From AI to startup "Dreams": How confidence and cost shape entrepreneurial intentions among accounting students

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Abstract

This study examines how AI-related capabilities influence entrepreneurial intention through the role of entrepreneurial self-efficacy and cost mindfulness among accounting students. The study focuses on three dimensions of AI capability, including AI ambidexterity, AI literacy, and AI utilisation, to understand how these elements contribute to the development of perceived entrepreneurial ability. Data were collected from university students and analysed using SmartPLS to assess both measurement and structural models. Practically, we used questionnaires distributed to accounting students in a particular university. In terms of the research procedure, the data collection process was carried out through direct engagement with students. The findings show that AI ambidexterity, AI literacy, and AI utilisation have significant relationships with entrepreneurial self-efficacy, highlighting that different forms of capability contribute in complementary ways. Entrepreneurial self-efficacy is also found to have a significant effect on entrepreneurial intention and mediates the relationship between AI-related capabilities and intention. In contrast, cost mindfulness does not show a direct effect on entrepreneurial intention, although it plays a moderating role in shaping how self-efficacy translates into intention. These results suggest that entrepreneurial intention is formed through a process where capability is interpreted as confidence before influencing action. The study contributes to lietrature by offering a more integrated understanding of how technological capability, self-perception, and resource awareness interact in shaping entrepreneurial intention in a digital context.

Keywords: *AI ambidexterity, AI literacy, entrepreneurial self-efficacy, cost mindfulness, entrepreneurial intention*

Introduction

The growing presence of artificial intelligence in everyday activities has begun to reshape how individuals learn, work, and make decisions. In educational settings, students are increasingly exposed to AI tools that support analysis, problem solving, and efficiency (Fossen et al., 2024; Kumar et al., 2025). This situation creates a new context in which technological capability becomes closely linked to how individuals perceive their own potential, including within entrepreneurial pathways (Kashive et al., 2020). Understanding this connection is important because entrepreneurship is often driven by how individuals evaluate their own ability to act under uncertainty (Güner et al., 2025; Duong and Vu, 2025). When students interact with AI in meaningful ways, they are not only gaining technical skills, they are also forming beliefs about what they can achieve (Fossen et al., 2024; Kumar et al., 2025). This makes it important to explore how different forms of AI-related capability contribute to entrepreneurial development, especially through the role of entrepreneurial self-efficacy, which has been widely recognized as a key driver of entrepreneurial intention (Güner et al., 2025; Duong & Vu, 2025).

There is a clear urgency to understand how educational institutions can prepare students

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for a rapidly changing digital environment (Fossen et al., 2024; Kashive et al., 2020). Many universities have introduced AI-related content but the focus often remains on technical knowledge without fully considering how this knowledge translates into confidence and action (Kumar et al., 2025). At the same time, students face increasing pressure to be innovative and self-reliant in uncertain economic conditions, where entrepreneurship becomes an important option (Duong and Vu, 2025). This creates a need to design learning experiences that strengthen students' belief in their ability to apply those skills in real situations (Güner et al., 2025). In this context, examining AI ambidexterity, AI literacy, and AI utilization becomes relevant because these variables capture different ways students engage with AI, from understanding to application and flexibility (Kumar et al., 2025; Fossen et al., 2024; Kashive et al., 2020). In addition, cost mindfulness reflects how students think about resources, which is important in shaping realistic and sustainable entrepreneurial decisions (Kicova et al., 2025; Tran et al., 2024).

Despite these developments, an important question remains unanswered. Previous studies show that AI-related capabilities can improve entrepreneurial outcomes (Fossen et al., 2024; Kumar et al., 2025). However, they give limited attention to how these capabilities become entrepreneurial intention. Most studies assume that students who have stronger AI capabilities will naturally develop stronger entrepreneurial intention (Fossen et al., 2024). This assumption overlooks an important psychological process. Students with similar AI capabilities often show different levels of entrepreneurial intention. For example Current research does not clearly explain why this happens. (Ayaz et al., 2025;Banna and Alam, A. (2025). Previous studies also examine AI literacy, AI utilisation, and AI ambidexterity separately. This approach provides useful findings. However, it does not explain how these three capabilities work together to build entrepreneurial confidence.

Recently, from an empirical perspective, there is still limited understanding of how these variables work together in shaping entrepreneurial intention (Kumar et al., 2025; Fossen et al., 2024). Prior studies often examine technological capability, self-efficacy, or intention separately, which leaves a gap in explaining how these elements interact as part of a continuous process (Güner et al., 2025; Duong and Vu, 2025). Additionally many prior studies just focus on sustainability aspect (Lazuardi et al., 2026). Our study addresses this gap by integrating AI-related capabilities with entrepreneurial self-efficacy and cost mindfulness into a single framework (Kicova et al., 2025; Tran et al., 2024). The inclusion of entrepreneurial self-efficacy helps explain how capability is interpreted at the individual level, while cost mindfulness adds a layer of evaluation that reflects real-world constraints (Güner et al., 2025; Kicova et al., 2025). For the conceptualization, we start our literature review and hypothesis development in the next paragraphs.

We use human capital theory as an underpinning theory. To our knowledge, it provides a strong foundation for understanding how individuals develop the capacity to engage in entrepreneurial activities by accumulating knowledge, skills, and competencies (Mgueraman and El Abboubi, 2025). In the context of this study, AI literacy, AI utilisation, and AI ambidexterity can be seen as critical forms of modern human capital. As explained in prior section, AI literacy reflects the depth of understanding individuals have about AI tools and systems, while AI utilisation captures their ability to apply these tools in practical situations. Then, AI ambidexterity goes a step further by representing the ability to simultaneously explore new AI possibilities and exploit existing technologies efficiently. These capabilities represent accumulated cognitive resources that shape how individuals perceive opportunities and challenges (Aboobaker and Ka, 2023). Obviously, these capabilities may influence how students process information, organize their thinking, and respond to unfamiliar situations. So, as students interact with AI in different contexts, they may begin to develop habits of efficiency, curiosity, and structured reasoning, which can influence how they approach opportunity recognition and problem solving in broader settings.

