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The Effects Of AI Anxiety, Intrinsic Motivation, Self-Efficacy, And Critical Thinking On Students' Intention To Use AI: The Mediating Role Of Experience Using AI In Entrepreneurship Programs

Analisis Pengaruh Faktor Afektif Dan Kognitif Terhadap Niat Menggunakan AI: Peran Mediasi Pengalaman Menggunakan AI Pada Mahasiswa Kewirausahaan

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ABSTRACT
This study analyzes how affective factors anxiety, self-efficacy, motivation, and critical thinking influence entrepreneurial skill development through Artificial Intelligence (AI) integration, examining variations between short-term (<3 months) and long-term (>1 year) exposure. Findings from a survey of 344 students at UPN "Veteran" East Java reveal that while initial AI use triggers anxiety, long-term exposure significantly boosts self-efficacy, motivation, and critical thinking, with over one year of experience fostering the most confidence. The study concludes that AI exposure duration is a critical determinant in stabilizing these factors, highlighting the need for early-stage support to mitigate anxiety and accelerate skill development.
Keywords: *Artificial Intelligence, Entrepreneurial Skills, Affective Factors, Self-Efficacy, Entrepreneurship Programs.*

ABSTRAK
Studi ini menganalisis bagaimana faktor afektif seperti kecemasan, efikasi diri, motivasi, dan berpikir kritis memengaruhi pengembangan keterampilan kewirausahaan melalui integrasi Kecerdasan Buatan (AI), dengan meneliti variasi antara paparan jangka pendek (<3 bulan) dan jangka panjang (>1 tahun). Temuan dari survei terhadap 344 mahasiswa di UPN "Veteran" Jawa Timur mengungkapkan bahwa meskipun penggunaan AI awal memicu kecemasan, paparan jangka panjang secara signifikan meningkatkan efikasi diri, motivasi, dan berpikir kritis, dengan pengalaman lebih dari satu tahun menumbuhkan kepercayaan diri yang paling tinggi. Studi ini menyimpulkan bahwa durasi paparan AI merupakan penentu penting dalam menstabilkan faktor-faktor tersebut, menyoroti perlunya dukungan sejak dini untuk mengurangi kecemasan dan mempercepat pengembangan keterampilan.
Kata Kunci: Kecerdasan Buatan, Keterampilan Kewirausahaan, Faktor Afektif, Efikasi Diri, Program Kewirausahaan.

1. Introduction

The advent of AI artificial intelligence has fundamentally changed the business landscape, creating a new era known as digital entrepreneurship. Entrepreneurial development programs are increasingly integrating AI as a key tool for idea exploration, market analysis, and product innovation. The massive integration of AI Artificial Intelligence technology, is a phenomenon that currently shows a significant paradigm shift in the entrepreneurial environment. With the entry of Artificial Intelligence (AI) into the higher education ecosystem, the way students acquire business competencies has changed. AI is now a crucial part of business model innovation, and not just as a support tool. However, according to (Chalmers et al., 2021), although AI is capable of automating cognitive tasks, the role of humans in terms of intuition and entrepreneurial psychology remains irreplaceable, resulting in new challenges in the interaction between technology and humans.

Although AI has exceptional analytical capabilities, the user's affective and cognitive variables play a crucial role in determining whether AI output can lead to effective business insights and decisions. This creates a complexity where the user's psychological response to the technology's performance conflicts. Psychological barriers often hinder the use of AI in entrepreneurship programs. According to (Chiu, 2021), the success of AI adoption is highly dependent on the affective involvement of users. If students feel anxious or threatened by the technology, their self-efficacy in entrepreneurship can decrease. Fear of job displacement creates anxiety that hinders technology adoption (Budhwar et al., 2023). They argue that the perception of AI as a threat influences economic behavior. This concept explains that increased revenue will increase consumption, but not proportionally, thereby increasing the risk of dependence on AI.

