

# AI ADOPTION, ENTREPRENEURIAL COMPETENCY, AND ENTREPRENEURIAL INTENTION AMONG GHANAIAN UNIVERSITY STUDENTS

**Timothy Kwabla Zilevu, Department of Marketing,  
University of Professional Studies Accra**

**Michael Kwame Mickson, Department of Business Administration  
University of Professional Studies Accra**

**Linda Ethel Naa Akaibi Narh, Department of marketing, University of  
Professional Studies Accra**

**Rockson Opare Boateng, Department of Marketing. University of  
Professional Studies Accra**

**Andrews Ayiku, University of Professional Studies Accra, Department of  
Marketing**

**Vasmine Mercy Yehowa Adom Asamoah Gyan, Department of Marketing.  
University of Professional Studies Accra**

## ABSTRACT

*Purpose – This study examined how artificial intelligence (AI) adoption shapes entrepreneurial intention (EI) among university students in Ghana. Specifically, it tested whether entrepreneurial competency mediates the AI adoption-EI relationship and whether AI literacy moderates the AI adoption-competency path within a moderated mediation framework*

*Design/methodology/approach – A quantitative cross-sectional survey was administered to 400 students from nine universities spanning the public, private, and technical university sectors in Ghana. All constructs were measured using validated Likert-scale instruments. Ordinary least squares regression, the Sobel test, and moderated mediation analysis were used to test five hypotheses, with perceived university support entered as a control variable.*

*Findings – AI adoption positively and significantly predicted entrepreneurial competency (beta = 0.344,  $p < 0.001$ ), which was in turn the strongest predictor of EI (beta = 0.461,  $p < 0.001$ ). Entrepreneurial competency partially mediated the AI adoption-EI relationship, transmitting 54.8% of the total effect (indirect beta = 0.177, Sobel  $z = 6.427$ ,  $p < 0.001$ ). AI literacy did not moderate the AI adoption-competency path (beta = 0.007,  $p = 0.871$ ) but exerted a significant independent main effect on competency. H4 and H5 were not supported.*

*Research limitations/implications – The cross-sectional design limits causal inference, and the sample is weighted toward younger undergraduates. A full confirmatory factor analysis using AMOS or R lavaan is recommended for replication. Future research should examine the dual-pathway AI-EI model in infrastructure-constrained settings.*

*Practical implications – Universities should embed AI tools directly into entrepreneurship curricula rather than treating them as peripheral resources. Investment in AI literacy instruction and AI tool provision should occur in parallel, as both independently build entrepreneurial competencies.*

*Originality/value – This is among the first empirical studies to test a moderated mediation model of AI adoption and entrepreneurial intention in sub-Saharan Africa. The study establishes entrepreneurial competency as the primary mechanism through which AI*

*adoption reaches EI in the Ghanaian university context and provides a context-specific model for theory development in developing economies.*

**Keywords:** AI adoption, entrepreneurial intention, entrepreneurial competency, AI literacy, Ghana, Theory of Planned Behavior.

## INTRODUCTION

Although entrepreneurship has been posited as a prime policy response to the high levels of graduate unemployment affecting about 12% of the graduate labor force in Ghana, the decision to become an entrepreneur is not a straightforward one. For student entrepreneurs who report holding positive intentions towards starting a business, the intention to be entrepreneurial does not automatically translate into actual entrepreneurship. A host of attitudinal, social and capability factors are likely to affect this transition process. This study examines the role of AI adoption in this process (Abreh et al., 2025).

While most research on EI in Ghana has relied on the Theory of Planned Behavior (TPB) finding attitude, subjective norms, and PBC to predict EI (Sedegah et al., 2024), there is also evidence that entrepreneurship education enhances EI dimensions such as risk taking, innovation, proactiveness, and others (Adu et al., 2020). In a very recent Ghanaian study, opportunity recognition was found to mediate the relationship between attitude and venture initiation intention (Ledi, Ameza-Xemalordzo&Owusu,2022). Other psychological predictors of EI have also been identified (Mahama et al., 2023), and financial self-efficacy (Agbemava et al., 2025).

Although notable progress has been made in research on the EI concept and its determinants, little is known about the potential impact of technology on EI. Most notably, there is a knowledge gap regarding the technology dimension of EI in the Ghanaian context. While research such as (Shi et al.,2022) found that adoption of social media and e-commerce decreased perceived barriers to venture creation among university students in Ghana (Salifu et al., 2025), no research has investigated the potential impact of AI adoption on EI through competencies.

The findings of this study are consistent with other studies conducted in different contexts. (Nuseir, Al-Mousa & Al-Khateeb, 2020) investigated the effect of an AI-focused entrepreneurship education on Saudi undergraduate students, and the findings showed a positive impact on their knowledge and self-efficacy. In the context of generative AI, (Xie & Wang, 2025) found that generative AI application in entrepreneurship education had a positive impact on students' entrepreneurial self-efficacy and EI. Through students' entrepreneurial mindset and business competency, (Moustafa et al., 2025) discovered the effect of AI adoption on digital entrepreneurial intentions among Egyptian students. In addition, (Zou & Guo, 2026) identified two opposite paths through which AI usage would affect students' entrepreneurial intention. The positive path was through opportunity recognition, whereas the counteracting path was through increased risk perception.

(Mustafa et al., 2023) reported in a cross-national study in Ghana and Malaysia that the interaction between university support for entrepreneurship and proactive personality predicted entrepreneurial career intentions. This study examines whether the differences between Ghana's infrastructure challenges and Malaysia's advanced digital infrastructure (particularly digital infrastructure that supports innovation) would moderate the effect of institutional support for encouraging entrepreneurship (EI) to intent for starting a business. This study is particularly relevant in the context of universities in Ghana where the levels of AI adoption and AI literacy could potentially vary significantly.