The accumulation of these capabilities may also relate to how students form beliefs about their own ability to engage in entrepreneurial roles (Mir et al., 2023). Similarly, some authors suggests that individuals who possess relevant knowledge and skills tend to feel more capable of performing certain activities, especially those that involve uncertainty and independent decision-making (Xie and Wang, 2025). Based on this context, students who are familiar with AI tools may develop a sense of familiarity with complex systems, which can influence how they approach challenges in a business environment (Alvarez-Icaza et al., 2025; Wang and Sun, 2025). In general, they explain that their experience with AI may support quicker information processing, alternative ways of generating ideas, and a more flexible approach to solving problems.

Their familiarity with digital tools may also support better planning and scenario evaluation, which can influence how they think about the feasibility of starting a business (Ghouse et al., 2024). At the same time, attention to costs may shape how students interpret their own capability, since careful consideration of resources can influence how confident they feel in moving forward with an idea. Based on the study from Ayaz et al. (2025), this creates a situation where knowledge, skill, and awareness of cost interact in shaping how students think about entrepreneurship, how they assess possible actions, and how they respond to the balance between opportunity and resource constraints. For the development of the hypotheses, this study presents the discussion in the following sections.

If we refer to prior discussions on capability development, the idea of handling both exploration and consistent use of knowledge sources often appears as an important element in shaping individual readiness (Ahmad, 2025). In this context, AI ambidexterity reflects a balanced orientation where individuals engage with new AI possibilities while also maintaining stable use of existing tools (Ahmad, 2025). Moreover, some studies describe this dual engagement as a way to expand cognitive exposure (Kong et al. 2025; Shao et al., 2022). They explain that individuals are continuously interacting with both unfamiliar and familiar structures. This pattern of interaction can influence how complexity is perceived, where repeated exposure to different forms of tasks contributes to a broader interpretive capacity. Similarly, others note that such experiences are often linked with a more developed sense of personal capability (Duong et al., 2026). As explained, individuals become accustomed to adjusting their approach across varying situations.

In addition, several studies highlight that the coexistence of exploratory and exploitative tendencies contributes to a more integrated cognitive framework (Kumar et al., 2025). For instance, engagement with new AI tools introduces uncertainty and novelty, and consistent use of existing tools reinforces familiarity and efficiency. We think, the interaction between these two tendencies creates a learning environment where individuals develop both openness and control in handling tasks. This combination can shape how individuals evaluate their own ability, especially in situations that involve decision-making under uncertainty (Upadhyay et al., 2023). In entrepreneurial contexts, where individuals are expected to generate ideas while also managing practical constraints, this dual capability becomes increasingly important. The ability to move between experimentation and structured execution can influence how individuals perceive their readiness to engage in such activities (Ahmad, 2025; Duong et al., 2026). Drawing from this perspective, AI ambidexterity is linked with how individuals form beliefs about their capability, which is reflected in entrepreneurial self-efficacy. Based on this discussion, we propose our first hypothesis as follows.

H1: There is positive relationship between AI ambidexterity and entrepreneurial self-efficacy

AI literacy reflects the extent to which individuals develop an understanding of AI systems, including their functions, limitations, and potential applications (Duong, 2025). This form of knowledge may shape how individuals process information and construct meaning from digital outputs. Such a level of understanding may support more refined

cognitive structures, where individuals are able to interpret complex information with greater clarity. This structured way of thinking, as explained by Nguyen et al. (2024), becomes particularly relevant in situations that involve uncertainty, where interpretation and judgment play a key role. In addition, several studies suggest that knowledge contributes to a more refined sense of awareness regarding task demands (Fossen et al., 2024). In entrepreneurial settings, where individuals are required to direct ambiguity and make independent decisions, such a form of understanding becomes increasingly important. So, a deeper familiarity with AI systems can influence how individuals frame opportunities, interpret risks, and organize their actions (Duong, 2025). Through this lens, AI literacy can be conceptualised to relate to the development of entrepreneurial self-efficacy. It is because the knowledge shapes both cognitive evaluation and the perception of personal capability in engaging with complex activities. Based on this discussion, we propose our second hypothesis as follows.
H2: There is positive relationship between AI literacy and entrepreneurial self-efficacy

According to several scholars who focus on experience-based learning, repeated engagement with AI tools and tasks is often associated with the development of internalized knowledge and practical understanding (Sundaresan and Zhang, 2022). Then, prior research often describes experience as a mechanism that reinforces familiarity (Zhang et al., 2025). It is because individuals learn through continuous exposure and application. Through repeated use, individuals begin to recognize patterns, refine their approach, and develop a sense of how tasks can be managed more effectively. We perceive that this accumulation of experience can influence how individuals interpret new situations because past interactions provide a reference point for future actions.

Furthermore, several studies highlight that consistent utilisation contributes to how individuals perceive their own performance and capability (Kashive et al., 2020). Such as individuals who frequently engage with tools that support efficiency and problem solving often develop expectations regarding their ability to achieve desired outcomes. This process shapes self-perception, where successful task completion reinforces a sense of competence. So, in entrepreneurial contexts, it exhibits how individuals perceive their ability to manage the demands associated with entrepreneurship (Banna and Alam, 2025). Once individuals feel that they can rely on learned processes to guide their actions, they are more likely to interpret entrepreneurial tasks as manageable and within their capability. As suggested in the work of Güner et al. (2025), this interpretation strengthens their internal belief, since they are able to connect their existing skills with the requirements of entrepreneurial activities. So, this ongoing interaction between experience, cognitive processing, and self-evaluation highlights how engagement with problem-solving tools contributes to a stronger belief in one's ability to perform entrepreneurial roles. Based on this discussion, we propose our third hypothesis as follows.
H3: There is positive relationship between AI utilisation and entrepreneurial self-efficacy

In the current study, entrepreneurial self-efficacy is attributed to how individuals evaluate their ability to perform key entrepreneurial tasks, including recognizing opportunities and organizing resources (Güner et al., 2025). This perception influences how individuals interpret the demands associated with entrepreneurship. It is because a stronger sense of capability is often linked with a more manageable view of those demands. Moreover, according to some scholars, individuals who perceive themselves as capable tend to construct a clearer mental representation of entrepreneurial activities, where tasks are seen as structured and achievable (Mgueraman and El Abboubi, 2025). If we refer to discussions in the literature, individuals who possess a stronger sense of capability tend to approach uncertain situations with a more constructive perspective (Aboobaker and Ka, 2023). In this context, business challenges are interpreted as part of the process rather than

as limiting factors. We perceive that this perspective shapes how individuals weigh the feasibility of engaging in entrepreneurship. Their belief in their own ability can support a more active consideration of action. So, through this evaluation, entrepreneurial self-efficacy becomes closely tied to the formation of intention. Based on this discussion, we propose our fourth hypothesis as follows.
H4: There is positive relationship between entrepreneurial self-efficacy and entrepreneurial intention