One of the biggest impacts of such dependency is the degradation of critical thinking skills. (Cui et al., 2021) state that AI can help in designing business strategies, but it also leads to an increase in rapid and less in-depth decision-making. This creates a paradox because although AI speeds up the process, it may directly reduce the sharpness of analysis, which is crucial for an entrepreneur when facing market risks. Various studies have shown a positive correlation between AI technology and operational efficiency. However, there are still few studies that explore the influence of affective and cognitive factors on AI-based business outcomes such as psychological barriers (anxiety). Research shows that technology anxiety is the most significant psychological barrier to technology acceptance. This anxiety prevents people from understanding concepts as well as making deep use of AI analytics features, which ultimately reduces the effectiveness of learning. Those with high anxiety may still use technology, but often only use it in a simple and in-depth way. Cognitive and affective drivers (Motivation and Critical Thinking), critical thinking and intrinsic motivation are the main drivers. Critical thinking is an important ability to interpret, evaluate, and validate AI outputs so as not to mislead, while high motivation predicts deeper and exploratory engagement. Then the control variable (Implementation Duration) because the implementation time is an important factor in determining the extent to which the use of technology affects a person's level of comfort and acceptance. If done quickly, implementation can reduce the negative impact of anxiety and on the contrary increase motivation and critical thinking.

Users' perspectives on AI challenges are dynamic and are heavily influenced by the length of their interaction with the technology, where there are significant differences between individuals who have recently been exposed to it and those who have been integrating it for a long time. Therefore, this study aims to test an integrative model that places the duration of AI implementation as a mediating variable that bridges the relationship between affective, cognitive, and entrepreneurial ability development factors. Based on this theoretical framework, this study specifically examines whether technology anxiety has a negative effect on the development of entrepreneurial skills (H1), as well as whether motivation (H2) and critical thinking (H3) have a significant positive influence. In addition, this study also investigates the long-standing role of AI implementation in mediating the relationship between these three variables on the development of entrepreneurial skills (H4) in order to produce more adaptive entrepreneurial programs in the future.

2. Literature Review

The Affective and Self-Efficacy Landscape in AI Adoption (The Affective Turn)

The integration of Artificial Intelligence (AI) in the entrepreneurial ecosystem marks a paradigm shift from simply digitization as a tool to AI as an autonomous collaborative partner (Chalmers et al., 2021). However, this transition triggers affective dynamics that are more complex than conventional technologies, often referred to as "AI Anxiety". Therefore, understanding the emotional dimension is crucial because the current literature still focuses too much on technical capabilities and often ignores the human side of entrepreneurs (Budhwar et al., 2023). To mitigate the negative impact of anxiety, the role of self-efficacy emerges as the main *buffer* that encourages resilience and active participation in the digital economy (Prameswara, 2025). Self-efficacy in the context of AI has to do not only with technical skills, but also with an individual's confidence to manage complex interactions with machines in business decision-making (Puriwat & Hoonsopon, 2022). Students with high self-efficacy tend to view AI as a catalyst for the identification of opportunities, rather than as a threat to their autonomy (Duong et al., 2024). By combining critical thinking as a meta-competence, individuals can validate AI *outputs* skeptically but productively, so that entrepreneurial intentions are maintained even in the midst of technological uncertainty (Cui et al., 2021; Liu et al., 2023).

In contrast to the adoption of ordinary technology, AI triggers specific concerns regarding the complexity of algorithms and fears of replacing human roles (F. Wang et al., 2023). This anxiety acts as a significant psychological barrier when students feel threatened by losing control over the creative process, their intention to adopt technology in entrepreneurship will decrease (ABAH et al., 2025; Chiu, 2021). Research shows that anxiety about technology creates significant psychological barriers. When students feel threatened by the complexity of AI algorithms, their self-efficacy tends to decline, which ultimately weakens their intention to engage in digital entrepreneurship (ABAH et al., 2025; F. Wang et al., 2023). This anxiety acts as a cognitive inhibitor that hinders the exploration of business opportunities. Self-efficacy emerged as the main buffer that encourages resilience in the digital economy (Prameswara, 2025). Students with high self-efficacy tend to view AI as a catalyst for the identification of opportunities, rather than as a threat to their autonomy (Duong et al., 2024). Confidence in one's abilities determines whether an entrepreneur will adopt AI productively (F. Wang et al., 2023).

Motivation and Autonomy in AI Adoption for Entrepreneurs

The application of Artificial Intelligence (AI) in the realm of entrepreneurship has evolved from just a digitalization tool to a strategic integration component that functions as a collaborative partner (Chalmers et al., 2021; Vial, 2019). In this context, *Self-Determination Theory* (SDT) provides a crucial framework for understanding how the need for competence and autonomy affects entrepreneurs' interactions with technology (Ryan & Deci, 2000). However, the presence of AI creates a paradox of autonomy while AI can make entrepreneurs feel more empowered through increased cognitive capabilities, there is a risk of dependency that can hinder decision-making independence if not managed with strong self-efficacy (Puriwat & Hoonsopon, 2022).

