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How AI Literacy Drives Digital Entrepreneurial Intention: Evidence from an Emerging Economy

Suchart Tripopsakul [1], Danupol Hoonsopon [2*]

[1] *School of Entrepreneurship and Management, Bangkok University, Pathumthani 12120, Thailand.*

[2] *Chulalongkorn Business School, Chualongkorn University, Bangkok 10330, Thailand.*

Abstract

The objective of this study is to examine how artificial intelligence literacy influences digital entrepreneurial intention through cognitive and motivational mechanisms. Drawing on the Theory of Planned Behavior and entrepreneurial cognition, the model incorporates perceived feasibility and perceived opportunity as mediating factors, while self-efficacy and risk-taking propensity are included as moderating variables. Data were collected from 312 adults in Thailand using a structured questionnaire, and the proposed relationships were analyzed using partial least squares structural equation modeling. The results indicate that artificial intelligence literacy has a direct and positive effect on digital entrepreneurial intention and also enhances individuals' perceptions of feasibility and opportunity. Further analysis confirms that perceived feasibility and perceived opportunity partially mediate the relationship between artificial intelligence literacy and entrepreneurial intention. The moderating analysis shows that self-efficacy strengthens the effect of artificial intelligence literacy on perceived feasibility, while risk-taking propensity has no significant influence on the relationship between artificial intelligence literacy and perceived opportunity. These findings contribute to the understanding of digital entrepreneurship by identifying artificial intelligence literacy as a critical personal capability that stimulates entrepreneurial engagement through both cognitive and motivational pathways, particularly within the context of emerging economies.

Keywords:

AI Literacy;

Digital Entrepreneurial Intention;

Entrepreneurial Cognition;

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1- Introduction

The rise of artificial intelligence (AI) has transformed economies, industries, and entrepreneurial environments by changing how value is created, captured, and scaled in digital markets [1, 2]. AI literacy, defined as the knowledge and skills needed to use AI effectively, is now crucial for individuals pursuing entrepreneurial careers in technology-rich contexts [3, 4]. Beyond its technical benefits, AI literacy helps individuals identify opportunities, develop new solutions, and navigate complex digital business landscapes marked by rapid technological change and uncertainty [5, 6]. Thus, AI literacy is increasingly seen not just as a practical skill, but as a strategic enabler of entrepreneurial intention in digital economies. Recent studies have begun to examine how digital competencies influence entrepreneurial behavior. AI-related skills significantly predict entrepreneurial intention through innovation attitudes [7]. Prior studies proposed an integrated model linking AI acceptance with digital entrepreneurship [6, 8]. However, prior research has often emphasized either technological readiness or digital literacy without integrating the cognitive mechanisms that explain how AI literacy translates into entrepreneurial intention. Moreover, most empirical evidence is drawn from developed economies, leaving a gap in understanding how AI literacy functions within emerging markets that face uneven digital transformation and educational limitations [5, 9]. Addressing this gap is essential, as AI capability increasingly determines national competitiveness and entrepreneurial dynamism.

* **CONTACT**: danupol@cbs.chula.ac.th

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Globally, entrepreneurship remains a fundamental driver of economic advancement and innovation, with approximately 665 million entrepreneurs worldwide, equating to roughly one in eight working-aged adults actively engaged in entrepreneurial pursuits [10]. The global startup ecosystem is also experiencing rapid expansion, projected to achieve an average annual growth rate of 21% in new ventures by 2025 [11]. Furthermore, digital entrepreneurship is increasingly interwoven with e-commerce, as global online commerce is anticipated to involve over 2 billion participants, with sales expected to surpass $7 trillion [12]. This digital transformation is evident in entrepreneurial behaviors, as 80% of entrepreneurs acknowledge that integrating digital tools enhances customer engagement and sales [10]. These statistics collectively emphasize the accelerating worldwide shift towards technology-enabled entrepreneurship and the growing significance of AI and digital literacy for business sustainability and competitiveness. In contrast, emerging economies like Thailand exhibit uneven development in AI literacy. A 2025 survey by BBDO Bangkok revealed that while approximately 73.84% of respondents in major Thai cities use AI daily, only 20% of the workforce utilizes AI tools professionally, indicating a substantial disparity in professional AI literacy and its integration into the workplace [13]. Additionally, the Thailand Cyber Wellness Index 2025 reported an average AI literacy score of 3.18 out of 5 among Thais, signifying a moderate understanding, with children and adults over 40 years old demonstrating the lowest scores [14]. To address these discrepancies, Thailand's national AI strategy aims to enhance AI literacy for 10 million citizens (approximately 14% of the population) and cultivate 90,000 AI specialists in the near future [15]. These initiatives highlight the nation's recognition that AI literacy is not merely a technological imperative but also a socio-economic necessity intrinsically linked to innovation capacity, entrepreneurial readiness, and long-term competitiveness.

Entrepreneurial intention (EI) research has consistently utilized cognitive and behavioral frameworks, such as the Theory of Planned Behavior [16] and Shapero's model of the entrepreneurial event [17], to underscore perceived feasibility and perceived opportunity as pivotal precursors to entrepreneurial activity [18, 19]. Perceived feasibility denotes an individual's conviction in their capacity to initiate and sustain a business, whereas perceived opportunity encompasses the identification and evaluation of advantageous market conditions [20]. Within digital entrepreneurial contexts, where technological volatility heightens uncertainty, AI literacy can potentially enhance feasibility perceptions by diminishing cognitive obstacles and augmenting opportunity recognition by expanding awareness of AI-enabled business models and applications [21]. Consequently, feasibility and opportunity function as essential mediating channels through which AI literacy influences digital entrepreneurial intention (DEI).

Concurrently, individual variations influence the extent to which AI literacy fosters entrepreneurial intention. Self-efficacy, defined as an individual's belief in their capacity to execute entrepreneurial tasks, has been consistently identified as a moderator influencing feasibility perceptions and subsequent intentions [22, 23]. Individuals possessing higher self-efficacy are better equipped to translate AI literacy into robust feasibility beliefs. Similarly, risk propensity, the inclination to accept uncertainty and potential losses, moderates the relationship between perceived opportunity and intention; risk-tolerant individuals are more prone to convert recognized opportunities into concrete entrepreneurial plans [24, 25]. Recent empirical evidence further substantiates these dynamics, indicating that technological and FinTech literacy enhance entrepreneurial intention through self-efficacy and outcome expectations [21], while digital entrepreneurship education and AI-related skills also influence intention, contingent upon varying levels of risk aversion [26].

Although increasing attention has been given to the role of artificial intelligence in shaping entrepreneurial behavior, there is still a lack of comprehensive models that simultaneously capture both the direct pathways and the underlying mechanisms through which artificial intelligence literacy affects digital entrepreneurial intention. Prior research has either focused narrowly on digital literacy [7, 27] or explored AI literacy in relation to entrepreneurial self-efficacy and identity aspiration, without adequately considering perceived feasibility and opportunity as mediating mechanisms [6]. Furthermore, there is a limited understanding of how self-efficacy and risk propensity interact with these mediating pathways. To fill these research gaps, this study constructs and validates an integrated framework examining how artificial intelligence literacy influences digital entrepreneurial intention both directly and through cognitive mediators, namely perceived feasibility and perceived opportunity. Furthermore, the study explores whether self-efficacy conditions the influence of artificial intelligence literacy on perceived feasibility and whether risk-taking propensity alters the association between perceived opportunity and digital entrepreneurial intention [28, 29].