As mentioned before, the presence of entrepreneurial self-efficacy introduces a layer of interpretation through which capabilities are translated into intention. Conceptually, AI-related capabilities do not directly determine whether individuals develop entrepreneurial intention. Instead, individuals first interpret these capabilities in relation to their own ability to perform entrepreneurial tasks (Alkhalaileh and Qasim, 2026). For instance, familiarity with AI tools, depth of understanding, and the ability to manage different approaches to AI contribute to how individuals construct a sense of readiness. This sense of readiness is reflected in entrepreneurial self-efficacy. It captures how individuals evaluate their capability in handling entrepreneurial responsibilities (Chen et al., 1998; Ratković et al., 2022). If we refer to several studies, this evaluative process plays a key role in shaping intention (Ratković et al., 2022). Individuals tend to consider actions that they perceive as within their capability. Through this perspective, entrepreneurial self-efficacy operates as an internal pathway that carries the influence of capability toward intention. Based on this discussion, we propose our fifth, sixth and seventh hypotheses as follows.
H5: Entrepreneurial self-efficacy mediates the positive effect of AI ambidexterity and entrepreneurial intention
H6: Entrepreneurial self-efficacy mediates the positive effect of AI literacy on entrepreneurial intention
H7: Entrepreneurial self-efficacy mediates the positive effect of AI utilisation on entrepreneurial intention

In this study we define cost mindfulness as an individual's tendency to pay close attention to financial resources, time, and effort during decision-making. This orientation encourages a more careful and reflective approach, where individuals evaluate potential trade-offs before forming a clear intention. In entrepreneurial contexts, this evaluative mindset can shape how opportunities are interpreted and assessed (Hameed and Irfan, 2019). In some studies, individuals who are more mindful of costs tend to develop a clearer understanding of the level of commitment required, which influences how attractive and realistic entrepreneurial engagement appears (Baron et al., 2012; Shepherd et al., 2015). For example, individuals begin to consider how resources will be allocated, how long certain processes may take, and how efficiently outcomes can be achieved within given constraints. Conceptually, this process supports a more deliberate form of thinking, in which opportunities are examined through a lens of feasibility and sustainability (Hameed and Irfan, 2019; Baron et al., 2012; Zayadin et al., 2023). Accordingly, entrepreneurial ideas are filtered through considerations of practicality, which influences how individuals judge whether an opportunity, is worth pursuing. Based on this discussion, we propose our eighth hypothesis as follows.
H8: There is positive relationship between cost mindfulness and entrepreneurial intention

For this topic, another aspect can be seen in how attention to cost-related considerations shapes the connection between perceived capability and entrepreneurial intention. We know that, confidence is present to be businessmen. However, to make it real is processed through a lens that considers whether available resources can support the intended action (Ratten, 2023). In this situation, confidence works together with cost awareness to shape a more balanced view of action, where individuals feel capable while also remaining attentive to possible constraints. In contrast, individuals who place less attention on cost tend to move more directly from confidence to intention, where belief in their ability plays a more dominant role in shaping their willingness to engage in entrepreneurial activity. We agree with some people that attention to cost encourages individuals to develop a habit of evaluating opportunities in a consistent and reflective manner, and their decisions are clearly guided by both internal belief and practical consideration (Kicova et al., 2025; Tran et al., 2024). This habit, according to some scholars, supports a more deliberate approach to entrepreneurial engagement, where individuals are able to connect what they believe they can do with what they are prepared to manage (Zayadin et al., 2023). Based on this discussion, we propose our ninth hypothesis as follows.

H9: Cost mindfulness moderates the positive relationship between entrepreneurial self-efficacy and entrepreneurial intention

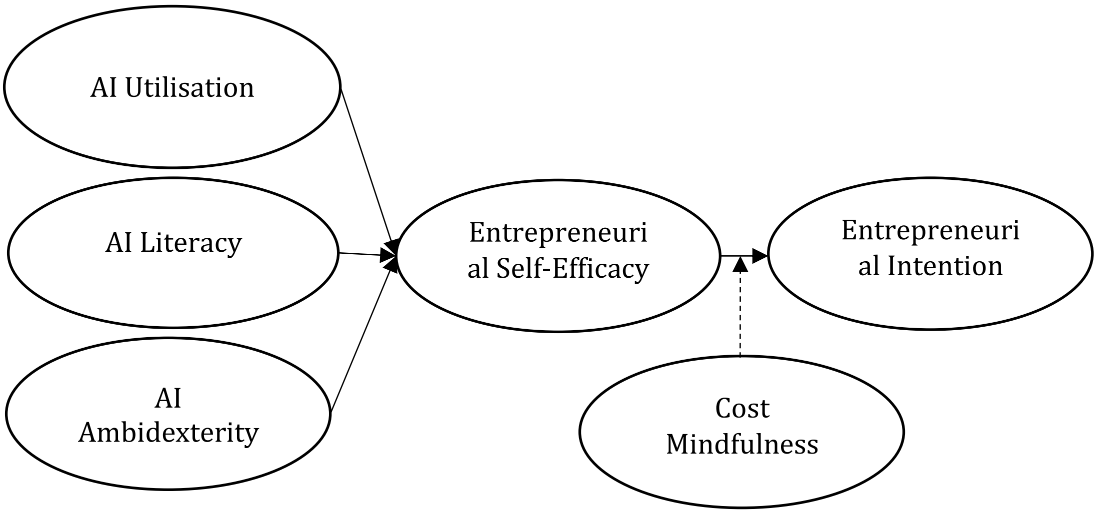

Figure 1. Research Model

Methods

This study adopted a quantitative with cross-sectional research design to examine the relationships among AI ambidexterity, AI literacy, AI utilisation, entrepreneurial self-efficacy, cost mindfulness, and entrepreneurial intention (see our research model in the Figure 1 in the appendix A). For the research context and sampling, this study focuses on accounting students from a university located in East Java Province. The selection of students is based on their relevance to the research context. In terms of sampling, the sampling approach follows a broad inclusion strategy. It is well-known as random sampling (Andersson, 2011). It means that all accounting students are considered eligible to participate in the study. There are no restrictive criteria applied in selecting participants because the curriculum ensures that students have been introduced to business-related content from the first semester. This shared academic experience provides a common foundation that supports their ability to respond to the questionnaire in a meaningful way. We selected one university because all students studied under the same curriculum and learning environment. They also had similar access to AI technologies and entrepreneurship education. This setting helped reduce differences caused by institutional factors. As a result, the observed relationships were more likely to reflect the proposed theoretical model rather than differences across universities.