Despite its transformative potential, there is a significant gap in the current literature that tends to focus too much on the development of *technical skills* alone (Budhwar et al., 2023). This technocentric approach often ignores the human side of entrepreneurial actors, such as affective dynamics and the perception of individual autonomy in the digital ecosystem (Chiu, 2021). In fact, environmental support and belief in *self-efficacy* greatly determine whether an entrepreneur will adopt AI productively or experience obstacles due to technological anxiety (F. Wang et al., 2023). Therefore, future research needs to bridge this gap by integrating psychological and social perspectives to understand how AI can strengthen entrepreneurs' identity and resilience without sacrificing human control over their business vision (Guerrero & Walsh, 2024; Martinez Dy, 2022).

Critical Thinking as a Meta-Competency in the Era of Automation

The transition from digitalization as a tool to the integration of AI as a collaborative partner has transformed the landscape of opportunity identification in entrepreneurship (Chalmers et al., 2021; Vial, 2019). However, this evolution raises a paradox between the speed of automation and the need for validation. When AI offers instant solutions, entrepreneurs are faced with the challenge of maintaining productive skepticism towards *algorithmic outputs*

(Dwivedi et al., 2021). Critical thinking is no longer just an additional cognitive skill, but rather a meta-competency that mediates the relationship between technology use and entrepreneurial intentions (Liu et al., 2023). Although the transformative potential of AI is enormous, the current literature is considered to be too focused on developing technical *skills* and tends to ignore the human side and cognitive maturity of entrepreneurs (Budhwar et al., 2023). Therefore, the position of AI must be shifted from just an execution tool to a "dialectical partner" that triggers a dialectic of critical thinking and evaluation through *chatbot-based* interactions and other intelligent systems (Fabio et al., 2025; Short & Short, 2023).

Temporal Dimensions and Learning Curves in AI Adoption

The temporal dimension plays a crucial role in determining how entrepreneurs integrate artificial intelligence technology, where the duration of interaction or exposure gradually changes an individual's perception of technology (Vial, 2019). This transition reflects the evolution from an initial stage of digitalization that was only experimental in nature to deep integration where AI acts as a collaborative partner in the process of identifying business opportunities (Chalmers et al., 2021; Nambisan, 2017). The continued integration of AI in entrepreneurial programs requires an understanding of how affection and metacognition evolve over time so that interactions do not create dependence, but rather increase strategic independence (Chiu, 2021). Without considering this temporal aspect, the effectiveness of AI as an external enabler will not reach its maximum potential in creating resilient ventures (Davidsson & Sufyan, 2023). Therefore, a holistic approach is needed that views AI exposure as an experiential learning process that permanently strengthens self-efficacy and digital entrepreneurial intentions (Puriwat & Hoonsopon, 2022; Rahmi, 2024).

Hypothesis Development

H1: AI Anxiety has a negative and significant effect on entrepreneurial intentions

H2: Self-Efficacy has a positive and significant effect on entrepreneurial intentions digital

In the context of AI, students with high self-efficacy do not see AI as a threat to autonomy, but rather as a strategic catalyst for the identification of opportunities (Duong et al., 2024; Prameswara, 2025). This belief strengthens the individual's intention to continue to innovate even in situations of uncertainty. Therefore, the integration between the management of affective aspects (anxiety) and the strengthening of cognitive aspects (self-efficacy) is the main foundation for the success of entrepreneurship education programs. Students who are able to mitigate anxiety through strong self-confidence will have more stable entrepreneurial intentions even in the midst of the uncertainty of AI technology development (Duong et al., 2024).

H3: Intrinsic motivation has a positive and significant effect on the intention of AI adoption and the development of entrepreneurial skills.

Intrinsic motivation is a key driver in AI learning, where AI acts as a catalyst that accelerates the identification of opportunities and the efficiency of business decision-making (Davidsson & Sufyan, 2023; Shepherd & Majchrzak, 2022). Conversely, a lack of intrinsic motivation and perception of AI as a technical burden can lower a person's intention to adopt the technology productively (Cui et al., 2021; F. Wang et al., 2023). Based on the argument regarding the central role of motivation in overcoming affective barriers, a hypothesis is proposed.

H4: Critical thinking has a positive and significant effect on entrepreneurial intentions through strengthening strategic validation.