Against the backdrop of an increasing trend of AI adoption in education, there is a

growing interest in the relationships between AI adoption and entrepreneurship learning outcomes. This study explores two potential mechanisms that underlie the positive relationship between AI adoption and EI. On the one hand, the regular use of AI tools and platforms may enhance students' entrepreneurial competencies such as opportunity recognition, business planning, and implementation resources. On the other hand, it raises a secondary question of whether AI literacy is necessary to extract competency value from AI adoption, i.e., students with higher levels of AI literacy may extract more competency value from the same level of AI adoption. This study aims to investigate the two potential mechanisms in a single moderated mediation model.

## LITERATURE REVIEW

### The Theory of Planned Behavior and Its Extensions

Ajzen (1991) in his TPB (Theory of Planned Behaviour) states that intentions are the best predictor of behaviour and are a function of attitude toward the behaviour, subjective norms with respect to the behaviour, and Perceived Behavioural Control (PBC). (Krueger & Carsrud, 1993) use an intention-based model to attempt to map the initiation process of ventures and the cognitive process and factors that influence the process of start-up decision making.

The original three-variable model of behaviour ( $INTENTION = c * PBC + a * ATTITUDE + b * NORMS + e$ ) has been extended in many ways in the last two decades. For example, some researchers have attempted to include mediators that explain how attitudinal, normative and control beliefs influence intentions to perform behaviours. Other researchers have explored the role of moderators that highlight under what circumstances the TPB has greater or lesser predictive power. For Ghana, examples of these extended models of behaviour are entrepreneurship education (Adu et al., 2020), opportunities for entrepreneurship (Ledi, Ameza-Xemalordzo & Owusu, 2022), personality (Nunfam et al., 2020), and culture (Mankpa et al., 2017), amongst others. (2020), and psychological attributes (Mahama et al., 2023). The current study contributes to the EI literature by exploring the possible association between PC and EI, and further investigates the potential roles of financial, human and social capital underlying the said association. Empirical evidence indicates that PC does not have a direct relationship with EI; nevertheless, the three forms of capital are found to have separate influences on EI, with social capital exerts the strongest influence in developed markets (Duong, 2024).

### University Context and Individual Characteristics

Perceived university support is not a standard TPB variable, but several studies position it as a contextual moderator. (Sampene et al., 2022) reported that perceived sustainability support from universities predicted students' intentions to adopt environmentally sustainable practices in a sample of 370 students. (Sedegah et al., 2024) drawing on 929 tourism and hospitality students across six Ghanaian universities, found that university support moderated both attitude and PBC in predicting sustainable tourism intentions. (Ayiku, Grant & Mensah, 2022) extended this to entrepreneurial contexts, using structural equation modelling with 354 hotel students to examine how institutional factors interact with attitudes and past behavior.

(Mustafa et al., 2023) provided the most directly relevant evidence: university support for entrepreneurship interacts with students' proactive personality to shape entrepreneurial career intentions in Ghana and Malaysia. Students with proactive personalities extracted greater EI benefits from the same institutional resources. (Twum et al., 2021) documented that individual entrepreneurial orientation, including innovativeness, risk-taking, and

proactiveness, predicts EI among Ghanaian students, while Nunfam et al. (2020) identified specific personality traits that are inversely associated with entrepreneurial behavior.

### **Digital Technology Adoption as a Pathway to Entrepreneurial Intention**

Although the recent increased attention to AI in the research literature on entrepreneurship and small business, several connections between general digital technology adoption and EI have been reported. Focusing on graduate students in Ghana, (Shi et al.,2022) found that social media adoption and e-commerce adoption both mediated the relationship between digital technology adoption and EI, and both media influenced students' perceptions of what ventures were feasible to start. In sum, technology adoption changed the feasibility calculus rather than directly enhanced EI.

The selected variables and their relationships have been studied in the context of AI in the AI-specific literature. Nuseir et al. (2020) found that entrepreneurship education that included AI moderated the relationship between self-efficacy and emotional intelligence (EI) and students' self-rated competency in the context of Saudi students. (Xie & Wang,2025) involved 346 Chinese students in their study and found that education on entrepreneurship that included generative AI enhanced students' entrepreneurial self-efficacy and EI. Building on the first study, (Moustafa et al.,2025) found that AI adoption predicted digital entrepreneurial intentions through students' entrepreneurial mindset and business competency. (Duong & Vu, 2025) applied Social Cognitive Career Theory and TPB on a sample of 604 Vietnamese students and found that there was a serial mediation effect from ChatGPT usage through students' cognitive and career-related variables towards their digital entrepreneurial intention. PBC fully mediated the relationship between AI performance expectancy, entrepreneurship education, and EI in the Lebanese context (Dabbous & Boustani, 2023). Using AI in opportunity searching has dual effects, where EI positively and significantly increases the risk perception that partially offsets the positive effects (Zou & Guo, 2026).

Several key variables, although conceptually distinct from intention, have been found in the literature to have EI in AI adoption, in that they predict adoption and effect adoption-related competency and confidence (e.g. mindset, self-efficacy, prior competency, positive past experiences with technology, etc.). But no research has attempted to apply these lessons to the specific EI that is needed to drive AI adoption in Ghana's institutions and infrastructure (Nuseir, Basheer & Aljumah, 2020).

### **Technology Acceptance Frameworks and AI Literacy**

(Ha et al., 2025) extended the TPB to examine how AI adoption interacts with sustainability-oriented employee innovation, noting that AI-specific control beliefs are sufficiently distinct from general PBC to warrant separate measurement. (Yang et al.,2025) integrated AI literacy into a unified TAM-TPB model using meta-analytic structural equation modelling, finding that AI literacy moderates technology adoption behavior across multiple samples. (Salifu et al., 2024) documented antecedents and consequences of AI adoption intentions among Ghanaian university students using a hybrid SEM-ANN approach, and Salifu et al. (2025) extended this using a multi-group UTAUT2 analysis across three African countries.

AI literacy describes the set of competencies that enable individuals to evaluate, use, and design AI effectively (Long & Magerko, 2020). Yang et al. (2025) operationalized AI literacy as a five-domain construct covering AI concepts, applications, limitations, ethics, and design. Their work suggests that AI literacy should moderate the effect of AI adoption on competency outcomes, because students with higher AI literacy are better positioned to

extract productive learning from AI tool use.