In terms of the research procedure, the data collection process was carried out through direct engagement with students. Because all variables were collected using a selfadministered questionnaire, common method bias was assessed. First, participants were approached and provided with a brief explanation of the research purpose, which includes an overview of the study focus and its relevance. Along with this explanation, attention was given to ethical considerations, where participants were informed about the voluntary nature of their participation, the confidentiality of their responses, and the use of data solely for academic purposes. This step ensures that participants are aware of their role in the study and are able to make an informed decision regarding their involvement. After receiving this information, students who expressed their willingness to participate were provided with the questionnaire. The distribution process was conducted in a structured manner to ensure that participants could complete the questionnaire with a clear understanding of the instructions. Throughout this process, emphasis was placed on maintaining a comfortable and transparent interaction, allowing participants to respond without pressure.

The demographic profile shows that out of 273 respondents, the majority are female students, accounting for 161 individuals (59.00%), and male students represent 112 individuals (41.00%). This sample size exceeded the minimum requirement suggested in using PLS-SEM. It also satisfied more rigorous recommendations based on statistical power analysis that the sample was adequate to estimate the proposed structural model and detect medium effect sizes with sufficient statistical power. In terms of semester distribution, most respondents are in the middle stage of their studies, with 103 students (37.70%) in semesters 4–6, followed by 98 students (35.90%) in semesters 1–3, and 72 students (26.40%) in semester 7 and above. This distribution indicates that the sample captures students across different stages of their academic journey, with a slightly higher representation from those who have gained moderate academic and learning experience.

It is also important to note that the measurement of variables in this study was developed by adapting established scales from prior studies. We first reviewed the original instruments to ensure that each item was conceptually consistent with the context of AI use and entrepreneurship among accounting students. Several items were slightly modified to match the educational setting but preserving their original meaning. Two accounting academics reviewed the questionnaire to assess content validity and clarity. Minor wording revisions were made before the final questionnaire was distributed. AI Utilisation (AIU) was measured using six items developed from Kashive et al. (2020). It captures the extent to which individuals engage with AI tools in supporting their tasks and decision-making related to potential entrepreneurial activities. AI Literacy (AIL) was assessed using six items from Fossen et al. (2024). Fo this study, it reflects individuals' understanding and ability to interpret and use AI-related knowledge for potential entrepreneurial activities. AI Ambidexterity (AIA) was measured using seven items adapted from Kumar et al. (2025), which capture the ability to balance different approaches in using AI for exploration and application purposes, related to potential entrepreneurial activities. Entrepreneurial Self-Efficacy (ESE) was measured using six items developed from Güner et al. (2025) that focuses on individuals' confidence in performing entrepreneurial activities. Cost Mindfulness (CM) was assessed using six items developed from Kicova et al. (2025) and Tran et al. (2024). It reflects individuals' awareness and consideration of financial, time, and effort-related resources for potential entrepreneurial activities. Finally, Entrepreneurial Intention (EI) was measured using seven items adapted from Duong and Vu (2025) that captures the extent to which individuals express readiness and willingness to engage in entrepreneurial activities. All items were measured using a 5 Likert scale.

For the data analysis, the analysis of the collected data was conducted through a series of systematic steps. The first step involved organizing and tabulating the data using spreadsheet software, which allows for initial data cleaning and preparation. During this stage, responses were checked for completeness and consistency to ensure that the dataset is ready for further analysis. This process helps in structuring the data in a way that supports accurate and reliable interpretation.

The second step involved importing the prepared dataset into SmartPLS for further analysis. We followed a structured procedure from Hair et al., (2019) starting with the assessment of the measurement model. This stage focused on evaluating indicator reliability through factor loadings to ensure that each item adequately represented its construct. Descriptive statistics were also reviewed to understand the distribution of responses. The analysis then continued with the assessment of internal consistency using Cronbach's alpha and convergent validity through the Average Variance Extracted (AVE). In addition, discriminant validity was examined using the Fornell-Larcker criterion, cross-loadings, and HTMT ratios to confirm that each construct remained distinct and measured a unique concept.

After confirming the adequacy of the measurement model, the analysis proceeded to the structural model. This stage involved testing the direct relationships between variables using path coefficients and significance values obtained through bootstrapping. The analysis also examined indirect effects to assess the mediating role of entrepreneurial self-efficacy and interaction effects to evaluate the moderating role of cost mindfulness.

Results

This section presents the empirical findings that begin with the assessment of the measurement model and then continue with the structural model evaluation. In this part, we followed the recommendations from Hair et al. (2019). For the measurement model assessment, the analysis starts with Table 1, which reports factor loadings along with descriptive statistics. The factor loadings show a strong pattern, where most items exceed the recommended threshold of 0.70. This result indicates that the indicators represent their respective constructs with a high level of consistency. A few items display relatively lower loadings, such as CM3 and AIL4, yet their values still remain acceptable within behavioural research. In parallel, the descriptive statistics show that the mean values range from 1.868 to 4.443, which reflects variation in respondents' perceptions. The standard deviations indicate a moderate spread of responses, while skewness and kurtosis values suggest that the data distribution remains within acceptable limits.

Building on this foundation, the relationships among constructs are first explored through Table 2, which presents the latent variable correlations. The results show moderate to strong positive relationships among AIA, AIL, AIU, EI, and ESE. For instance, AIA shows a strong correlation with ESE, while EI also correlates strongly with ESE. These patterns provide an initial indication that the proposed relationships in the model are meaningful. At the same time, compliance mindset shows very weak correlations with other variables, which signals its limited direct association with the core constructs.