This paper is organized into seven main sections. The second section reviews prior studies related to artificial intelligence literacy, digital entrepreneurial intention, perceived feasibility, perceived opportunity, and key moderating variables. The third section formulates research hypotheses based on the theoretical foundations and empirical evidence. The fourth section explains the research design in detail, including the instruments used, the data collection process, and the analytical techniques employed. The fifth section reports the empirical results derived from the analysis. The sixth section interprets these results and discusses their theoretical relevance and managerial implications. The final section summarizes the main conclusions, highlights the limitations of the present study, and proposes potential directions for future investigations.

2- Literature Review

This section outlines the conceptual foundations and theoretical perspectives that form the basis of the current research. It commences with an exploration of AI literacy as a pivotal capability within digital economies and its implications for entrepreneurial endeavors. Subsequently, the discussion transitions to the cognitive mechanisms of perceived feasibility and perceived opportunity, which are well-established within entrepreneurial intention research as central antecedents connecting individual knowledge to entrepreneurial action. Finally, the section reviews two individual-level moderating factors, self-efficacy and risk propensity, that influence how AI literacy translates into digital entrepreneurial intention. Taken together, these components provide a solid theoretical basis for constructing the conceptual model of this study and deriving the corresponding research hypotheses.

2-1- AI Literacy and Digital Entrepreneurship

Digital entrepreneurship, which encompasses both the establishment of new ventures and the digital transformation of existing ones, has become a critical catalyst for business model innovation and the enhancement of brand value within the modern digital economy [30]. In this context, artificial intelligence literacy has emerged as an essential capability that influences how individuals and organizations recognize opportunities, create innovative solutions, and participate in entrepreneurial endeavors. Artificial intelligence literacy can be described as a combination of knowledge, skills, and critical awareness that enables people to comprehend, interact with, and assess artificial intelligence systems effectively. Beyond technical competence, it also includes an understanding of ethical considerations, social consequences, and the strategic use of artificial intelligence in organizational and entrepreneurial practices [3, 31, 32]. In entrepreneurial contexts, AI literacy functions as a cognitive and strategic resource that enables individuals to recognize emerging opportunities, reduce uncertainty, and enhance decision-making in dynamic markets [5, 6]. As digital entrepreneurship increasingly relies on advanced technologies to drive value creation, AI literacy becomes not only a technical asset but also a determinant of entrepreneurial orientation and intention.

Existing research highlights those individuals with higher AI literacy demonstrate greater confidence in assessing the feasibility of entrepreneurial ventures and in leveraging AI-enabled tools to explore innovative business models [20, 21]. Technological literacy directly influences entrepreneurial outcomes through enhanced self-efficacy and opportunity recognition [21]. AI literacy shapes e-entrepreneurial self-efficacy and identity aspiration, both of which strengthen entrepreneurial intention [6]. These findings collectively suggest that AI literacy equips individuals to navigate the complex decision-making processes inherent in entrepreneurship, particularly in digital environments where technological turbulence can magnify uncertainty. Recent systematic reviews have shown that the use of large language models can strengthen learners' self-efficacy, stimulate deeper cognitive engagement, and foster creative approaches to problem-solving in entrepreneurial education. However, these technologies also introduce potential challenges, including excessive dependence on automated outputs and ethical concerns regarding responsible use [33].

Moreover, AI literacy plays a dual role in fostering digital entrepreneurship: it reduces cognitive barriers to business creation by simplifying the perceived complexity of AI applications, and it broadens entrepreneurial horizons by enabling the identification of new AI-driven opportunities [27, 34]. An integration supports not only the technical capacity of aspiring entrepreneurs but also their adaptability, creativity, and long-term competitiveness [5]. In this sense, AI literacy can be understood as a strategic capability that underpins entrepreneurial action, serving as the entry point through which individuals translate technological understanding into concrete entrepreneurial intentions.

2-2- Entrepreneurial Intention, Perceived Feasibility and Opportunity

Entrepreneurial intention is widely regarded as a key antecedent of entrepreneurial action, representing an individual's deliberate mindset and determination to establish and pursue a business venture over time [35, 36]. As intentions precede action, understanding the cognitive antecedents of EI is critical to explain why some individuals pursue entrepreneurial opportunities while others do not [37]. Intention-based models such as the Theory of Planned Behavior (TPB) [16] and Shapero's Model of the Entrepreneurial Event (SEE) [17] provide the dominant frameworks in this domain. Both models emphasize cognitive evaluations, particularly perceived feasibility and perceived opportunity as key antecedents that translate individual characteristics into entrepreneurial action [38]. The Theory of Planned Behavior framework provides a strong explanatory basis for understanding digital entrepreneurial intention and subsequent actions. It emphasizes that attitudes, perceived social expectations, and perceived behavioral control are pivotal belief-driven factors shaping entrepreneurial decision-making within digital environments [39].

Perceived feasibility refers to the individual's belief in their capability to establish and manage a new venture. Rooted in self-efficacy theory [40], feasibility perceptions are shaped by knowledge, prior experiences, and access to resources. Research consistently demonstrates that higher feasibility beliefs strengthen entrepreneurial intentions by reducing uncertainty and building confidence in the ability to perform entrepreneurial tasks [23, 38, 41]. In digital contexts, feasibility perceptions are particularly salient because technological turbulence often magnifies complexity and uncertainty. Here, competencies such as AI literacy can play a crucial role in lowering perceived barriers and bolstering the belief that entrepreneurial initiatives are realistically achievable [5, 21].

Perceived opportunity, in contrast, reflects the recognition and evaluation of favorable conditions in the environment that can be exploited through entrepreneurship. Opportunity perception is central to entrepreneurship theory, as the act of seeing and framing opportunities is what differentiates entrepreneurs from non-entrepreneurs [42]. Studies confirm that individuals who can identify opportunities are more motivated to transform those insights into entrepreneurial action [43, 44]. In digital markets, opportunities often emerge through technological advancements and platform-based ecosystems, and AI literacy expands the cognitive horizon for recognizing such opportunities, including data-driven business models and algorithm-enabled services [6, 27].

Together, feasibility and opportunity perceptions function as cognitive mechanisms that mediate the relationship between individual capabilities and entrepreneurial intention. While feasibility provides the confidence that "I can do it," opportunity perception motivates that "it is worth doing" [45]. The integration of these constructs into entrepreneurial intention models not only enhances their predictive validity but also aligns with recent empirical evidence highlighting the mediating role of feasibility and opportunity in shaping entrepreneurial intention across contexts [20, 21]. In the digital era, where knowledge-intensive capabilities such as AI literacy increasingly determine entrepreneurial success, these cognitive evaluations become essential pathways linking technological competence to digital entrepreneurial intention [5, 46].