Critical thinking acts as a meta-competence that mediates the relationship between technology use and entrepreneurial intentions (Liu et al., 2023). Individuals who are able to integrate deep reflection with the speed of AI automation will have a competitive advantage in validating complex business opportunities (Cui et al., 2021). As a result, critical thinking skills ensure that the use of AI remains within the strategic control of humans which reinforces the intention to be entrepreneurial.

H5: The duration of implementation (temporal dimension) mediates the relationship between affective-cognitive variables on the development of entrepreneurial abilities and intentions.

However, the current literature still shows significant gaps because it focuses more on short-term technical outcomes and ignores the human side and cognitive development of entrepreneurs in the learning curve (Budhwar et al., 2023). In line with this argument, the duration of exposure to AI gradually mitigates anxiety and strengthens self-efficacy and digital entrepreneurial intentions (Puriwat & Hoonsopon, 2022). As a result, the temporal dimension acts as a variable that bridges the user's adaptation process from the experimental stage to sustainable strategic use.

3. Research Methods

This study uses a quantitative approach with a causal-comparative design through a cross-sectional survey. The focus of the study was to examine the influence of affective factors (anxiety, motivation, and critical thinking) on the intention to use AI, with long mediation of AI implementation. This approach was chosen because of its ability to capture certain behavioral phenomena in the higher education environment at a given point (Anthonysamy & Singh, 2025).

Complex structural relationships and mediating effects were tested simultaneously through partial least squares structural equation modeling (PLS-SEM) data analysis (Hair et al., 2021). Based on its explanatory nature, this study is categorized as causal associative research, which is research that seeks cause-and-effect relationships between independent, mediator, and dependent variables.

Sampling And Data Collection

The population of this study includes all students of the Entrepreneurship Study Program at UPN Veteran East Java. The sampling technique used is purposive sampling. The main inclusion criteria are students who have been exposed to or used AI technology in their curriculum or entrepreneurial projects during the study period, categorized by cohort (20222025). The use of the force as a proxy for the old implementation is based on the assumption that older generation students have longer exposure to technology in the campus ecosystem than the newer generation.

These experiences are considered to be important factors that shape affective perceptions, such as decreased anxiety or increased critical skills, as well as increasing their intentions to use AI in a sustainable manner. The total sample includes 344 students from different academic years to reflect the different phases of study. In line with logic
(Anthonysamy & Singh, 2025).

Measurements

The measurement of variables in this study was conducted using questionnaire instruments adapted from previous studies and adjusted to the context of Artificial Intelligence use in entrepreneurship learning. These instruments were selected due to their established validity and reliability in measuring research constructs (Chan & Hu, 2023; Dwivedi et al., 2023).All items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), which effectively captures respondents' perceptions and attitudes. This scale is widely used in studies related to technology adoption, creativity, and user behavior in higher education (Kasneci et al., 2023).

The measurement indicators were adapted without altering their conceptual meaning to ensure relevance to students as AI users in academic and creative contexts, while maintaining theoretical consistency (Park et al., 2025). This perception-based approach is appropriate as the study focuses on students' subjective experiences in facing AI usage challenges and their impact on cognitive processes and creativity (Syam et al., 2025).

Operational Definitions Of Variables

The challenge of AI Anxiety

Anxiety regarding AI use is measured through indicators related to individuals' levels of worry, discomfort, fear, and self-doubt when using AI technology. These indicators include anxiety when operating AI, concerns about misuse, fear of AI outcomes, and discomfort when interacting with AI-based technology.

The challenge of Self Efficacy

Self-efficacy is measured based on an individual's belief in their ability to use AI technology. This variable encompasses the ability to operate AI, solve problems while using AI, understand AI features, and feel confident in utilizing AI to support daily activities.

The challenges of Motivation Intrinsic

Intrinsic motivation is measured based on an individual's internal drive to use AI technology without pressure from others. This variable is measured using several indicators, including interest in using AI, enjoyment of using AI, desire to learn how to use AI, and personal satisfaction derived from using AI technology.

The challenges of Critical Thinking

Critical thinking is measured through an individual's ability to analyze, evaluate, and consider information obtained from AI before using it in decision-making. This measurement is carried out using indicators such as the ability to evaluate AI responses, compare information, and verify the accuracy of AI-generated results.

AI Experience

The AI experience variable is measured based on an individual's level of experience and involvement in using Artificial Intelligence technology. This variable includes frequency of AI use, duration of AI use, understanding of AI features, and experience using various types of AI-based applications.