This result suggests that AI-related capabilities do not capture the same aspect of students' development. Instead, each capability contributes in a different way. AI-related capabilities represent students' technological resources. Entrepreneurial self-efficacy reflects their confidence in using those resources. Entrepreneurial intention represents their willingness to start entrepreneurial activities. In contrast, cost mindfulness shows very weak correlations with the other constructs. This result is also meaningful because cost mindfulness does not directly create entrepreneurial confidence or intention. Instead, it reflects how students think about costs, time, and available resources before making decisions.

Following this, the analysis moves to reliability and convergent validity as presented in Table 3. The Cronbach's alpha values range from 0.877 to 0.958, which demonstrates strong internal consistency across all constructs. In addition, the Average Variance Extracted (AVE) values range from 0.710 to 0.829. These values exceed the recommended threshold of 0.50, which confirms that each construct explains a substantial portion of variance in its indicators. This evidence supports the presence of convergent validity.

Table 1. Factor Loadings and Descriptive Statistics

Items	Factor Loadings	Mean	SD	Excess Kurtosis	Skewness
AIA1	0.902	3.363	1.516	-1.253	-0.396
AIA2	0.930	2.696	1.292	-0.652	0.714
AIA3	0.811	4.070	1.019	3.766	-1.934
AIA4	0.829	1.868	1.330	0.345	1.351
AIA5	0.845	2.538	1.234	-0.171	1.110
AIA6	0.856	3.810	1.417	-0.385	-0.980
AIA7	0.896	3.516	1.278	-0.575	-0.814
AIL1	0.886	2.319	1.169	-0.231	0.547
AIL2	0.907	3.293	1.391	-1.198	-0.133
AIL3	0.915	3.132	0.940	0.979	-0.160
AIL4	0.748	3.846	0.921	4.392	-2.094
AIL5	0.888	3.828	1.212	0.400	-1.181
AIL6	0.867	2.201	1.048	1.854	1.431
AIU1	0.886	2.542	1.089	0.562	1.123
AIU2	0.951	2.656	1.119	-0.083	0.426
AIU3	0.819	3.952	1.495	-0.354	-1.115
AIU4	0.927	2.963	1.361	-0.884	0.102
AIU5	0.925	3.029	1.109	0.061	0.088
AIU6	0.835	2.425	1.738	-1.420	0.613
CM1	0.925	3.623	1.356	-0.938	-0.629
CM2	0.868	4.443	1.274	2.881	-2.125
CM3	0.564	2.403	1.051	1.032	1.343
CM4	0.956	4.059	1.423	-0.585	-1.062
EI1	0.836	3.733	1.207	0.461	-1.222
EI2	0.947	3.183	1.282	-0.866	-0.179
EI3	0.867	2.033	1.146	1.284	1.388
EI4	0.851	2.436	1.033	0.895	1.297
EI5	0.934	2.619	1.362	-0.908	0.609
EI6	0.897	3.656	1.210	-0.590	-0.399
EI7	0.887	3.275	1.498	-1.181	-0.583
ESE1	0.892	4.040	1.159	1.112	-1.343
ESE2	0.913	3.696	1.536	-1.322	-0.584
ESE3	0.820	2.374	1.295	0.093	1.151
ESE4	0.931	3.524	1.455	-1.518	-0.345
ESE5	0.959	2.879	1.413	-1.207	0.317
ESE6	0.940	2.985	1.353	-1.274	0.357

Table 2. Latent Variable Correlations

Variables	AIA	AIL	AIU	CM	EI	ESE
AIA	1.000	0.340	0.450	0.018	0.340	0.662
AIL	0.340	1.000	0.336	-0.045	0.433	0.574
AIU	0.450	0.336	1.000	0.001	0.384	0.591
CM	0.018	-0.045	0.001	1.000	-0.070	-0.036
EI	0.340	0.433	0.384	-0.070	1.000	0.625
ESE	0.662	0.574	0.591	-0.036	0.625	1.000

Table 3. Construct Reliability and Validity

Variables	Cronbach's Alpha	Average Variance Extracted
AIA	0.945	0.753
AIL	0.935	0.757
AIU	0.948	0.796
CM	0.877	0.710
EI	0.956	0.791
ESE	0.958	0.829

To support the results of Convergent validity in the Tables 1, 2 and 3, we conducted discriminant validity. The analysis begins with Table 4, which presents the Fornell–Larcker criterion. The diagonal values, which represent the square root of the Average Variance Extracted (AVE), are consistently higher than the correlations with other constructs. For example, AIA shows a value of 0.868, which exceeds its correlations with AIL (0.340), AIU (0.450), and ESE (0.662). A similar pattern appears across all constructs, including AIU (0.892), EI (0.889), and ESE (0.910). This result indicates that each construct shares more variance with its own indicators than with other constructs. If looking at the work of Hair et al. (2019), as a result, each construct maintains a clear conceptual boundary.

This finding also strengthens the quality of the measurement model. The results show that each construct captures its intended concept more strongly than it captures other constructs. Therefore, the observed relationships are less likely to arise because different constructs measure the same underlying concept. This distinction is important because the proposed model includes several AI-related variables that may appear conceptually similar. The Fornell–Larcker results above confirm that AI ambidexterity, AI literacy, and AI utilisation remain empirically distinct even though they all describe different aspects of AI capability. At the same time, entrepreneurial self-efficacy, entrepreneurial intention, and cost mindfulness also maintain clear conceptual boundaries. As a result, the measurement model provides a reliable foundation for testing the structural relationships among the constructs.