2-3- The Moderating Roles of Self-Efficacy and Risk Propensity in Digital Entrepreneurship

While perceived feasibility and perceived opportunity represent critical mediating mechanisms linking AI literacy to digital entrepreneurial intention (DEI), individual-level differences determine the strength of these relationships. Two personal factors, self-efficacy and risk propensity, have consistently been highlighted in the entrepreneurship literature as key moderators influencing how knowledge and cognitive evaluations translate into entrepreneurial action [25, 47, 48]. Within entrepreneurial contexts, higher self-efficacy strengthens the relationship between perceived feasibility and intention by enhancing confidence in one's ability to overcome barriers and mobilize resources [22, 23]. In digital entrepreneurship, where AI-driven technologies are rapidly evolving, individuals with strong self-efficacy are more likely to leverage their AI literacy to form robust feasibility beliefs, perceiving the launch of AI-enabled ventures as attainable rather than overwhelming [5, 29]. Recent studies confirm that technology literacy and entrepreneurial education enhance intentions primarily when coupled with high self-efficacy, suggesting their role as a boundary condition for the relationship between feasibility and intention [6, 21].

Risk propensity, on the other hand, reflects the individual's tendency to take risks and tolerate uncertainty in pursuit of potential rewards [49, 50]. Entrepreneurship inherently involves uncertain outcomes, and individuals with higher risk propensity are more inclined to act upon recognized opportunities [25]. Research demonstrates that risk-tolerant individuals are more likely to translate perceived opportunities into entrepreneurial intentions, particularly in volatile or technology-driven markets where outcomes are less predictable [51]. In the digital domain, where AI-enabled opportunities may involve untested business models and disruptive innovations, risk propensity becomes a critical factor that determines whether opportunity recognition results in entrepreneurial commitment [52]. Self-efficacy and risk propensity together offer a more complete picture of how AI literacy influences DEI. Self-efficacy strengthens the link between AI literacy and perceived feasibility, ensuring that technical knowledge leads to confidence in action. Risk propensity enhances the connection between opportunity and intention, enabling individuals to pursue AI-enabled opportunities and form concrete entrepreneurial plans despite uncertainty. By including these moderators, this study explains individual differences in how people respond to AI literacy, providing a richer model of digital entrepreneurial intention.

3- Hypotheses Development

This study's theoretical underpinning is rooted in the Theory of Planned Behavior (TPB) [16] and subsequent models of entrepreneurial cognition, which highlight the pivotal role of cognitive evaluations in shaping entrepreneurial intentions. Within this theoretical lineage, perceived feasibility and perceived opportunity have consistently emerged as crucial antecedents that bridge individual knowledge and skills with entrepreneurial action [45]. AI literacy, defined as the requisite knowledge, skills, and awareness for understanding and strategically applying artificial intelligence, has recently garnered recognition as a strategic asset within digital economies [5]. Individuals possessing higher levels of AI literacy are ostensibly better equipped to identify innovative business opportunities, mitigate uncertainties inherent in digital markets, and perceive the initiation of AI-enabled ventures as feasible [53]. Prior research substantiates that proficiency in emergent technologies, such as FinTech and AI, augments digital entrepreneurial self-efficacy and outcome expectations, thereby stimulating entrepreneurial intention [21]. Drawing upon these insights, this study posits that AI literacy not only directly cultivates digital entrepreneurial intention but also operates indirectly through evaluations of feasibility and opportunity.

H1: AI literacy has a positive effect on digital entrepreneurial intention (DEI).

H2: AI literacy positively affects perceived feasibility.

H3: AI literacy positively affects perceived opportunity.

Prior research, particularly grounded in the Theory of Planned Behavior and Shapero's Entrepreneurial Event Model, has consistently identified perceived feasibility and perceived opportunity as crucial mediating constructs linking cognitive antecedents to entrepreneurial intention [54, 55]. Perceived feasibility denotes an individual's confidence in their capacity to initiate and manage a new business venture, while perceived opportunity refers to the ability to discern and assess propitious market conditions [56]. Both constructs have been empirically demonstrated to significantly predict entrepreneurial intention across a variety of contexts [20]. In the domain of digital entrepreneurship, where AI-driven innovations introduce both inherent uncertainties and substantial potential, these constructs hold particular salience. Consistent with established mediation patterns observed for fintech literacies within a TPB framework, it is hypothesized that AI literacy will influence Digital Entrepreneurial Intention through the mediation of perceived feasibility and perceived opportunity [34]. Accordingly, the following hypotheses are proposed:

H4: Perceived feasibility positively predicts digital entrepreneurial intention (DEI).

H5: Perceived opportunity positively predicts digital entrepreneurial intention (DEI).

H6: Perceived feasibility mediates the link between AI literacy and DEI.

H7: Perceived opportunity mediates the link between AI literacy and DEI.

Beyond these mediating pathways, individual differences are instrumental in shaping how AI literacy translates into entrepreneurial outcomes. Self-efficacy, defined as an individual's confidence in their capacity to execute entrepreneurial tasks, magnifies the influence of knowledge on feasibility perceptions [57, 58]. Recent research indicates that both technological and financial literacy more profoundly enhance entrepreneurial outcomes when self-efficacy levels are elevated [21]. In a similar vein, the tendency to take risks, reflecting an individual's openness to uncertainty, has been recognized as an important factor moderating the association between perceived opportunity and entrepreneurial intention [23]. People with higher levels of risk-taking propensity are generally more motivated to transform perceived opportunities into actual entrepreneurial pursuits, especially in dynamic and technology-intensive environments [24]. Based on these arguments, the following hypotheses are proposed:

H8: Self-efficacy amplifies the positive effect of artificial intelligence literacy on perceived feasibility.

H9: Risk-taking propensity strengthens the positive effect of perceived opportunity on digital entrepreneurial intention.

Figure 1 illustrates the proposed conceptual model, where AI literacy directly influences DEI and indirectly operates through perceived feasibility and opportunity, with self-efficacy and risk propensity serving as critical moderators.

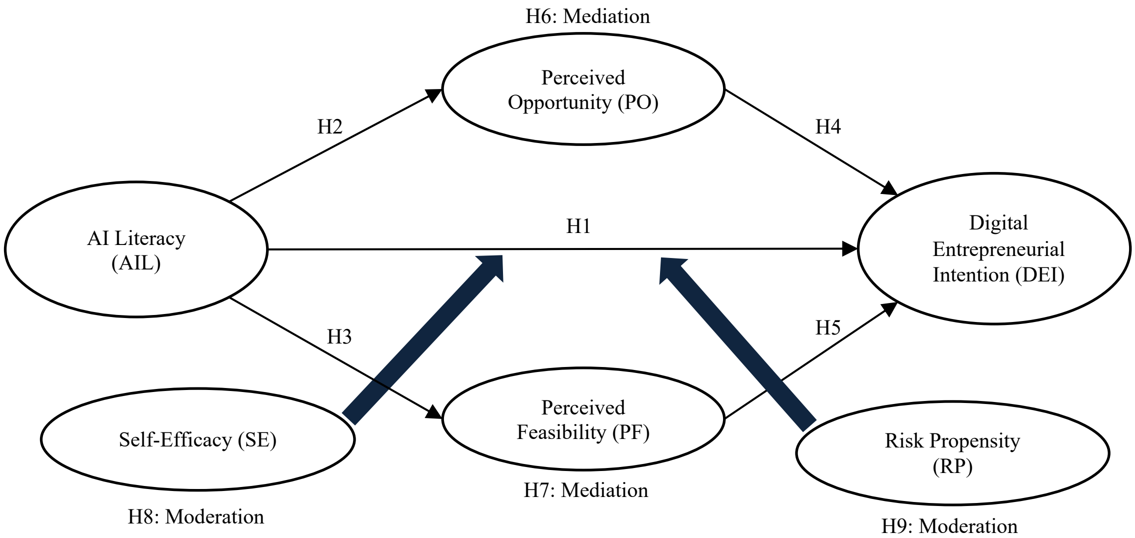


Figure 1. The conceptual framework

4- Research Method

This research adopted a quantitative survey approach to explore how artificial intelligence literacy shapes digital entrepreneurial intention. The model also tested the mediating roles of perceived feasibility and perceived opportunity, together with the moderating effects of self-efficacy and risk-taking propensity. The conceptual framework was grounded in the Theory of Planned Behavior and entrepreneurial cognition perspectives, emphasizing the role of cognitive assessments as essential antecedents of entrepreneurial action. The study focused on Thai adults aged between 18 and 64 who possessed varying degrees of experience with digital technologies and artificial intelligence applications. Data were collected using a structured self-administered questionnaire distributed online through social media platforms and further circulated via universities and entrepreneurship development programs.