### Theoretical Synthesis and Hypotheses Development

The mechanisms through which AI contributes to EI are threefold: technology, AI-supported education, and AI adoption that build entrepreneurial human capital by providing AI tools, AI-supported education that enables analysis, planning, and generation, and fosters entrepreneurial competency and mindset (Nuseir et al., 2020, 2025; Xie & Wang, 2025). AI adoption also decreases perceived barriers to entrepreneurship and increases PBC towards venturing through the TPB control mechanism (Dabbous & Boustani, 2023). Third, and in parallel, AI literacy can also shape the future trajectories in how AI is integrated into education by enabling students to make the most of current AI offerings (Yang et al., 2025).

From this synthesis, five hypotheses follow FIGURE 1:

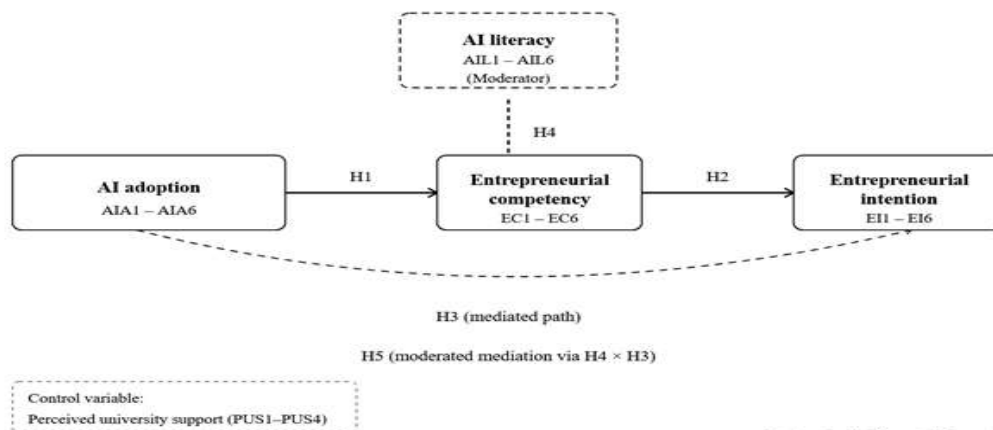
**H1:** AI adoption has a positive and significant effect on entrepreneurial competency.

**H2:** Entrepreneurial competency has a positive and significant effect on entrepreneurial intention.

**H3:** Entrepreneurial competency mediates the relationship between AI adoption and entrepreneurial intention.

**H4:** AI literacy moderates the relationship between AI adoption and entrepreneurial competency, such that the positive effect of AI adoption on competency is stronger among students with higher AI literacy.

**H5:** The indirect effect of AI adoption on entrepreneurial intention through entrepreneurial competency is moderated by AI literacy (moderated mediation).



**FIGURE 1**  
**Proposed Moderated Mediation Model of AI Adoption and Entrepreneurial Intention**

### METHODOLOGY

#### Research Design

This study adopted a quantitative cross-sectional survey design, consistent with prior

EI research in the Ghanaian context (Sedegah et al., 2024; Adu et al., 2020). Standardized path coefficients from OLS regression were used to test the hypotheses, following the approach recommended by Rucker et al. (2011) for moderated mediation analysis.

### **Population and Sampling**

The target population for the study was university students, particularly those reading business and management related courses in universities in Ghana. A multi-stage stratified sampling design was adopted for the study. At the first stage, the universities were grouped into public, private and technical universities. From each category, three universities were sampled. The sampled universities were located in Accra, Kumasi, Cape Coast and Tamale. At the second stage, students from the various universities were sampled using systematic random sampling from faculty enrolment lists.

The theoretical model underlying the survey data is an integrated structural model that consists of five latent constructs including Organizational commitment, Job satisfaction, Team collaboration, Psychological strain and Health behavior. A total of 28 measures are used to represent these constructs. On the basis of the common rule of thumb of 10 or more cases per estimated parameter (Kline, 2016), taking into account a 15% non-response rate in surveys, the goal was to collect 480 valid questionnaires. However, with the initial 480 distributed questionnaires all being completed and returned, after screening, the effective sample size for this study is 400.

### **Measurement Instruments**

All constructs were measured using established scales. A five-point Likert-type scale (1 = strongly disagree to 5 = strongly agree) was used throughout. The six items for AI adoption were adapted from (Salifu et al., 2025) and (Moustafa et al., 2025). Entrepreneurial competency (six items) was adapted from (Moustafa et al., 2025) and (Bird, 1995). AI literacy (six items) was adapted from (Yang et al., 2025) and (Long & Magerko, 2020). Entrepreneurial intention (six items) was adapted from Linan and Chen (2009). Perceived university support (four items, control variable) was adapted from (Sampene et al., 2022) and (Mustafa et al., 2023). A pilot test on 40 students confirmed item reliability and scale coherence prior to main data collection (Brislin, 1970)

### **Validity and Reliability Assessment**

Construct validity was assessed using principal component extraction as a proxy for confirmatory factor analysis. Average variance extracted (AVE) values above 0.50 (Fornell & Larcker, 1981) and composite reliability (CR) values above 0.70 were required for convergent validity. Discriminant validity was assessed using the heterotrait-monotrait (HTMT) ratio, with a threshold of 0.85 (Henseler, Ringle & Sarstedt, 2015). Common method bias was assessed procedurally through survey design safeguards and statistically using a marker variable approach (Lindell and Whitney, 2001).

### **Data Collection and Ethical Considerations**

Data were collected over six weeks using a self-administered questionnaire distributed both online via Google Forms and in paper form in lecture theatres. Research assistants supported distribution and collection at each site. Participation was voluntary and anonymous, with no incentives offered. Full ethical clearance was obtained from the Institutional Review Board (IRB) of the affiliated university, and all participants provided

informed consent prior to completion.