Table 4. Fornell-Larcker Criterion

Variables	AIA	AIL	AIU	CM	EI	ESE
AIA	0.868					
AIL	0.340	0.870				
AIU	0.450	0.336	0.892			
CM	0.018	-0.045	0.001	0.843		
EI	0.340	0.433	0.384	-0.070	0.889	
ESE	0.662	0.574	0.591	-0.036	0.625	0.910

Table 5. Cross Loadings

Items	AIA	AIL	AIU	CM	EI	ESE
AIA1	0.902	0.308	0.434	-0.050	0.309	0.610
AIA2	0.930	0.276	0.389	0.074	0.288	0.603
AIA3	0.811	0.287	0.387	0.049	0.293	0.525
AIA4	0.829	0.273	0.411	0.087	0.261	0.567
AIA5	0.845	0.261	0.354	0.051	0.259	0.551
AIA6	0.856	0.318	0.372	-0.070	0.315	0.551
AIA7	0.896	0.338	0.385	-0.026	0.338	0.609
AIL1	0.264	0.886	0.303	-0.060	0.390	0.511
AIL2	0.291	0.907	0.313	-0.065	0.422	0.539
AIL3	0.353	0.915	0.300	-0.042	0.387	0.545
AIL4	0.238	0.748	0.229	0.032	0.337	0.420
AIL5	0.295	0.888	0.294	-0.025	0.374	0.494
AIL6	0.325	0.867	0.306	-0.065	0.343	0.477
AIU1	0.401	0.308	0.886	0.031	0.326	0.521
AIU2	0.436	0.321	0.951	0.018	0.368	0.566
AIU3	0.379	0.265	0.819	-0.046	0.311	0.496
AIU4	0.394	0.328	0.927	0.020	0.379	0.545
AIU5	0.408	0.332	0.925	-0.027	0.353	0.549
AIU6	0.387	0.233	0.835	0.008	0.310	0.481
CM1	0.021	-0.043	0.047	0.925	-0.054	-0.030
CM2	-0.001	-0.059	-0.039	0.868	-0.049	-0.035
CM3	0.007	-0.076	0.088	0.564	-0.002	0.010
CM4	0.024	-0.031	-0.007	0.956	-0.082	-0.035
EI1	0.307	0.371	0.306	0.004	0.836	0.515
EI2	0.319	0.386	0.350	-0.024	0.947	0.587
EI3	0.267	0.394	0.325	-0.135	0.867	0.524
EI4	0.270	0.339	0.335	-0.105	0.851	0.530
EI5	0.305	0.406	0.369	-0.060	0.934	0.596
EI6	0.338	0.381	0.361	-0.041	0.897	0.565
EI7	0.308	0.414	0.338	-0.080	0.887	0.569
ESE1	0.613	0.511	0.497	-0.072	0.568	0.892
ESE2	0.607	0.506	0.535	-0.020	0.603	0.913
ESE3	0.521	0.497	0.533	0.001	0.491	0.820
ESE4	0.606	0.503	0.529	-0.066	0.566	0.931
ESE5	0.630	0.563	0.579	-0.031	0.594	0.959
ESE6	0.633	0.553	0.555	-0.008	0.587	0.940

This initial evidence is then reinforced by Table 5, which reports cross-loadings. The cross-loading analysis verifies that each indicator measures its intended construct more strongly than any other construct. This step is particularly important because several constructs in this study describe different dimensions of AI capability and may appear conceptually related. The cross-loading results show that the indicators remain clearly associated with their own constructs despite these conceptual similarities. In other words, a consistent pattern appears where each indicator loads highest on its associated construct. For instance, AIA1 to AIA7 show their strongest loadings on AIA, all above 0.80, while their loadings on other constructs remain substantially lower. The same pattern holds for AIL, AIU, EI, and ESE indicators. Even in the case of CM3, which shows a relatively lower loading on CM (0.564), its loadings on other constructs remain minimal, which still supports construct distinction. This pattern across all items confirms that the indicators capture their intended constructs with clarity and without overlap.

This finding strengthens the conceptual structure of the proposed model and increases confidence that the relationships observed in the structural model reflect the proposed theoretical constructs rather than measurement ambiguity. As a final criterion of discriminant validity, the analysis then moves to Table 6, which presents the HTMT ratios. As reported, all values remain well below the threshold of 0.85, with the highest value observed between AIA and ESE at 0.695. Other relationships, such as AIA–AIL (0.361) and CM–ESE (0.041), show even lower values. These results indicate that the constructs remain empirically distinct.

In terms of the structural model results, after establishing the quality of the measurement model, the analysis proceeds to the structural relationships (see the picture of pls output in the Appendix). The direct relationships are reported in Table 7. The findings show that AIA has a positive and significant effect on entrepreneurial self-efficacy (ESE) (β = 0.418, Sig. = 0.000). This result supports *H1*, which is accepted. In a similar pattern, AIL also shows a positive and significant effect on ESE (β = 0.335, Sig. = 0.000), which supports *H2*, and therefore H2 is accepted. Likewise, AIU demonstrates a positive and significant effect on ESE (β = 0.291, Sig. = 0.000), which confirms H3, and H3 is accepted.

Moreover, Table 7 also show that ESE has a strong positive and significant effect on entrepreneurial intention (EI) (β = 0.636, Sig. = 0.000). This finding provides support for *H4*. In contrast, the relationship between cost mindfulness (CM) and entrepreneurial intention shows a negative coefficient with a significance value of 0.491 (β = -0.040, Sig. = 0.491). This value exceeds the acceptable threshold, which indicates a lack of statistical significance. As a result, *H8* is rejected.

In terms of the indirect effects, the results are presented in Table 8. The results show that AIA has a positive and significant indirect effect on EI through ESE (β = 0.266, Sig. = 0.000). This finding supports *H5*. Similarly, AIL shows a significant indirect effect on EI through ESE (β = 0.213, Sig. = 0.000), which confirms *H6*. In the same way, AIU also demonstrates a significant indirect effect on EI through ESE (β = 0.185, Sig. = 0.000), which confirms *H7*, and H7 is confidently accepted.

Then, the interaction effect is reported in Table 9. "he interaction effect was statistically significant based on the bootstrap t-test (β = -0.151, p = 0.018). This finding supports H9. However, the percentile of confidence interval slightly corsses zero (-0.244, 0.009). Therefore, the moderation effect should be interpreted with caution, and future studies should confirm this relationship using alternative bootstrap confidence interval methods and larger samples.