Behavioral Intention

The intention to use AI variable is measured based on an individual's desire and tendency to continue using AI technology in the future. This measurement is carried out using indicators such as the desire to use AI continuously, interest in trying other AI features, and plans to use AI in daily activities.

Figure 1 illustrates a structural model depicting the relationships between the research constructs. This study used four main variables: AI anxiety, self-efficacy, intrinsic motivation, and critical thinking. The four dimensions of AI challenges presented directly influence the intention to use AI, which is positioned as the outcome variable in this study. The variable of experience using AI serves as a mediating variable connecting the independent and dependent

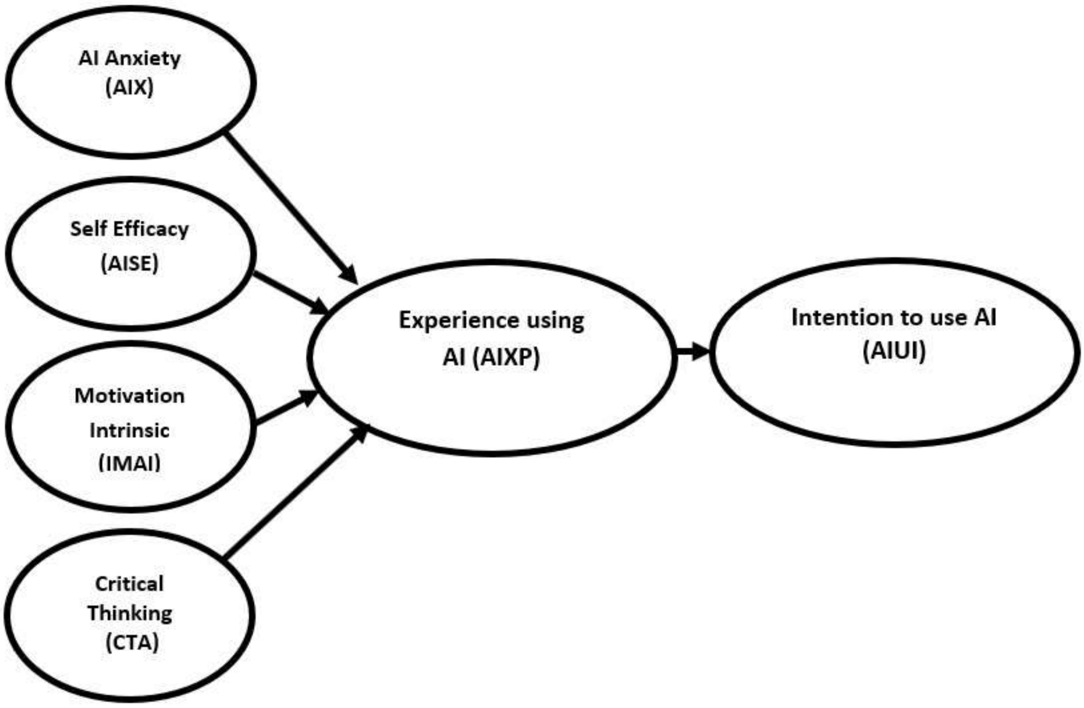

Figure 1. Structural model results

Data Analysis Techniques

The data that has been collected is analyzed using the Structural Equation Modeling–Partial Least Squares (SEM-PLS) approach. This method was chosen because it is able to analyze the relationship between latent variables simultaneously and is suitable for research with predictive models and a relatively limited number of samples.

4. Results and Discussions

Results

Participants

The demographic characteristics of the respondents in this study are presented in the table 1, table describes the distribution of respondents.

Table 1. Respondent demographic profile

Characteristics	Category	Frequency	Percentage (%)
Gender	Male	186	55
	Female	152	45
Age	<18	54	16
	19-20	200	59
	21-22	80	24
	>23	4	1
College Semester	1-2	125	37
	3-4	91	27
	5-6	87	26
	7	35	10
Entrepreneurial Status	Pre-venture stage.	229	68
	In the launch phase.	90	27

Operating an active venture.	19	5

Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) was conducted using the PLS-SEM approach to develop the measurement model, including outer loadings, Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE). This analysis aimed to ensure that each indicator validly and reliably represents its respective latent construct: independent variables: AI anxiety, self-efficacy, intrinsic motivation, critical thinking, and intention to use AI (dependent variable). Experience using AI served as a mediating variable.