## RESULTS

### Demographic Profile of Respondents

Table 1 presents the demographic characteristics of the 400 respondents. Males constituted 49.5% (n = 198) and females 46.8% (n = 187). The largest age group was 18 to 22 years (44.8%). Most respondents were undergraduates, with Year 3 (22.8%) and Year 4 (22.5%) students most represented. Business Administration was the most common field of study (30.0%), and public universities contributed the largest share of respondents (52.2%). A substantial majority (81.5%, n = 326) reported current use of at least one AI tool.

Variable	Category	n	%
Gender	Male	198	49.5
	Female	187	46.8
	Prefer not to say	15	3.8
Age	18-22	179	44.8
	23-27	127	31.8
	28-32	62	15.5
	33 and above	32	8.0
Level of study	Undergraduate Year 1	58	14.5
	Undergraduate Year 2	90	22.5
	Undergraduate Year 3	91	22.8
	Undergraduate Year 4	90	22.5
	Postgraduate	71	17.8
Field of study	Business Administration	120	30.0
	Accounting/Finance	109	27.3
	Marketing	70	17.5
	Management	65	16.2
	Other	36	9.0
University type	Public	209	52.2
	Private	117	29.2
	Technical	74	18.5
AI tool use	Yes	326	81.5
	No	74	18.5

Note. Percentages may not sum to 100 due to rounding.

## Descriptive Statistics and Measurement Model Assessment

### Descriptive Statistics

Table 2 reports item-level and construct-level descriptive statistics. All composite means fall between 3.38 and 3.62, indicating moderate to moderately high agreement. AI adoption recorded the highest composite mean ( $M = 3.617$ ,  $SD = 1.053$ ), while EI registered the lowest ( $M = 3.381$ ,  $SD = 0.946$ ). All skewness and kurtosis values fall within the acceptable thresholds of plus or minus 2 and plus or minus 7, respectively, indicating approximately normal distributions suitable for regression-based analysis (Kline, 2016).

<b>Construct/Item</b>	<b>M</b>	<b>SD</b>	<b>Skew</b>	<b>Kurt</b>	<b>CITC</b>	<b>Load.</b>	<b><math>\alpha</math></b>	<b>AVE/CR</b>
<b>AI Adoption (AIA)</b>	3.617	1.053					0.961	0.839/0.969
AIA1	3.743	1.129	-0.707	-0.182	0.881	0.918		
AIA2	3.587	1.151	-0.510	-0.545	0.884	0.921		
AIA3	3.705	1.147	-0.683	-0.265	0.872	0.912		
AIA4	3.520	1.189	-0.469	-0.664	0.877	0.915		
AIA5	3.583	1.158	-0.477	-0.560	0.878	0.916		
AIA6	3.565	1.124	-0.507	-0.512	0.871	0.911		
<b>Entrepreneurial Competency (EC)</b>	3.585	0.873					0.942	0.775/0.954
EC1	3.640	0.986	-0.377	-0.494	0.825	0.881		
EC2	3.535	0.988	-0.308	-0.417	0.823	0.880		
EC3	3.627	1.006	-0.329	-0.552	0.827	0.882		
EC4	3.410	1.005	-0.280	-0.372	0.821	0.877		
EC5	3.635	1.017	-0.340	-0.593	0.822	0.879		
EC6	3.660	0.947	-0.305	-0.494	0.829	0.883		

<b>AI Literacy (AIL)</b>	3.578	1.011					0.959	0.830/0.967
AIL1	3.580	1.105	- 0.465	- 0.446	0.861	0.904		
AIL2	3.570	1.106	- 0.461	- 0.502	0.879	0.918		
AIL3	3.590	1.109	- 0.586	- 0.215	0.869	0.910		
AIL4	3.540	1.096	- 0.388	- 0.502	0.868	0.910		
AIL5	3.623	1.108	- 0.565	- 0.333	0.869	0.910		
AIL6	3.567	1.137	- 0.479	- 0.472	0.874	0.914		
<b>Entrepreneurial Intention (EI)</b>	3.381	0.946					0.954	0.812/0.963
EI1	3.310	1.054	- 0.206	- 0.597	0.850	0.897		
EI2	3.305	1.046	- 0.239	- 0.434	0.846	0.894		
EI3	3.317	1.063	- 0.182	- 0.706	0.849	0.896		
EI4	3.397	1.033	- 0.264	- 0.495	0.868	0.910		
EI5	3.598	1.038	- 0.402	- 0.472	0.855	0.901		
EI6	3.360	1.065	- 0.231	- 0.618	0.864	0.907		
<b>Perceived University Support (PUS)</b>	3.482	0.878					0.910	0.787/0.937
PUS1	3.490	0.999	- 0.192	- 0.639	0.791	0.884		
PUS2	3.562	0.994	- 0.158	- 0.647	0.803	0.892		
PUS3	3.465	1.001	- 0.144	- 0.604	0.791	0.885		
PUS4	3.410	0.964	- 0.122	- 0.543	0.795	0.887		

Note. M = mean; SD = standard deviation; CITC = corrected item-total correlation; Load. = approximate first-factor loading;  $\alpha$  = Cronbach's alpha; AVE = average variance

extracted; CR = composite reliability.

**Reliability and Convergent Validity**

Cronbach's alpha coefficients ranged from 0.910 (PUS) to 0.961 (AIA), all exceeding the 0.70 threshold recommended by (Nunnally,1978). All corrected item-total correlations exceeded 0.79. All item loadings exceeded 0.87, surpassing the 0.70 benchmark (Hair et al., 2019). AVE values ranged from 0.775 (EC) to 0.839 (AIA), and CR values ranged from 0.937 (PUS) to 0.969 (AIA), meeting the required thresholds throughout.

**Discriminant Validity**

Table 3 presents the Fornell-Larcker criterion matrix. The square root of each construct's AVE (on the diagonal) exceeded its correlation with all other constructs. The highest off-diagonal correlation was between AI adoption and AI literacy (r = 0.664), which remained below the square root of each construct's AVE (0.916 and 0.911, respectively). HTMT ratios ranged from 0.283 to 0.691, all below the 0.85 threshold.