The questionnaire was divided into two sections. The first part collected demographic information such as gender, age, education, occupation, income, and AI usage patterns. The second part measured the study's core constructs: AI Literacy (AIL), Perceived Feasibility (PF), Perceived Opportunity (PO), Self-Efficacy (SE), Risk Propensity (RP), and Digital Entrepreneurial Intention (DEI). AI Literacy (AIL) was conceptualized as a multidimensional construct with four dimensions: Awareness (AW), Use (US), Evaluation (EV), and Ethics (ET) [6]. Perceived Feasibility (PF) captured individuals' confidence in their capability to start and manage a digital business. Perceived Opportunity (PO) reflected the recognition of AI-enabled opportunities in digital markets. Self-Efficacy (SE) measures confidence in performing entrepreneurial tasks. Risk Propensity (RP) assessed willingness to accept uncertainty and potential losses. Digital Entrepreneurial Intention (DEI) reflected determination to engage in digital entrepreneurship [46, 59, 60]. All constructs used five-point Likert scales (1 = strongly disagree to 5 = strongly agree), except Self-Efficacy (SE), which used a five-point confidence scale (1 = not at all confident to 5 = extremely confident). To guarantee both linguistic accuracy and cultural relevance within the Thai setting, a back-translation technique was employed, and any inconsistencies were reconciled by bilingual specialists. A comprehensive summary of the constructs and their corresponding measurement indicators is provided in Table 1.

Table 1. Constructs and corresponding measurement indicators used in this study

Construct	Code	Measurement items
Awareness (AW)	AW1	I can distinguish which platforms, applications, or devices use AI and which do not.
	AW2	I know how AI can support me in learning, working, or starting and running a digital business.
	AW3	I can identify which AI components (e.g., natural language processing, image processing, recommendation systems) are embedded in the applications or services I use.
Use (US)	US1	I can effectively use AI applications or tools to support my learning, work, and digital entrepreneurial activities.
	US2	In general, I can learn to use new AI tools relatively quickly.
	US3	Using AI significantly enhances my work processes, efficiency, or business performance.
Evaluation (EV)	EV1	After using AI for a while, I can evaluate the capabilities and limitations of each AI tool.
	EV2	When AI provides multiple solutions or options, I can select the most appropriate one for my goals or business tasks.
	EV3	I can choose the most suitable AI tool for a given task or process from several available options.
Ethics (ET)	ET1	I consistently adhere to ethical standards when applying artificial intelligence in my activities.
	ET2	I am attentive to issues of privacy and data protection whenever I use artificial intelligence in professional or business contexts.
	ET3	I utilize artificial intelligence in a responsible manner, avoiding actions that may cause harm, spread misinformation, or breach legal and regulatory requirements.
Perceived Feasibility (PF)	PF1	I believe I have the ability to start a digital business.
	PF2	If I really started, I am confident that I could handle the technical and operational issues involved in starting a digital business.
	PF3	I can gather the necessary resources (e.g., knowledge, tools, networks) to get started.
	PF4	Overall, starting a digital business is feasible for me.
Perceived Opportunity (PO)	PO1	I can recognize unmet needs or gaps in the digital market.
	PO2	I often identify new opportunities that emerge from using AI in business.
	PO3	The next 12 months will be a good time to start or expand a digital business.
	PO4	I believe I can capture and leverage digital opportunities when I find them.
Self-Efficacy (SE)	SE1	I am confident in identifying and selecting promising digital business opportunities.
	SE2	I am confident in developing and testing prototypes of digital products or services (e.g., websites, apps, content).
	SE3	I am confident in conducting digital marketing to acquire initial customers.
	SE4	I am confident that I can handle unexpected problems and obstacles during business startup.
	SE5	I am confident in planning and pitching my project/business to partners or investors.
Risk Propensity (RP)	RP1	I am willing to accept uncertainty in exchange for business growth opportunities.
	RP2	If an idea has potential, I am willing to experiment even if it carries risk.
	RP3	I am comfortable making decisions where short-term outcomes are not yet clear.
	RP4	Overall, I am quite willing to take calculated risks when I see a good opportunity.
Digital Entrepreneurial Intention (DEI)	DEI1	I am ready to take all necessary steps to become a digital entrepreneur.
	DEI2	My ultimate career aspiration is to build and run my own digital business.
	DEI3	I intend to invest significant effort into launching and managing a digital venture.
	DEI4	I have a strong determination to create a digital enterprise in the future.
	DEI5	I have given serious consideration to starting a digital business.
	DEI6	I am fully committed to establishing my own digital business someday.

Note: AI Literacy (AIL) is the higher-order construct of Awareness (AW), Use (US), Evaluation (EV), and Ethics (ET)

5- Results

5-1-Sample profiles

Most respondents were female (53.1%), aged 18–25 years (38.5%), single (59.6%), and held an undergraduate degree (64.8%). Students were the largest occupational group (42.2%), followed by private-sector employees (28.3%) and entrepreneurs and self-employed individuals (15.4%). About one-third earned USD 501–1,000 per month (31.8%), while 27.4% earned below USD 500. Regarding AI use, 46.9% used AI tools three to four days per week and 19.6% five to six days; only 3.1% reported daily use, and 8.5% rarely or never used them. In terms of duration, 34.4% spent one to three hours per week, 28.8% four to six hours, 14.1% seven to ten hours, and 9.3% more than ten hours. The most frequently used tools were ChatGPT (71.6%), Gemini (52.8%), Microsoft Copilot (41.5%), Canva AI (36.9%), and Perplexity (30.6%). Leading purposes were learning and general Q&A (62.9%), content creation (55.3%), business planning and strategy (47.8%), opportunity recognition (44.6%), feasibility analysis (42.1%), and digital marketing (38.9%). For entrepreneurial status, 28.2% were exploring ideas, 21.6% planned to start within twelve months, 12.7% had started within the past twelve months, 15.6% were already operating a digital business, and 21.9% were not interested (see Table 2).