Based on the results of the convergent validity test, there are two indicators that have outer loading values below 0.50-0.70, namely the AI anxiety variable which has an outer loading value of 0.478 in AIX4 and 0.544 in AIX1. However, this indicator is maintained because the AVE and composite reliability values still meet the established criteria. In addition, most other indicators have stable outer loading values above 0.50-0.70 so that the research construct is declared quite valid. The results of the intrinsic motivation and critical thinking tests have values that have met the requirements, namely above 0.70. Self-efficacy has a very stable value above 0.80 (range 0.776-0.839). The intention to use AI also shows that all indicators are above 0.70 (range 0.776-0.892). This indicates its very good validity. And experience using AI has the highest value above 0.80 (range 0.844-0.866). Detailed outer loading results are presented in Table 2.

Discriminant And Convergent Validity

Convergent Validity

Convergent validity in this study was evaluated using outer loading, Composite Reliability (CR), and Average Variance Extracted (AVE) within the PLS-SEM framework. Based on the Average Variance Extracted (AVE) test results, all variables had AVE values above 0.50. However, one variable, AI anxiety, had an AVE value below 0.50. Nevertheless, this variable can still be retained because it has a Cronbach's Alpha (CA) and Composite Reliability (CR) value above 0.70, thus the research construct is still considered reliable. Thus, overall, the variables in this study are still suitable for further analysis.

Discriminant Validity

The Fornell-Larcker Criteria and the Heterotrait Monotrait Ratio (HTMT) are used to evaluate. According to the study (Hair et al., 2021), the Fornell and Larcker criteria cannot be used alone as a marker of discriminant validity if the weight of the indicators in a construct is quite different. Another metric used in SmartPLS to evaluate discriminant validity is the Heterotrait Monotrait correlation ratio (HTMT). This metric helps researchers determine whether the constructs in the model have a noticeable difference from each other. Based on the results of the discriminant validity test using the Heterotrait Monotrait Ratio (HTMT) criteria in Table 4, all ratio values between variables were below the threshold of 0.90. The highest ratio value was found in the relationship between Intrinsic MotivationTo Use AI and AI Usage Intention of 0.841, which remains conservatively qualified, below 0.85. Thus, it can be concluded that each construct in this research model has good discriminant validity, which means that each latent variable is statistically completely different from each other.

Table 2. Outer Loadings

Item	Sig.	Standart (<0,05)	Information
AIX1	0,544	<0,05	Valid
AIX2	0,818	<0,05	Valid
AIX3	0,622	<0,05	Valid
AIX4	0,559	<0,05	Valid
AIX5	0,478	<0,05	Valid

AIX6	0,685	<0,05	Valid
IMAI1	0,688	<0,05	Valid
IMAI2	0,797	<0,05	Valid
IMAI3	0,831	<0,05	Valid
IMAI4	0,795	<0,05	Valid
IMAI5	0,859	<0,05	Valid
AISE1	0,768	<0,05	Valid
AISE2	0,839	<0,05	Valid
AISE3	0,815	<0,05	Valid
AISE4	0,835	<0,05	Valid
AISE5	0,829	<0,05	Valid
CTAI1	0,772	<0,05	Valid
CTAI2	0,767	<0,05	Valid
CTAI3	0,830	<0,05	Valid
CTAI4	0,815	<0,05	Valid
CTAI5	0,746	<0,05	Valid
AIXP1	0,844	<0,05	Valid
AIXP2	0,863	<0,05	Valid
AIXP3	0,866	<0,05	Valid
AIUI1	0,827	<0,05	Valid
AIUI2	0,891	<0,05	Valid
AIUI3	0,892	<0,05	Valid
AIUI4	0,776	<0,05	Valid
AIUI5	0,844	<0,05	Valid

Table 3. Construct Reliability & Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI Usage Intention (AIUI)	0.754	0.807	0.927	0.718
Self-Efficacy (AISE)	0.821	0.825	0.910	0.668
Intrinsic Motivation (IMAI)	0.901	0.908	0.896	0.633
AI Experience (AIXP)	0.848	0.857	0.893	0.736
Critical Thinking (CTAI)	0.855	0.868	0.890	0.619
AI Anxiey (AIX)	0.876	0.877	0.791	0.349

Correlation

Correlation analysis was conducted to examine the direction and strength of the relationships between latent constructs using a PLS-SEM correlation matrix. Based on the results of the correlation test, the independent variables were related to both the mediating and dependent variables. Self-efficacy had a strong relationship with experience using AI, with a correlation value of 0.616, which is considered strong. Intrinsic motivation had a strong relationship with experience using AI, with a correlation value of 0.620, and critical thinking had a moderately strong relationship with experience using AI, with a correlation value of 0.428.