	AIA	EC	AIL	EI	PUS
1. AI Adoption (AIA)	0.916				
2. Entrepreneurial Competency (EC)	0.442	0.880			
3. AI Literacy (AIL)	0.664	0.515	0.911		
4. Entrepreneurial Intention (EI)	0.399	0.590	0.469	0.901	
5. Perceived University Support (PUS)	0.318	0.418	0.264	0.394	0.887

Note. Diagonal values are square roots of AVE. Off-diagonal values are inter-construct Pearson correlations. HTMT ratios for all pairs ranged from 0.283 to 0.691, all below the 0.85 criterion.

**Correlation Analysis**

Table 4 presents bivariate correlations among the four constructs. All correlations were positive and significant at  $p < 0.001$ . The strongest correlation was between EC and EI (r = 0.590), consistent with H2. AI adoption correlated more strongly with AI literacy (r = 0.664) than with EC (r = 0.442) or EI (r = 0.399), an overlap confirmed not to threaten discriminant validity by the HTMT analysis.

Construct	M	SD	1	2	3	4
1. AI Adoption	3.617	1.053	1.000			

2. Entrepreneurial Competency	3.585	0.873	0.442***	1.000		
3. AI Literacy	3.578	1.011	0.664***	0.515***	1.000	
4. Entrepreneurial Intention	3.381	0.946	0.399***	0.590***	0.469***	1.000

Note. \*\*\*  $p < 0.001$ . Perceived university support (PUS) is included as a control variable and excluded from this table for parsimony.  $N = 400$ .

## Hypothesis Testing

The hypotheses were tested using OLS regression, with perceived university support entered as a control variable in all models. Standardized beta coefficients are reported throughout. Table 5 summarizes all hypothesis decisions, Table 7 presents model fit statistics, and Table 6 presents conditional indirect effects.

### *H1: AI Adoption and Entrepreneurial Competency*

AI adoption was a significant positive predictor of entrepreneurial competency (beta = 0.344, SE = 0.045,  $t = 7.661$ ,  $p < 0.001$ ), explaining 28.1% of the variance in EC above and beyond perceived university support (Adj.  $R^2 = 0.277$ ,  $F(2, 397) = 77.54$ ,  $p < 0.001$ ). H1 is supported.

### *H2: Entrepreneurial Competency and Entrepreneurial Intention*

Entrepreneurial competency was the strongest predictor of EI in the bivariate model (beta = 0.516, SE = 0.044,  $t = 11.807$ ,  $p < 0.001$ ), with the model explaining 37.5% of the variance in EI (Adj.  $R^2 = 0.371$ ,  $F(2, 397) = 118.86$ ,  $p < 0.001$ ). Perceived university support also contributed significantly (beta = 0.178,  $p < 0.001$ ). H2 is supported.

### *H3: Mediation by Entrepreneurial Competency*

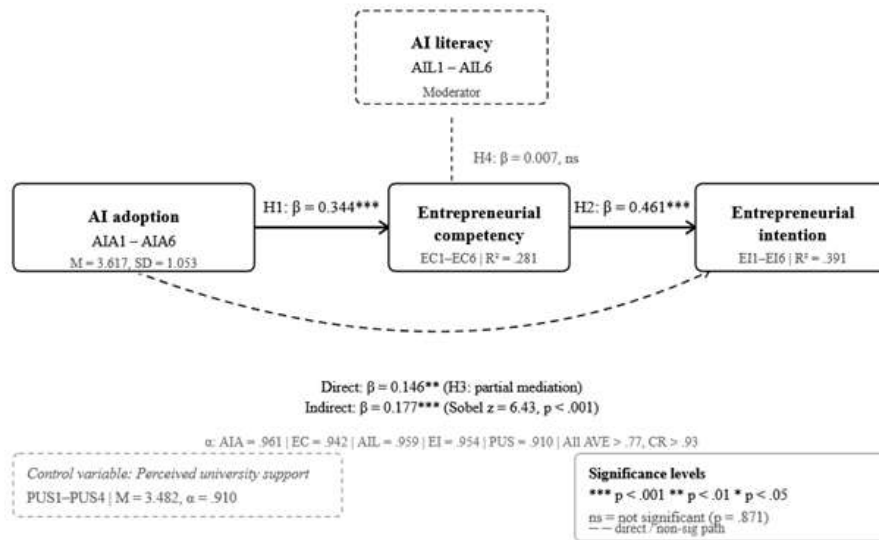
The mediation test followed the four-step procedure of (Baron & Kenny, 1986), supplemented by the Sobel test. After EC was entered into the model alongside AIA and PUS, the direct effect of AIA on EI was substantially attenuated (beta = 0.146, SE = 0.044,  $t = 3.302$ ,  $p = 0.001$ ) compared to its total effect without EC (beta = 0.274,  $p < 0.001$ ). EC remained a strong predictor (beta = 0.461, SE = 0.046,  $t = 9.972$ ,  $p < 0.001$ ). The model explained 39.1% of the variance in EI (Adj.  $R^2 = 0.387$ ,  $F(3, 396) = 84.85$ ,  $p < 0.001$ ). A Sobel test confirmed a significant indirect effect (indirect = 0.159, SE = 0.025,  $z = 6.427$ ,  $p < 0.001$ ), accounting for 54.8% of the total effect (0.159/0.291). Because the direct path remained significant, the mediation was partial rather than full. H3 is supported.

### *H4: Moderation by AI Literacy*

The interaction term AIA\_c x AIL\_c was not significant (beta = 0.007, SE = 0.030,  $t = 0.162$ ,  $p = 0.871$ ), and the change in  $R^2$  attributable to the interaction was negligible (delta  $R^2 < 0.001$ ). The main effect of AI literacy on competency was substantial (beta = 0.320, SE = 0.047,  $t = 6.767$ ,  $p < 0.001$ ). AI literacy raises competency independently but does not condition the AI adoption-competency path. H4 is not supported.