Table 2. Demographic profile of respondents

Item	Description	Frequency	(%)
Gender	Male	146	46.9
	Female	166	53.1
Age	18–25	120	38.5
	26–35	92	29.5
	36–45	55	17.6
	46–55	30	9.6
	56 and above	15	4.8
Marital Status	Single	186	59.6
	Married	114	36.5
	Other	12	3.9
Education	Below Undergraduate	41	13.1
	Undergraduate	202	64.8
	Postgraduate	69	22.1
Occupation	Student	132	42.2
	Private Sector Employee	88	28.3
	Public Sector Employee	39	12.5
	Entrepreneur / Self-employed	48	15.4
	Other	5	1.6
Monthly Income (USD)	< 500	86	27.4
	501–1,000	99	31.8
	1,001–1,500	73	23.3
	> 1,500	54	17.5
AI Usage Days/Week	Rarely/Never	28	8.5
	1–2 days	68	21.9
	3–4 days	146	46.9
	5–6 days	61	19.6
	Every day	9	3.1
AI Usage Hours/Week	< 1 hour	42	13.5
	1–3 hours	107	34.4
	4–6 hours	90	28.8
	7–10 hours	44	14.1
	> 10 hours	29	9.3
AI Tools Used (Multiple responses permitted)	ChatGPT	223	71.6
	Gemini	165	52.8
	Microsoft Copilot	129	41.5
	Canva AI	115	36.9
	Perplexity	96	30.6
	Others	86	27.4
Purposes of AI Use (Multiple responses permitted)	Learning/Q&A	197	62.9
	Content Creation	173	55.3
	Business Planning	149	47.8
	Opportunity Recognition	139	44.6
	Feasibility Analysis	131	42.1
	Digital Marketing	121	38.9
Entrepreneurial Status	Not interested	68	21.9
	Exploring ideas	88	28.2
	Planning within 12 months	67	21.6
	Started (<12 months)	40	12.7
	Operating (≥12 months)	49	15.6

5-2- The Measurement Model Assessment

Partial least squares structural equation modeling (PLS-SEM) was applied to evaluate the hypothesized relationships among artificial intelligence literacy, perceived feasibility, perceived opportunity, and digital entrepreneurial intention, while considering self-efficacy and risk-taking propensity as individual-level moderators. Although the sample size of 312 participants was sufficient for covariance-based SEM, PLS-SEM was preferred because it aligns with prediction-oriented objectives, manages complex model structures effectively, and remains robust under non-normal data conditions. The analytical model includes multiple latent constructs with reflective indicators and moderation paths, which were estimated using the disjoint two-stage procedure. In addition, PLS-SEM enables the computation of latent variable scores that can be used for extended predictive assessments, providing methodological advantages compared with covariance-based SEM [61]. The sample size adhered to the prescribed guideline for PLS-SEM, which recommends a minimum of ten times the maximum number of structural paths directed toward any single construct, thereby ensuring adequate statistical power for the developed model.

In this research, artificial intelligence literacy was conceptualized as a multidimensional variable consisting of four dimensions: awareness, usage, evaluation, and ethics. Perceived feasibility and perceived opportunity were treated as core components of entrepreneurial cognition. To address the higher-order structure and moderation effects, the disjoint two-stage procedure was implemented. This analytical process involved three main steps: (1) assessing the reliability and validity of the lower-order constructs, (2) verifying the higher-order constructs where applicable, and (3) examining the structural relationships among the variables [62]. To mitigate the influence of potential confounding factors, prior entrepreneurial experience and AI exposure were statistically controlled. Entrepreneurial experience was operationalized by respondents' self-reported entrepreneurial status, while AI exposure was quantified based on the frequency and duration of their AI tool usage. These variables were subsequently integrated as exogenous predictors within the models for perceived feasibility, perceived opportunity, and digital entrepreneurial intention. All statistical analyses were performed using the SmartPLS 4 software package [63].

5-2-1- Assessment of the Lower-Order Constructs (LOCs)

The convergent and discriminant validity of the lower-order constructs were assessed following established guidelines [64]. To confirm the reliability of the measurement model, factor loadings, average variance extracted (AVE), Cronbach’s alpha, and composite reliability were evaluated. Given that artificial intelligence literacy encompasses multiple dimensions—awareness, usage, evaluation, and ethics—each dimension was first examined individually before being integrated into the higher-order construct. Likewise, perceived feasibility, perceived opportunity, self-efficacy, risk-taking propensity, and digital entrepreneurial intention were each validated separately at the lower-order construct level.

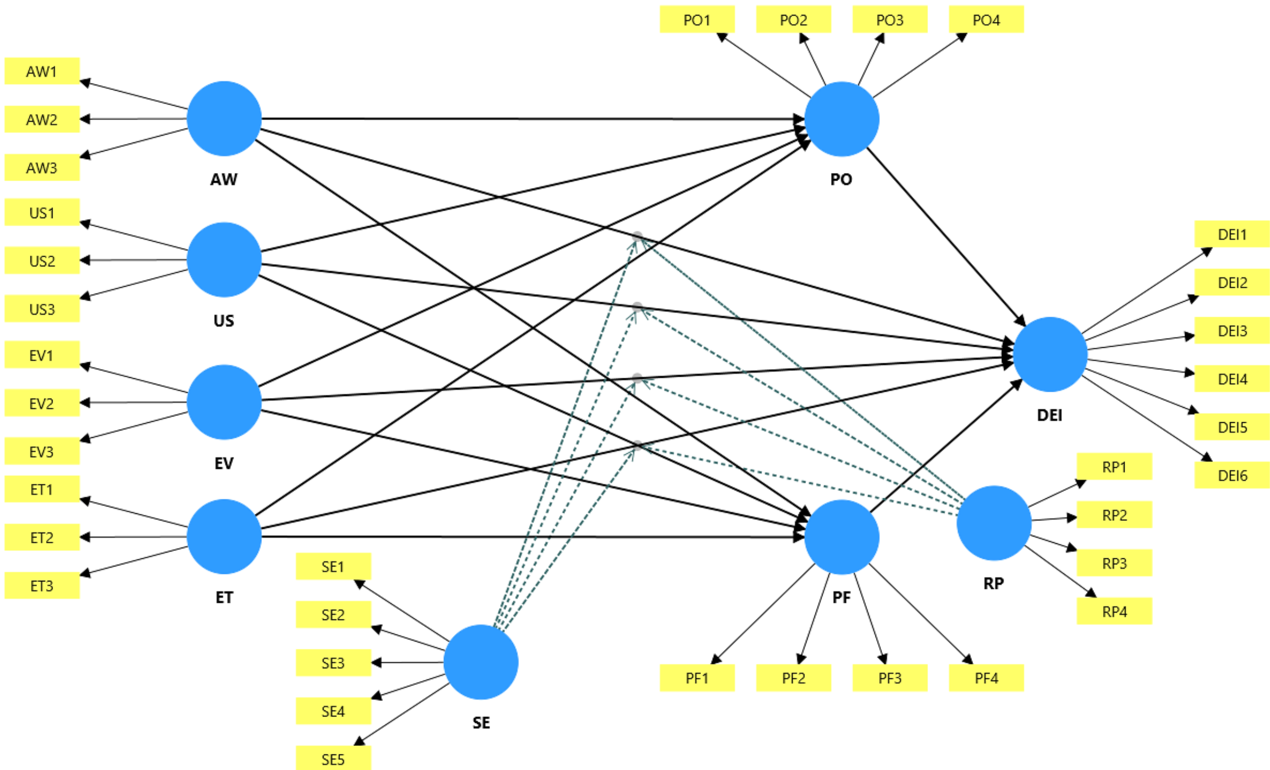


Figure 2. The first stage of the disjoint two-stage approach

As illustrated in Figure 2, each lower-order construct was associated with its corresponding theoretical dimension during the initial phase of analysis. The reliability of individual indicators was evaluated through factor loadings and cross-loadings. Most loading values exceeded the recommended cutoff of 0.70 and were statistically significant at the 0.05 level [61], as summarized in Table 3. To improve construct validity, four indicators, PO3, SE4, DEI4, and DEI6, were removed due to their loadings falling below the threshold. Following their exclusion, all remaining items loaded more strongly on their designated constructs than on any others, fulfilling both the Fornell–Larcker criterion and HTMT ratio standards for discriminant validity. Internal consistency reliability was also confirmed, as all constructs achieved Cronbach's alpha and composite reliability values above 0.70. Additionally, convergent validity was established since each construct's average variance extracted exceeded the 0.50 benchmark. Overall, these findings demonstrate that the measurement model exhibits satisfactory reliability and validity, supporting its suitability for subsequent structural model assessment.