Meanwhile, experience using AI had a strong relationship with intention to use AI, with a correlation value of 0.711, which is considered strong. These results indicate that experience using AI has a strong relationship in influencing intention to use AI.However, some variables had very weak correlations, such as the relationship between AI anxiety and experience using AI, with a correlation value of -0.100. This value indicates a relationship in the opposite direction, with a very weak correlation, so the influence between the variables is not significant.

Table 4. Latent Variable Correlations

	AI Anxiey (AIX)	**AI Experience (AIXP)**	**AI Usage Intention (AIUI)**	**Critical Thinking (CTAI)**	**Intrinsic Motivation (IMAI)**	**Self-Efficacy (AISE)**
AI Anxiey (AIX)	1.000	-0.100	-0.075	-0.040	-0.143	-0.141
AI Experience (AIXP)	-0.100	1.000	0.722	0.428	0.620	0.616
AI Usage Intention (AIUI)	-0.075	0.722	1.000	0.495	0.739	0.641
Critical Thinking (CTAI)	-0.040	0.428	0.495	1.000	0.538	0.438
Intrinsic Motivation (IMAI)	-0.143	0.620	0.739	0.538	1.000	0.721
Self-Efficacy (AISE)	-0141	0.616	0.641	0.438	0.721	1.000

Hypothesis Testing

Hypothesis testing in this study was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with a bootstrapping procedure to evaluate the influence of each construct. Evaluation criteria included path coefficients (original sample), t-statistics, and p-values, with a significance level of 5% (α = 0.05).

As presented in Table 5, the analysis results show that AI anxiety has a coefficient value of -0.002 with a significance value of 0.976 (>0.05), and critical thinking has a coefficient value of 0.109 with a significance value of 0.073 (>0.05). This indicates that AI anxiety and critical thinking do not significantly influence AI usage intentions. Although the direction of the relationship is negative, the effect is very weak and not statistically significant (not accepted).

Conversely, the challenge of using AI has a coefficient value of 0.722 with a significance value of 0.000 (<0.05). This indicates that experience using AI has a positive and significant effect on AI usage intentions. This indicates that the hypothesis is accepted. Intrinsic motivation has a coefficient value of 0.317 with a significance value of 0.000 (<0.05). Similarly, self-efficacy has a coefficient value of 0.340 with a significance value of 0.000 (<0.05).

Overall, the findings indicate that only experience using AI has a significant influence on intention to use AI. This suggests that intrinsic motivation and self-efficacy play a more dominant role than AI challenge anxiety and critical thinking in shaping students' creative exploration.

Table 5. Path Coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI Anxiey (AIX)> AI Experience (AIXP)	-0.002	-0.016	0.073	0.031	0.975
AI Experience (AIXP)> AI Usage Intention (AIUI)	0.722	0.721	0.032	22.237	0.000
Critical Thinking (CTAI)> AI Experience (AIXP)	0.109	0.111	0.063	1.721	0.086
Intrinsic Motivation (IMAI)> AI Experience (AIXP)	0.317	0.313	0.075	4.217	0.000
Self-Efficacy (AISE)> AI Experience (AIXP)	0.340	0.339	0.066	5.185	0.000

Discussion

This study aims to analyze the influence of affective and cognitive factors on intention to use AI and use experience as a mediator. The results indicate that not all dimensions play an equal role in influencing intention to use AI. Specifically, self-efficacy, intrinsic motivation, and intention to use AI were shown to have significant effects, while experience with AI significantly influenced intention to use AI. AI anxiety and critical thinking, however, did not show significant effects.

a) The Effect of AI Anxiety on AI Experience

The results of the hypothesis testing indicate that AI anxiety does not significantly influence AI experience. This is demonstrated by a path coefficient of -0.002 with a p-value of 0.976 <0.05. This indicates that students, as part of the digital generation, no longer view AI as a threat but rather as a relevant tool for entrepreneurship learning. These findings align with research by Venkatesh et al., 2023, published in the journal MIS Quarterly, which states that the younger generation focuses more on the practical benefits of technology than on fear.