**H5: Moderated Mediation**

Table 6 presents conditional indirect effects at three levels of AI literacy. The conditional indirect effect is 0.047 at one SD below the mean, 0.050 at the mean, and 0.053 at one SD above the mean. None differs significantly from zero (all  $z < 1.90$ , all  $p > 0.05$ ). Because H4 was not supported, H5 is also not supported FIGURE 2.



**FIGURE 2**  
**Moderated Mediation Model**

H	Path	Std. beta	SE	t / z	p	Decision
H1	AIA → EC (ctrl PUS)	0.344	0.045	t = 7.661	< .001	Supported
H2	EC → EI (ctrl PUS)	0.516	0.044	t = 11.807	< .001	Supported
H3a	AIA → EI direct (ctrl EC, PUS)	0.146	0.044	t = 3.302	.001	Partial mediation
H3b	Indirect: AIA → EC → EI	0.177	0.025	z = 6.427	< .001	Supported
H4	AIA x AIL → EC	0.007	0.030	t = 0.162	.871	Not supported
H5	Moderated mediation index	approx. 0	—	—	> .05	Not supported

Note. Std. beta = standardized beta coefficient; SE = standard error. Control variable (PUS) included in all models but not shown.

AI Literacy Level	Cond. a	Indirect effect	SE	p
Low (M - 1SD)	0.084	0.047	0.031	.134
Mean	0.089	0.050	0.026	.059
High (M + 1SD)	0.094	0.053	0.032	.095

Note. Indirect effects are the product of conditional path a (AIA to EC at each level of AIL) and path b (EC to EI). SE computed via the delta method.

Model	Predictors	R <sup>2</sup>	Adj. R <sup>2</sup>	F	p
M1	AIA, PUS → EC	0.281	0.277	77.54	< .001
M2	EC, PUS → EI	0.375	0.371	118.86	< .001
M3	AIA + EC + PUS → EI	0.391	0.387	84.85	< .001
M4	AIA_c + AIL_c + AIA × AIL + PUS → EC	0.357	0.350	54.80	< .001

Note. All models include perceived university support (PUS) as a control variable. AIA\_c and AIL\_c are mean-centred composites.

### Supplementary Analyses

A one-way ANOVA found no significant sex difference in EI ( $F(2, 397) = 0.090, p = 0.914$ ): males reported  $M = 3.370$  ( $SD = 0.922$ ) and females  $M = 3.399$  ( $SD = 0.978$ ). A second ANOVA found no significant difference in EI across university types ( $F(2, 397) = 0.191, p = 0.826$ ). An independent-samples t-test comparing AI tool users ( $M = 3.401, SD = 0.939, n = 326$ ) and non-users ( $M = 3.295, SD = 0.976, n = 74$ ) yielded no significant difference ( $t(398) = 0.868, p = 0.386, Cohen's d = 0.112$ ), confirming that binary AI use status does not differentiate EI.

## DISCUSSION

### AI Adoption as a Builder of Entrepreneurial Competency

The significant positive effect of AI adoption on entrepreneurial competency ( $\beta = 0.344, p < 0.001$ ) confirms H1 and extends prior evidence from Saudi Arabia (Nuseir et al., 2020), China (Xie & Wang, 2025), and Egypt (Moustafa et al., 2025) to the Ghanaian university context. Students who regularly use AI tools report greater confidence in identifying business opportunities, developing business plans, mobilizing resources, and evaluating competitive dynamics. This finding aligns with the human capital pathway described by (Zhao et al., 2019) AI adoption accumulates concrete and actionable competencies rather than abstract attitudes.

## Entrepreneurial Competency as the Primary Driver of Intention

Entrepreneurial competency was the strongest predictor of EI in both the bivariate model ( $\beta = 0.516$ ) and the full mediation model ( $\beta = 0.461$ ), confirming H2. This is consistent with (Bird, 1995) and (Moustafa et al., 2025) and reinforces the argument that EI in the Ghanaian university setting is not driven by attitude or exposure alone but by perceived capability. Students who feel equipped to execute entrepreneurial tasks are more likely to form entrepreneurial intentions, and AI adoption contributes to that sense of capability (Ha et al., 2025).

### Partial Mediation: The Competency Channel

Results show that entrepreneurial competency partially mediates the relationship between AI adoption and entrepreneurship intention (EI). Findings explain 54.8% of the total effect (indirect  $\beta = 0.177$ , Sobel  $z = 6.427$ ,  $p < 0.001$ , for H3). Most importantly, findings show that there is a direct effect of AI adoption on EI that still hold even when entrepreneurial competency is controlled in the model ( $\beta = 0.146$ ,  $p = 0.001$ ). This direct effect transfers the effect of AI adoption through other paths, namely those which technology intended to cover. In line with the technological-based entrepreneurial intention model (Dabbous & Boustani, 2023), one of these residual paths is perceived feasibility. Students who expose to AI believe that starting up a venture is less effort intensive and less barrier intensive.

We use a competency-based explanation for intentions to adopt AI that generalizes to law schools in Egypt (Moustafa et al., 2025) and medical schools in Saudi Arabia (Nuseir et al., 2020). The explanation applies in different settings, with different technologies, and in different cultures of higher education. Although the effect of the mechanism is presumably not the same in these distinct contexts, replication across them provides evidence that the mechanism is reasonably robust (Arkorful & Hilton, 2021).

### AI Literacy as an Independent Predictor, Not a Moderator

The hypothesis H4 was not supported. Interestingly, we found that AI literacy had a strong independent main effect on competency ( $\beta = 0.320$ ,  $p < 0.001$ ), and it was the second strongest predictor of entrepreneurial competency, surpassed only by AI adoption as a competency building input. Therefore, it seems that AI adoption and AI literacy are two parallel rather than interacting sources of competency building inputs.

