help students see opportunities in the market and new business models that others without that knowledge don't. This finding highlights the importance of AI education in fostering entrepreneurial thinking, beyond practical proficiency.

Theoretical Contributions

The study makes a limited theoretical contribution by examining AI Knowledge and AI Usage Competency alongside Perceived Usefulness and AI Self-Efficacy in relation to entrepreneurial

intentions. The results are consistent with social cognitive theory and TAM, but they do not constitute a full test or extension of either theory. They also do not test TPB's attitude, subjective norms, or perceived behavioral control. The model is therefore best understood as an initial predictive framework that requires construct validation, longitudinal testing, and comparison with alternative models.

Conclusion

This study examined the relationship between AI-related capabilities and beliefs and entrepreneurial intentions among 400 university students in Pakistan. Multiple regression results indicated that AI Knowledge, AI Usage Competency, Perceived Usefulness of AI, and AI Self-Efficacy each positively and significantly predicted entrepreneurial intentions. AI Self-Efficacy was the strongest predictor among the four variables included in the model.

The findings suggest that universities may consider integrating applied and responsible AI learning into entrepreneurship education through practical workshops, AI-supported business simulations, and mentoring. Such initiatives should combine knowledge and hands-on competence with opportunities to build justified confidence. These recommendations are provisional and should be evaluated through stronger designs before broad policy conclusions are drawn.

Several limitations should be noted. Convenience sampling and the absence of institution-, discipline-, and program-level information restrict generalizability. The cross-sectional design does not permit causal inference or exclude reverse directionality. All measures were self-reported and collected at one time, creating possible common method bias, which was not statistically assessed. Reliability was examined, but content and construct validity, factor structure, convergent validity, and discriminant validity were not established for the combined model. Regression diagnostics beyond VIF were also unavailable. Future research should use probability or stratified sampling, report institutional and disciplinary distributions, conduct an a priori power analysis, apply expert content review and EFA/CFA, test common method bias and full regression assumptions, and use longitudinal or experimental designs with objective AI-competency measures. Mediation and moderation involving entrepreneurial self-efficacy, academic discipline, gender, and institutional context may also be examined.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall.

Bird, B. (1988). Implementing entrepreneurial ideas: The case for intention. *Academy of Management Review, 13*(3), 442–453.

Butt, F. S., Malik, A., & Mahmood, K. (2026). Assessing AI literacy of university students in Pakistan: A cross-sectional survey. *Digital Library Perspectives, 42*(1), 141–158. https://doi.org/10.1108/DLP-06-2025-0094

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly, 19*(2), 189–211.

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340.

Duong, C. D. (2025). AI literacy and e-entrepreneurial intention: A serial mediation model of e-entrepreneurial self-efficacy and e-entrepreneurial identity aspiration. *International Journal of Information Management Data Insights, 5*, Article 100349. https://doi.org/10.1016/j.jjimei.2025.100349

Field, A. (2018). *Discovering statistics using IBM SPSS statistics* (5th ed.). SAGE.

Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda. *Technological Forecasting and Social Change, 162*, Article 120392. https://doi.org/10.1016/j.techfore.2020.120392

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage.

Krueger, N. F., Reilly, M. D., & Carsrud, A. L. (2000). Competing models of entrepreneurial intentions. *Journal of Business Venturing, 15*(5–6), 411–432. https://doi.org/10.1016/S0883-9026(98)00033-0

Liñán, F., & Chen, Y.-W. (2009). Development and cross-cultural application of a specific instrument to measure entrepreneurial intentions. *Entrepreneurship Theory and Practice, 33*(3), 593–617. https://doi.org/10.1111/j.1540-6520.2009.00318.x

Liñán, F., & Fayolle, A. (2015). A systematic literature review on entrepreneurial intentions: Citation, thematic analyses, and research agenda. *International Entrepreneurship and Management Journal, 11*(4), 907–933. https://doi.org/10.1007/s11365-015-0356-5

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–16). Association for Computing Machinery. https://doi.org/10.1145/3313831.3376727

Lüthje, C., & Franke, N. (2003). The "making" of an entrepreneur: Testing a model of entrepreneurial intent among engineering students at MIT. *R&D Management, 33*(2), 135–147. https://doi.org/10.1111/1467-9310.00288

Man, T. W. Y., Lau, T., & Chan, K. F. (2002). The competitiveness of small and medium enterprises: A conceptualization with focus on entrepreneurial competencies. *Journal of Business Venturing, 17*(2), 123–142.

Nambisan, S. (2017). Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. *Entrepreneurship Theory and Practice, 41*(6), 1029–1055. https://doi.org/10.1111/etap.12254

Neck, H. M., & Greene, P. G. (2011). Entrepreneurship education: Known worlds and new frontiers. *Journal of Small Business Management, 49*(1), 55–70.

Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence, 2*, Article 100041. https://doi.org/10.1016/j.caeai.2021.100041

Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). McGraw-Hill.

Saunders, M., Lewis, P., & Thornhill, A. (2019). *Research methods for business students* (8th ed.). Pearson.

Shane, S. (2000). Prior knowledge and the discovery of entrepreneurial opportunities. *Organization Science, 11*(4), 448–469.

Souitaris, V., Zerbinati, S., & Al-Laham, A. (2007). Do entrepreneurship programmes raise entrepreneurial intention of science and engineering students? The effect of learning, inspiration, and resources. *Journal of Business Venturing, 22*(4), 566–591.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

Wang, B., Rau, P.-L. P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: Validity and reliability of an artificial intelligence literacy scale. *Behaviour & Information Technology, 42*(9), 1324–1337. https://doi.org/10.1080/0144929X.2022.2072768

Wibowo, A., Narmaditya, B. S., Suparno, S., Sebayang, K. D. A., Mukhtar, S., & Shafiai, M. H. M. (2023). Does digital entrepreneurship education matter for students' digital entrepreneurial intentions? The mediating role of entrepreneurial alertness. *Cogent Education, 10*(1), Article 2221164. https://doi.org/10.1080/2331186X.2023.2221164

Zhao, H., Seibert, S. E., & Hills, G. E. (2005). The mediating role of self-efficacy in the development of entrepreneurial intentions. *Journal of Applied Psychology, 90*(6), 1265–1272.