Table 6. Heterotrait-Monotrait Ratio (HTMT)

Variables	AIA	AIL	AIU	CM	EI	ESE
AIA						
AIL	0.361					
AIU	0.476	0.355				
CM	0.069	0.079	0.065			
EI	0.358	0.458	0.402	0.070		
ESE	0.695	0.605	0.621	0.041	0.653	

Table 7. Direct Effect

Paths	β	SD	Sig.	Confidence Interval	
				Lower [2.5%]	Upper [97.5%]
H1: AIA -> ESE	0.418	0.043	0.000	0.330	0.498
H2: AIL -> ESE	0.335	0.038	0.000	0.255	0.400
H3: AIU -> ESE	0.291	0.043	0.000	0.213	0.390
H4: ESE -> EI	0.636	0.038	0.000	0.551	0.699
H8: CM -> EI	-0.040	0.058	0.491	-0.132	0.094

Table 8. Indirect Effect

Paths	β	SD	Sig.	Confidence Interval	
				Lower [2.5%]	Upper [97.5%]
H5: AIA -> ESE -> EI	0.266	0.031	0.000	0.199	0.322
H6: AIL -> ESE -> EI	0.213	0.028	0.000	0.151	0.263
H7: AIU -> ESE -> EI	0.185	0.030	0.000	0.131	0.253

Table 9. Interacted Effect

Paths	β	SD	Sig.	Confidence Interval	
				Lower [2.5%]	Upper [97.5%]
H9: ESE*CM -> EI	-0.151	0.064	0.018	-0.244	0.009

This negative and significant interaction effect shows that higher levels of cost mindfulness reduce the strength of the positive relationship between entrepreneurial self-efficacy and entrepreneurial intention. In other words, individuals who demonstrate stronger cost awareness tend to translate their confidence into entrepreneurial intention at a lower level. They may place greater attention on potential costs and constraints when considering entrepreneurial actions. As an additional analysis, the overall model fit is assessed using several indicators, as presented in the model fit results (See Table 10). These results provide further support for the robustness of the proposed model.

Table 10. Model Fit

Creteria	Saturated Model	Estimated Model	rms Theta	Value
SRMR	0.043	0.048	rms Theta	0.154
d_ULS	1.213	1.506		
d_G	1.256	1.262		
Chi-Square	2002.436	2009.069		
NFI	0.825	0.825		

As shown, the Standardized Root Mean Square Residual (SRMR) shows values of 0.043 for the saturated model and 0.048 for the estimated model. Both values fall below the commonly accepted threshold of 0.08, which indicates a good model fit. This result suggests that the difference between the observed data and the model-implied data remains low. These results are supported by the values of d_ULS and d_G. The d_ULS increases slightly from 1.213 in the saturated model to 1.506 in the estimated model, while d_G shows a very small change from 1.256 to 1.262. These small differences indicate that the discrepancy between the empirical covariance matrix and the model-implied matrix remains within an acceptable range.

Moreover, in the Table 10, the Chi-Square values show a slight increase from 2002.436 to 2009.069. However, this pattern reflects a minor difference between the saturated and estimated models, which still indicates that the model captures the data structure in a satisfactory way. In addition, the Normed Fit Index (NFI) reports a value of 0.825 for both models. This value indicates an acceptable level of fit. Then, the rms Theta value of 0.154 provides further evidence regarding residual correlations. This value remains within an acceptable range for PLS-SEM analysis, which supports the overall quality of the model.

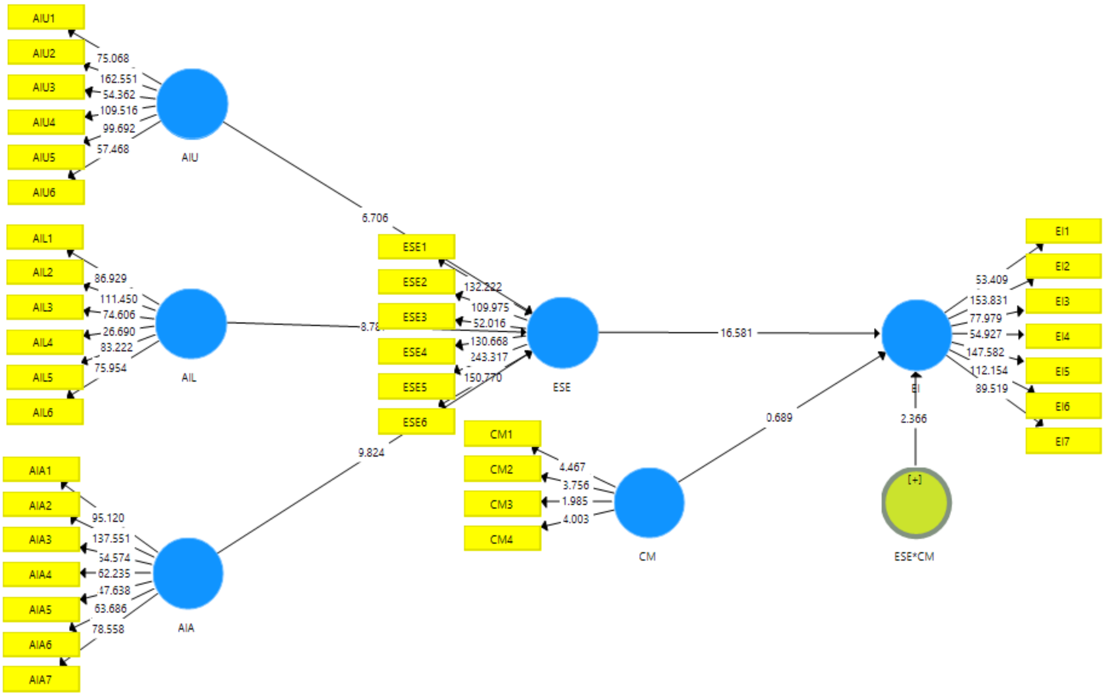

Figure 2. Path Model in Research

The findings of this study provide insight into how AI-related capabilities are connected to entrepreneurial development, particularly through the role of entrepreneurial self-efficacy. The results indicate that AI ambidexterity, AI literacy, and AI utilisation show significant relationships with entrepreneurial self-efficacy. This pattern contributes to prior studies by offering a fresh understanding of how technology-related capabilities shape perceived entrepreneurial ability. Earlier research often presents knowledge and skills as strong predictors of self-efficacy (Kumar et al., 2025; Fossen et al., 2024). However, the current results suggest that these effects depend on how individuals internalize and apply those capabilities.

This contribution becomes clearer in how each capability supports a different layer of self-efficacy formation. Essentially, this contribution becomes clearer when AI capability is viewed as a set of complementary resources. The findings show that different AI capabilities strengthen entrepreneurial self-efficacy in different ways, yet they work together to build the same outcome. This result suggests that confidence does not develop from one type of capability alone. Instead, students combine knowledge, practical experience, and the ability to adapt before they feel confident to pursue entrepreneurship. Therefore, entrepreneurial self-efficacy develops through a continuing learning process instead of a single learning experience. This finding extends previous studies that often treat capability as one broad construct (Zayadin et al., 2023). It shows that different forms of AI capability make unique contributions to entrepreneurial self-efficacy, while together they provide a more complete explanation of how technological capability becomes entrepreneurial confidence.