This finding could have two alternative explanations. Firstly, the possible null interaction could be due to the possible restriction in range in terms of early adopters of AI, who on average scored in the moderate range on AI literacy ( $M = 3.578$ ,  $SD = 1.011$ ). Secondly, in a less technologically advanced setting like Ghana, adoption of AI could serve as a proxy for AI literacy differently than it does in more technologically advanced contexts with greater variance in AI literacy attainment (Yang et al., 2025).

### Implications for Policy and Practice

This research has a number of implications for universities with entrepreneurship programs and their students who are entrepreneurs using AI to grow their startups. Specifically, for universities, there are educational benefits when AI tools are provided to entrepreneurship students as part of regular curriculum as opposed to add-on resources. Additionally, there are educational benefits when students are educated on how to use AI while simultaneously being taught how to reap full benefits of AI tools. Finally, the AI

adoption-competency-intention pathway appears to be accessible to students in both co-educational and single-sex universities as well as men and women provided that there are no structural or other impediments that would preclude consistent and meaningful use of critical AI infrastructure (Hayes, 2018; Salifu, 2024).

### Limitations and Future Research

Although many efforts have been devoted to the study of Emotional Intelligence (EI) and Artificial Intelligence (AI) adoption and intentions in educational contexts, there remain some limitations in this study. Firstly, although every effort has been made to systematically investigate EI and AI adoption intentions in educational settings, the current study's limitations stem from the cross-sectional design of the study; therefore, it is possible that there are students with high EI who are motivated to adopt more AI in their academic work and studies. Secondly, although principal component extraction was used here as a proxy for CFA, true CFA would have allowed the reporting of several other key model fit indices such as the CFI, TLI and RMSEA; replication of the current study using a statistics program such as AMOS or the R lavaan package would provide a more complete assessment of the study's psychometric qualities. Finally, while the sample in the current study was primarily comprised of students less than 30 years of age (typical undergraduate age), future research could attempt to recruit a more mature, part-time student sample to generalise to.

### CONCLUSION

Despite the growing interest in the nexus between AI adoption and entrepreneurial intentions, the study remains a vacant terrain in the context of Ghana. This study thus sought to investigate whether there existed a positive relationship between university students' AI adoption and their entrepreneurial intentions, and further examine whether entrepreneurial competency (EC) maybe partially, acts as a mediator. Findings from the regression analyses revealed that there was a significant positive relationship between AI adoption and entrepreneurial competency (H1:  $\beta = 0.344$ ;  $p < 0.01$ ), and a positive relationship between entrepreneurial competency and entrepreneurial intentions (H2:  $\beta = 0.461$ ;  $p < 0.01$ ). Further findings showed that entrepreneurial competency (EC) partially mediated the total effect of AI adoption on EI (H3: 54.8%;  $p < 0.01$ ). Contrary to my expectations, findings showed that AI literacy (both self-rated and objective) did not affect the relationship between AI adoption and entrepreneurial competency (H4 and H5). However, AI literacy predicted entrepreneurial competency which thus entered the EI model as a parallel predictor rather than a moderator.

This study contributes a context specific model to the emerging body of evidence albeit with the majority of studies and models emanating from Asia and the Middle East. The competency-building model posits that AI adoption and AI-based AI education enhances EI and impacts EI intention through entrepreneurial literacy. Interestingly, the mediating role of entrepreneurial literacy holds even in a country with different infrastructure context to the rest of the world. The study has very practical implications for universities in Ghana and similar developing economies. Specifically, AI tools and AI education should not be treated as add-ons to the entrepreneurship curriculum but embedded as core elements in the mainstream of the entrepreneurship curriculum.

### Acknowledgement

I sincerely acknowledge the use of artificial intelligence tools in this work for grammatical correction and language refinement. The AI support helped improve sentence

clarity, spelling, punctuation, and general readability.

All ideas, analysis, interpretations, and conclusions presented in this work remain entirely my own. The use of AI was limited to editing support and did not replace my original thinking, academic judgment, or responsibility for the content.

I take full responsibility for any errors or omissions in this work.

## REFERENCES

- Abreh, M. K., Arthur, F., Akwetey, F. A., & Nortey, S. A. (2025). Modelling STEM students' intention to learn artificial intelligence (AI) in Ghana: a PLS-SEM and fsQCA approach. *Discover Artificial Intelligence*, 5(1), 223.
- Adu, I. N., Boakye, K. O., Suleman, A. R., & Bingab, B. B. B. (2020). Exploring the factors that mediate the relationship between entrepreneurial education and entrepreneurial intentions among undergraduate students in Ghana. *Asia Pacific Journal of Innovation and Entrepreneurship*, 14(2), 215-228.
- Agbemava, E., Agbanu, P. G., Kornu, D. D., & Okyere, B. (2025). Financial self-efficacy in aspiring entrepreneurs in Ghana: the moderating role of financial risk tolerance in predicting entrepreneurial intentions of university students. *Cogent Education*, 12(1), 2578875.
- Arkorful, H., & Hilton, S. K. (2021). Locus of control and entrepreneurial intention: a study in a developing economy. *Journal of Economic and Administrative Sciences*, 38(2), 333-344.
- Ayiku, A., Grant, E. S., & Mensah, P. K. (2022). Stimulating university student entrepreneurship: evidence from an African developing country. *Journal of Comparative International Management*, 25(2), 221-245.
- Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology*, 51(6), 1173.
- Bird, B. (1995). Toward a theory of entrepreneurial competency.
- Brislin, R. W. (1970). Back-translation for cross-cultural research. *Journal of cross-cultural psychology*, 1(3), 185-216.
- Dabbous, A., & Boustani, N. M. (2023). Digital explosion and entrepreneurship education: Impact on promoting entrepreneurial intention for business students. *Journal of Risk and Financial Management*, 16(1), 27.
- Duong, C. (2024). ChatGPT adoption and digital entrepreneurial intentions: An empirical research based on the theory of planned behaviour. *Entrepreneurial Business and Economics Review*, 12(2), 129-142.
- Duong, C. D., & Vu, T. N. (2025). Entrepreneurial education and higher education students' e-entrepreneurial intention: a moderated mediation model of generative AI incorporation and e-entrepreneurial self-efficacy. *Higher Education, Skills and Work-Based Learning*, 15(5), 1024-1048.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, 18(1), 39-50.
- Ha, S. T., Phan, T. T. H., Ngo, T. V. N., Duong, C. D., & Ha, N. T. (2025). Integrating artificial intelligence competencies into the theory of planned behavior: Explaining sustainability-oriented entrepreneurial intentions. *Journal of Entrepreneurship, Management and Innovation*, 21(4), 30-53.
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European business review*, 31(1), 2-24.
- Hayes, A. F. (2018). Mediation, moderation, and conditional process analysis. *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*, 1(6), 12-20.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, 43(1), 115-135.
- Kline, R. B. (2016). *Principles and practice of structural equation modeling*. Guilford publications.
- Krueger, N. F., & Carsrud, A. L. (1993). Entrepreneurial intentions: Applying the theory of planned behaviour. *Entrepreneurship & regional development*, 5(4), 315-330.
- Ledi, K. K., Ameza-Xemalordzo, E., & Owusu, J. (2022). The role of entrepreneurial attitude and opportunity recognition on entrepreneurial intention of university students. *International Journal of Entrepreneurial Knowledge*, 10(2), 54-67.
- 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.
- Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of applied psychology*, 86(1), 114.
- Long, D., & Magerko, B. (2020, April). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI conference on human factors in computing systems* (pp. 1-16).