Table 3. The details of the constructs and model measurement assessment

Construct	Items	Loading	Cronbach's α	CR	AVE
Awareness (AW)	AW1	0.782	0.802	0.872	0.680
	AW2	0.829			
	AW3	0.861			
Use (US)	US1	0.812	0.791	0.870	0.684
	US2	0.847			
	US3	0.823			
Evaluation (EV)	EV1	0.842	0.816	0.890	0.732
	EV2	0.873			
	EV3	0.852			
Ethics (ET)	ET1	0.803	0.811	0.879	0.714
	ET2	0.859			
	ET3	0.872			
Perceived Feasibility (PF)	PF1	0.845	0.832	0.892	0.678
	PF2	0.762			
	PF3	0.817			
	PF4	0.865			
Perceived Opportunity (PO)	PO1	0.824	0.791	0.872	0.697
	PO2	0.847			
	PO3	Deleted			
	PO4	0.833			
Self-Efficacy (SE)	SE1	0.801	0.841	0.889	0.677
	SE2	0.846			
	SE3	0.829			
	SE4	Deleted			
	SE5	0.814			
Risk Propensity (RP)	RP1	0.912	0.913	0.946	0.796
	RP2	0.871			
	RP3	0.901			
	RP4	0.884			
Digital Entrepreneurial Intention (DEI)	DEI1	0.819	0.853	0.902	0.685
	DEI2	0.837			
	DEI3	0.802			
	DEI4	Deleted			
	DEI5	0.852			
	DEI6	Deleted			

The discriminant validity of the measurement model was evaluated using both the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio [61]. As shown in Table 4, the square root of the average variance extracted (AVE) for each construct exceeded its correlations with other constructs, thereby confirming discriminant validity. In addition, all HTMT values were below the recommended threshold of 0.90, further supporting that the constructs are empirically distinct from one another.

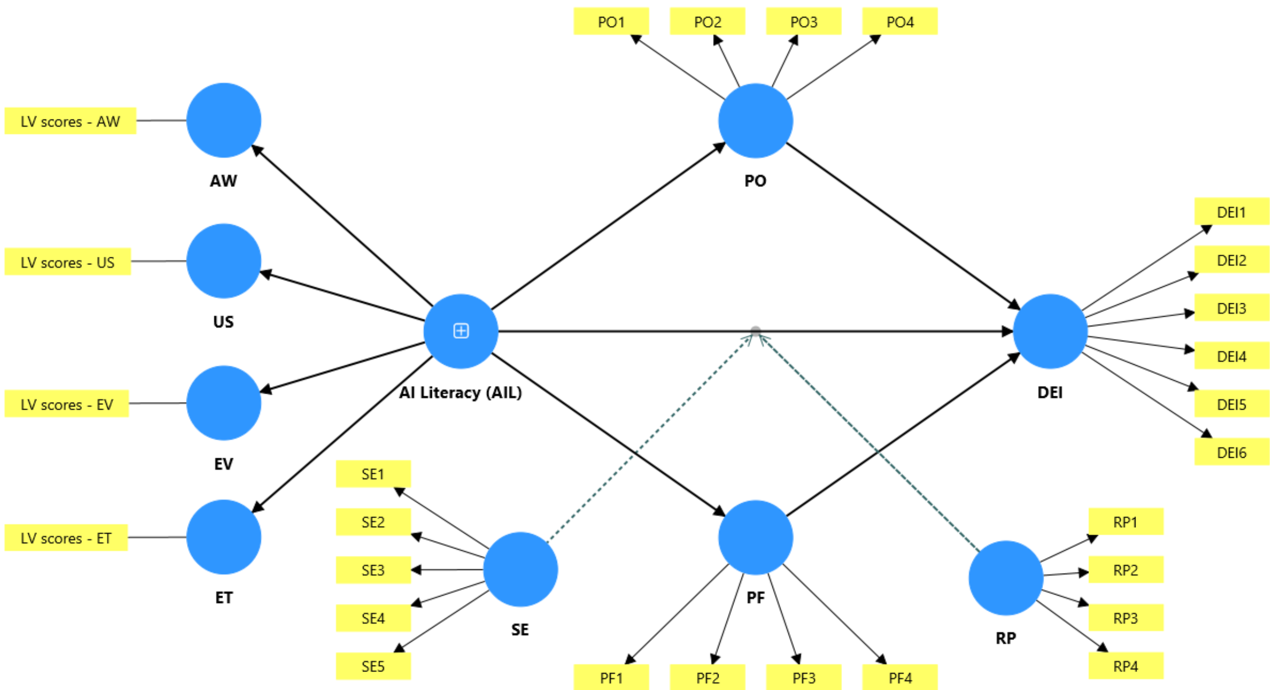
Table 4. The Fornell-Larcker criterion and the HTMT ratio are in the first stage

Construct	AW	US	EV	ET	PF	PO	SE	RP	DEI
AW	0.825								
US	0.536 (0.561)	0.827							
EV	0.621 (0.648)	0.547 (0.574)	0.856						
ET	0.318 (0.347)	0.297 (0.325)	0.339 (0.367)	0.845					
PF	0.557 (0.584)	0.471 (0.498)	0.612 (0.639)	0.392 (0.417)	0.823				
PO	0.679 (0.702)	0.559 (0.586)	0.653 (0.681)	0.441 (0.468)	0.504 (0.531)	0.835			
SE	0.603 (0.629)	0.582 (0.609)	0.636 (0.663)	0.427 (0.453)	0.549 (0.576)	0.543 (0.570)	0.823		
RP	0.524 (0.551)	0.603 (0.629)	0.492 (0.520)	0.371 (0.399)	0.521 (0.549)	0.557 (0.584)	0.536 (0.563)	0.892	
DEI	0.576 (0.603)	0.493 (0.520)	0.556 (0.584)	0.438 (0.464)	0.588 (0.616)	0.726 (0.754)	0.594 (0.621)	0.457 (0.484)	0.828

Note: the square root of AVE is presented in diagonal; the value within the bracket is the value of the HTMT ratio; AW = Awareness; US = Use; EV = Evaluation; ET = Ethics; PF = Perceived Feasibility; PO = Perceived Opportunity; SE = Self-Efficacy; RP = Risk Propensity; DEI = Digital Entrepreneurial Intention.