b) The Influence of Self-Efficacy on AI Experience

The Based on the results of the hypothesis testing, self-efficacy has a positive and significant influence on AI experience. This is indicated by a path coefficient of 0.340 with a p-value of 0.000 < 0.05. Thus, the hypothesis of the influence of self-efficacy on AI experience is accepted. These results indicate that increased self-efficacy plays a role in supporting a more optimal AI experience. This research finding supports the theory that self-confidence in using technology increases student engagement in AI use (Kusuma Wardani & Usman, 2022).

c) The Influence of Intrinsic Motivation on AI Experience

Based on the results of the hypothesis test, intrinsic motivation has a positive and significant influence on AI experience. This is indicated by a path coefficient of 0.317 with a p-value of 0.000 < 0.05. These results indicate that higher intrinsic motivation leads to increased AI experience. This finding indicates that internal drive drives independent exploration and mastery of technology (Nwosu et al., 2022).

d) The Effect of Critical Thinking on AI Experience

Based on the data analysis, critical thinking did not have a positive and significant effect on AI experience, with a path coefficient of 0.109 and a p-value of 0.073 < 0.05. Therefore, the hypothesis of the effect of critical thinking on AI experience is rejected. These results indicate that improving critical thinking has not significantly improved AI experience. Critical thinking has not made a strong contribution to the formation of the mediating variable (AI experience). The findings of this study indicate that students tend to utilize AI for efficiency rather than conducting in-depth evaluation of the resulting output (Monllor et al., 2021).

e) The Effect of AI Experience on Intention to Use AI

The test results show that AI experience has a positive and significant effect on intention to use AI. The path coefficient of 0.722, with a p-value of 0.000 <0.05, indicates that the hypothesis is accepted and is the strongest relationship in this model. This means that greater experience using AI leads to increased intention to use AI. AI experience plays a crucial role in increasing intention to use AI because it acts as a link between the independent variables (AI anxiety, intrinsic motivation, self-efficacy, and critical thinking) and the dependent variable (intention to use AI). Theoretically, this confirms that direct experience using AI is a key factor driving the intention to use technology sustainably (Dwivedi et al., 2021).

5. Conclusion

This research confirms that the integration of Artificial Intelligence (AI) in the student entrepreneurship ecosystem is no longer just a technical choice, but a strategic imperative driven by practical experience and affective power. Key findings prove that AI experience is the strongest predictor of intentional use of technology in a sustainable manner (B = 0.772, P = 0.000), which validates that regular exposure is able to turn skepticism into strategic adoption (Chalmers et al., 2021; Dwivedi et al., 2021). Assertively, this study rejects the assumption that technology anxiety (AI Anxiety) is the main obstacle for the digital generation; instead, students view AI as an inevitable curriculum instrument. This proves that self-efficacy and intrinsic motivation are much more crucial in shaping digital entrepreneurial behavior than just fear of automation (Prameswara, 2025; Puriwat & Hoonsopon, 2022).

However, this integration leaves a critical gap in the meta-competency aspect. While intrinsic motivation and self-efficacy have driven interactions with AI, there is a tendency for students to prioritize speed of results over in-depth validation. The fact that critical thinking has not been optimally monitored in practical use indicates the risk of eroding the integrity of business decisions (ABAH et al., 2025). Therefore, AI must be repositioned not only as an efficiency tool, but as a dialectical partner that demands full human cognitive involvement (Short & Short, 2023). The success of future digital entrepreneurs will not be determined by how sophisticated the technology they use, but rather by how resilient their human autonomy and critical evaluation acumen are in directing the output of the algorithm (Liu et al., 2023; Shepherd & Majchrzak, 2022).

As a recommendation for the future, educational institutions need to redesign the entrepreneurship curriculum by shifting the focus from teaching technical skills (how to) to developing meta-competencies of critical thinking and AI ethics. This step is important so that students do not only become passive users, but also become algorithmic supervisors who are able to validate opportunities independently. In addition, psychological-based interventions are needed through business incubation programs that include growth mindset training and technostress management to ensure entrepreneurial resilience is maintained in the midst of technological fluctuations (Duong et al., 2024; Guerrero & Walsh, 2024). Finally, further research is recommended to use a longitudinal approach to explore the temporal dimension in more depth, so that it can be known whether the integration of AI in the long term really strengthens entrepreneurial autonomy or actually creates systemic dependency that has the potential to undermine original creativity.

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