Interestingly, we found that entrepreneurial self-efficacy mediates the effects of AI ambidexterity, AI literacy, and AI utilisation on entrepreneurial intention. This finding is attribute closely to earlier studies by offering a clearer explanation of how capability is translated into intention through an internal process of self-evaluation (Duong and Vu, 2025). Prior research consistently highlights that knowledge, skills, and technological exposure play an important role in shaping entrepreneurial outcomes, particularly through their influence on confidence and perceived ability (Güner et al., 2025; Kashive et al., 2020). The current results support these arguments, at the same time, also extending them by showing that these capabilities do not directly lead to intention. Instead, individuals interpret their capability and develop a sense of confidence before forming an intention. Clearly, the current findings demonstrate that these influences operate through a process of self-evaluation. Individuals assess their experiences with AI, interpret their level of competence, and then form a belief about their ability to engage in entrepreneurial activities. This contribution strengthens earlier findings by providing a clearer process through which capability becomes meaningful for entrepreneurial behaviour. For example, this broadens earlier discussions by highlighting the importance of internal cognitive processing in entrepreneurial intention formation (Shepherd et al., 2015).

Moreover, we do not have sufficient evidence to support the direct effect of cost mindfulness on entrepreneurial intention. Earlier research suggests that individuals who are more attentive to financial and resource-related considerations tend to evaluate opportunities more carefully, which can influence their willingness to engage in entrepreneurial activities. The current result offers a more nuanced view by indicating that such awareness does not necessarily translate directly into a stronger entrepreneurial intention. From this study, cost mindfulness introduces a form of cognitive restraint, where individuals become more attentive to the implications of their decisions. We believe that this attention can lead to a more balanced view of opportunities, where potential benefits are considered alongside required commitments. As a result, individuals may reach a point of steadiness in their evaluation, where opportunities are seen as realistic yet demanding at the same time. So, in such a situation, intention does not automatically increase because the awareness of constraints can offset the attractiveness of potential outcomes. Accordingly, this explains why cost mindfulness does not show a direct effect, as its role is more closely related to shaping the way individuals think rather than determining what they decide.

This point is indirectly complemented by its moderating role on the relationship between entrepreneurial self-efficacy and entrepreneurial intention. This can be understood by considering that cost mindfulness shapes the context in which perceived capability is interpreted and expressed (Kicova et al., 2025; Tran et al., 2024). Entrepreneurial self-efficacy reflects an internal belief about one's ability to perform entrepreneurial tasks, while cost mindfulness introduces a layer of evaluation that focuses on resource constraints and practical considerations. The interaction between these two elements creates a situation where confidence is filtered through an awareness of feasibility, which influences how strongly that confidence is translated into intention (Güner et al., 2025; Duong and Vu, 2025). When attention to cost is higher, individuals tend to engage in more structured and deliberate evaluation, which shapes how their confidence is expressed in intention. Their belief in their ability remains important. However it is interpreted alongside considerations of efficiency, sustainability, and resource availability. This perspective connects with prior research that emphasizes the role of cognitive evaluation in entrepreneurial decision-making and extending it by showing how cost awareness conditions this process (Fossen et al., 2024; Kumar et al., 2025).

Conclusion

The findings show that entrepreneurial intention develops through a gradual process. AI ambidexterity, AI literacy, and AI utilisation help students build the knowledge and experience needed for entrepreneurship. However, these capabilities do not directly create entrepreneurial intention. Students first need to believe that they can apply their AI capabilities in entrepreneurial activities. This belief is reflected in entrepreneurial self-efficacy. Therefore, entrepreneurial self-efficacy becomes the key link between AI capability and entrepreneurial intention. The findings suggest that having AI skills alone is not enough. Students must also feel confident about using those skills in real business situations before they develop the intention to become entrepreneurs. The results also show that cost mindfulness plays a different role. It does not directly increase entrepreneurial intention. Instead, it shapes how students evaluate their confidence before deciding to start a business. So, students who pay greater attention to costs, time, and available resources tend to make more careful decisions. Here, they balance their confidence with practical considerations before forming entrepreneurial intention. As such, these findings suggest that entrepreneurial intention depends on both confidence in one's capabilities and careful evaluation of available resources.

As practical implications, the findings of this study suggest that universities and educators can strengthen entrepreneurial intention by focusing on how students build confidence from their experience with AI. It is important to go beyond teaching technical knowledge and create learning activities that allow students to actively use AI tools, solve real problems, and reflect on their abilities. This helps students turn their skills into a stronger sense of capability, which then supports their intention to engage in entrepreneurship. At the same time, introducing awareness of cost, time, and effort in a practical and balanced way can help students think more carefully about their decisions without reducing their motivation. So, by combining hands-on experience, reflective learning, and realistic evaluation, educational programs can better support students in developing both confidence and readiness for entrepreneurial activities.

Equally important, this study has several limitations that open directions for future research. First, the sample focuses on accounting students from a single university, which limits the diversity of perspectives and experiences. Students from other disciplines or institutions may have different levels of exposure to AI and entrepreneurship, which can influence the results. Second, the study relies on self-reported data, where responses reflect personal perceptions that may change over time or be influenced by individual bias. Third, the cross-sectional design captures responses at one point in time, so it does not fully show how entrepreneurial intention and self-efficacy develop as individuals gain more experience. In addition, the study focuses on selected variables, while other factors such as social influence, institutional support, or prior entrepreneurial exposure may also play a role.

Future studies can expand this work by involving a broader and more diverse sample, including students from different fields, universities, or even early-stage entrepreneurs. A longitudinal approach would also be valuable to observe how AI-related capabilities and entrepreneurial self-efficacy develop over time and how they influence intention in the long term. In addition, future research can include other variables such as environmental support, digital ecosystems, or personality traits to provide a more comprehensive understanding of entrepreneurial intention. It would also be useful to explore different contexts, such as industry-based settings or startup environments, to see how these relationships operate beyond the academic setting.

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