5-2-2- Assessment of the Higher-Order Construct (HOC) in the Measurement Model

After validating the lower-order constructs, the analysis proceeded to examine the higher-order construct of artificial intelligence literacy. In this research, artificial intelligence literacy was modeled as a second-order reflective–reflective construct encompassing four dimensions: awareness, usage, evaluation, and ethics. Consistent with the disjoint two-stage procedure [65], scores of the lower-order dimensions were first derived and subsequently employed as manifest indicators in the second-stage assessment of the higher-order construct. The remaining constructs perceived feasibility, perceived opportunity, self-efficacy, risk-taking propensity, and digital entrepreneurial intention were maintained as reflective constructs. The structure of the second-stage model is presented in Figure 3.



Note: AI Literacy (AIL) is the higher-order construct of Awareness (AW), Use (US), Evaluation (EV), and Ethics (ET)

Figure 3. The second stage of the disjoint two-stage approach

During the second stage of analysis, the measurement model for the higher-order construct was evaluated based on factor loadings, internal consistency, and convergent validity. As summarized in Table 5, the higher-order construct of artificial intelligence literacy demonstrated acceptable levels of reliability and validity, with satisfactory values of factor loadings, Cronbach's alpha, composite reliability, and average variance extracted.

Table 5. Indicator loadings, reliability, and validity of HOC

Sub-constructs of HOC	Loadings	CA	CR	AVE
AI Literacy (AIL)		0.853	0.907	0.710
Awareness (AW)	0.864			
Use (US)	0.821			
Evaluation (EV)	0.846			
Ethics (ET)	0.867			

Note: CA = Cronbach's alpha; CR = Composite reliability; AVE = Average Variance Extracted

In addition, Table 6 shows that the Fornell–Larcker criterion was satisfied, confirming the discriminant validity of the higher-order construct (AIL) with other study constructs.

Table 6. Intercorrelations and Fornell–Larcker Criterion of Latent Variables

	AIL	PF	PO	SE	RP	DEI
AIL	0.842					
PF	0.628 (0.652)	0.823				
PO	0.684 (0.709)	0.552 (0.574)	0.835			
SE	0.603 (0.627)	0.571 (0.593)	0.567 (0.589)	0.822		
RP	0.537 (0.561)	0.514 (0.538)	0.558 (0.582)	0.543 (0.566)	0.895	
DEI	0.657 (0.682)	0.588 (0.613)	0.741 (0.768)	0.602 (0.628)	0.468 (0.492)	0.828

Note: The square root of AVE is presented on the diagonal; the value within the bracket is the value of the HTMT ratio

Multicollinearity was evaluated using the variance inflation factor (VIF) statistics. The VIF values ranged between 1.07 and 2.54, remaining well below the accepted cutoff of 3.0, thereby confirming the absence of multicollinearity issues [61]. To assess potential common method bias, Harman's single-factor test was performed. The principal component analysis yielded four separate factors, with the first factor explaining 34.2% of the total variance—significantly lower than the 50% threshold—indicating that common method bias was not a concern in this study [66]. Overall, the measurement model exhibited adequate levels of reliability, convergent validity, and discriminant validity, confirming its suitability for further structural model evaluation.

5-3- Structural Model Assessment

To evaluate the proposed hypotheses and confirm the conceptual framework, Partial Least Squares Structural Equation Modeling (PLS-SEM) was performed using a bootstrapping procedure with 5,000 resamples. The results, summarized in Table 7, reveal that artificial intelligence literacy exerted a significant positive direct effect on digital entrepreneurial intention ($\beta = 0.216$, $t = 5.147$, $p < 0.001$, $f^2 = 0.08$), thereby supporting H1. Furthermore, artificial intelligence literacy significantly enhanced perceived feasibility ($\beta = 0.412$, $t = 8.963$, $p < 0.001$, $f^2 = 0.19$) and perceived opportunity ($\beta = 0.368$, $t = 8.127$, $p < 0.001$, $f^2 = 0.17$), lending support to H2 and H3. Both perceived feasibility ($\beta = 0.298$, $t = 6.254$, $p < 0.001$, $f^2 = 0.14$) and perceived opportunity ($\beta = 0.341$, $t = 7.083$, $p < 0.001$, $f^2 = 0.21$) positively influenced digital entrepreneurial intention, confirming H4 and H5. These findings suggest that artificial intelligence literacy affects entrepreneurial intention both directly and indirectly through cognitive mechanisms of feasibility and opportunity. The explanatory power of the model was strong (R^2 for DEI = 0.617; PF = 0.492; PO = 0.473), while predictive relevance was validated using Stone–Geisser's Q^2 (DEI = 0.401; PF = 0.317; PO = 0.298). Overall, the model demonstrated robustness and highlighted the pivotal role of artificial intelligence literacy in promoting digital entrepreneurial intention through cognitive pathways.

Table 7. Hypothesis testing results

Hypotheses Path	β Coefficient	T-statistics	P-value	f²	Result
H1: AIL → DEI	0.216***	5.147	0.000	0.08	Supported
H2: AIL → PF	0.412***	8.963	0.000	0.19	Supported
H3: AIL → PO	0.368***	8.127	0.000	0.17	Supported
H4: PF → DEI	0.298***	6.254	0.000	0.14	Supported
H5: PO → DEI	0.341***	7.083	0.000	0.21	Supported

Note: ***p < 0.001; AIL = AI Literacy; PF = Perceived Feasibility; PO = Perceived Opportunity; DEI = Digital Entrepreneurial Intention.

The mediation results further confirmed the indirect influence of perceived feasibility and perceived opportunity, as reported in Table 8. Perceived feasibility was found to partially mediate the association between artificial intelligence literacy and digital entrepreneurial intention (specific indirect effect: β = 0.123, t = 4.786, p < 0.001). Similarly, perceived opportunity served as a partial mediator in the link between artificial intelligence literacy and digital entrepreneurial intention (specific indirect effect: β = 0.126, t = 4.319, p < 0.001). The direct path from artificial intelligence literacy to digital entrepreneurial intention remained significant (β = 0.216, p < 0.001), producing a total effect of 0.465 (t = 9.073, p < 0.001), indicative of complementary mediation. Overall, these outcomes demonstrate that artificial intelligence literacy not only exerts a direct impact on digital entrepreneurial intention but also indirectly reinforces it through cognitive assessments of feasibility and opportunity, emphasizing its dual function as both a driver and facilitator of entrepreneurial cognition.

Table 8. The results of the mediation analysis

Path	Effects	Estimate	S.E.	T-Statistics	P-Values	Conclusion
AIL → PF → DEI	Specific indirect	0.123***	0.026	4.786	0.000	Partial Mediation
AIL → PO → DEI	Specific indirect	0.126***	0.029	4.319	0.000	Partial Mediation
AIL → DEI	Direct	0.216***	0.042	5.147	0.000	—
	Total	**0.465*** **	**0.051**	**9.073**	**0.000**	—

Note: ***p < 0.001; AIL = AI Literacy; PF = Perceived Feasibility; PO = Perceived Opportunity; DEI = Digital Entrepreneurial Intention.

To assess the moderating influence of individual characteristics, two moderation tests were performed using the interaction modeling function in SmartPLS 4. This procedure creates product terms between predictor and moderator variables to evaluate their conditional effects on the dependent constructs. As reported in Table 9, the interaction between artificial intelligence literacy and self-efficacy on perceived feasibility was significant (β = 0.231, t = 3.214, p < 0.001), confirming H8. This finding suggests that individuals with greater self-efficacy tend to perceive higher feasibility when applying their artificial intelligence literacy. Conversely, the interaction between perceived opportunity and risk-taking propensity on digital entrepreneurial intention was not significant (β = 0.041, t = 0.822, p = 0.411), providing no empirical support for H9. This implies that, within this study's sample, the inclination to take risks does not meaningfully amplify the association between perceived opportunity and entrepreneurial intention.