- Mahama, I., Eshun, P., Amos, P. M., Antwi, T., Amoako, B. M., & Eggley, V. E. (2023). Psychological precursors of entrepreneurial intentions among higher education students in Ghana. *Discover Education*, 2(1), 29.
- Moustafa, A., Ragheb, M. A., Ayad, H., & AbdelAziz, K. (2025). The Impact of Generative AI Adoption on Digital Entrepreneurship Intentions among Egyptian University Students: Examining the Mediating Roles of Entrepreneurial Mindset and Business Model Innovation. *Pakistan Journal of Life & Social Sciences*, 23(1).
- Mustafa, M. J., Chin, J. W., Nungsari, M., & Morris, K. J. (2023). Do proactive students benefit more from university support for entrepreneurship when it comes to choosing entrepreneurship as a career choice? An examination of Ghanaian and Malaysian students. *The International Journal of Management Education*, 21(3), 100868.
- Nunfam, V. F., Asitik, A. J., & Afrifa-Yamoah, E. (2020). Personality, entrepreneurship education and entrepreneurial intention among Ghanaian students. *Entrepreneurship Education and Pedagogy*, 5(1), 65-88.
- Nunnally, J. C. (1978). *Psychometric Theory* 2nd ed: Mcgraw hill book company.
- Salifu, I., Arthur, F., Acquah, B. Y. S., Opoku, E., Northey, S. A., & Boateng, E. (2025). Exploring graduate students' use of generative artificial intelligence in Ghana: insights from an extended UTAUT2 model, PLS-SEM, IPMA and fsQCA. *Discover Education*, 4(1), 305.
- Salifu, I., Arthur, F., Arkorful, V., Abam Northey, S., & Solomon Osei-Yaw, R. (2024). Economics students' behavioural intention and usage of ChatGPT in higher education: A hybrid structural equation modelling-artificial neural network approach. *Cogent Social Sciences*, 10(1), 2300177.
- Sampene, A. K., Li, C., Khan, A., Agyeman, F. O., & Opoku, R. K. (2022). Yes! I want to be an entrepreneur: A study on university students' entrepreneurship intentions through the theory of planned behavior. *Current Psychology*, 42(25), 21578-21596.
- Sedegah, D. D., Nutsugbodo, R. Y., Arthur-Amisshah, A., Wireko-Gyebi, S., Duodu, G. A., Bempong, V. E. K., ... & Tuffour, M. (2024). Entrepreneurial intentions of tourism and hospitality students in Ghana: an application of the theory of planned behaviour. *Journal of Small Business and Enterprise Development*, 31(4), 724-741.
- Shi, J., Nyedu, D. S. K., Huang, L., & Lovia, B. S. (2024). Graduates' entrepreneurial intention in a developing country: The influence of social media and e-commerce adoption (SMEA) and its antecedents. *Information Development*, 40(1), 20-35.
- T. Nuseir, M., Basheer, M. F., & Aljumah, A. (2020). Antecedents of entrepreneurial intentions in smart city of Neom Saudi Arabia: Does the entrepreneurial education on artificial intelligence matter?. *Cogent Business & Management*, 7(1), 1825041.
- Twum, K.K., et al. (2021), "Individual entrepreneurial orientation, network ties and entrepreneurial intention among Ghanaian university students", *Journal of Entrepreneurship in Emerging Economies*.
- Xie, Y., & Wang, S. (2025). Generative artificial intelligence in entrepreneurship education enhances entrepreneurial intention through self-efficacy and university support. *Scientific Reports*, 15(1), 24079.
- Yang, H., Xu, N., Lin, X., & Zhang, W. (2025). Integrating AI literacy into the TAM-TPB model to explain students' intention to use educational AI through MASEM approach. *Computers in Human Behavior Reports*, 100833.
- Zhao, H., et al. (2019), "Psychological capital, entrepreneurial capital and entrepreneurial intention: a moderated mediation study", *Frontiers in Psychology*, Vol. 10, p. 908.
- Zou, X. and Guo, Y. (2026), "How AI usage shapes entrepreneurial intention among undergraduates: a dual-pathway model based on the theory of planned behavior", *Journal of Business Venturing Insights*.

**Received:** 22-Apr-2026, Manuscript No. AMSJ-26-17217; **Editor assigned:** 23-Apr-2026, PreQC No. AMSJ-26-17217(PQ); **Reviewed:** 07-May-2026, QC No. AMSJ-26-17217; **Revised:** 14-May-2026, Manuscript No. AMSJ-26-17217(R); **Published:** 22-May-2026