Table 9. The results of the moderating effects of self-efficacy and risk propensity

Path	Moderator	β Coefficient	T-statistics	P-value	Result
AIL → PF (H8)	Self-Efficacy (SE)	0.231***	3.214	0.000	Supported
PO → DEI (H9)	Risk Propensity (RP)	0.041	0.822	0.411	Not supported

Note. ***p < 0.001; AIL = AI Literacy, PF = Perceived Feasibility, PO = Perceived Opportunity, DEI = Digital Entrepreneurial Intention.

The simple slope plot in Figure 4 provides a visual illustration of the moderating influence of self-efficacy on the link between artificial intelligence literacy and perceived feasibility. The positive association between artificial intelligence literacy and perceived feasibility becomes more pronounced at higher levels of self-efficacy (+1 SD) and diminishes at lower levels (–1 SD). This finding indicates that individuals with stronger self-efficacy are better able to translate their artificial intelligence literacy into heightened perceptions of feasibility, emphasizing the pivotal role of confidence in utilizing artificial intelligence for entrepreneurial evaluation. In contrast, the simple slope plot in Figure 5 depicts the interaction between perceived opportunity and risk-taking propensity on digital entrepreneurial intention. The differences in slope between high and low levels of risk propensity were not statistically significant, suggesting that risk propensity neither strengthens nor weakens the relationship between opportunity perception and entrepreneurial intention in this context. Thus, while opportunity identification remains important, an individual's tendency to take risks may not be a determining factor in converting perceived opportunities into entrepreneurial intentions.

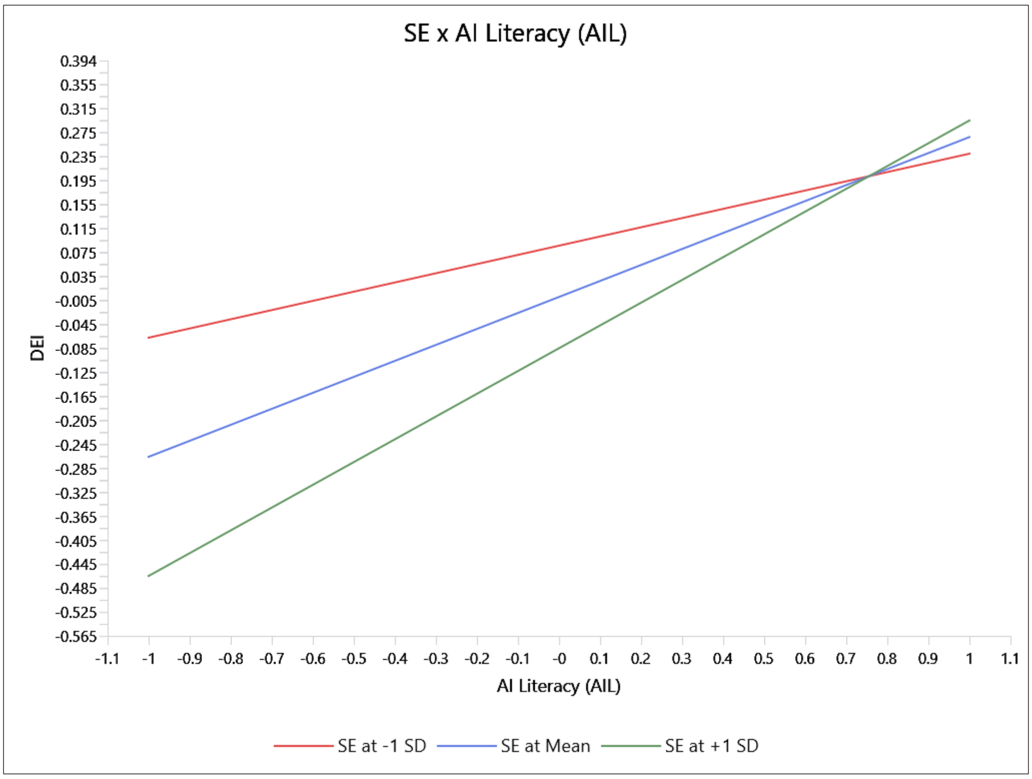


Figure 4. **Simple slope analysis of self-efficacy (SE) as a moderator between AI literacy and perceived feasibility**

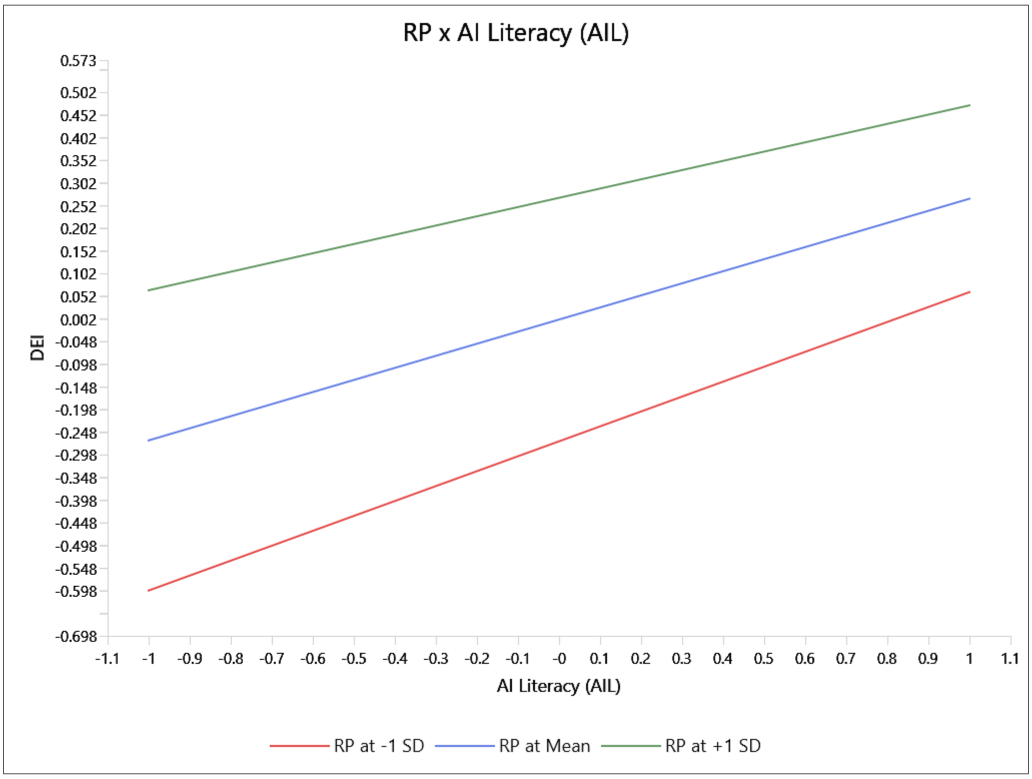


Figure 5. **Simple slope analysis of risk propensity (RP) as a moderator between perceived opportunity and digital entrepreneurial intention**

6- Discussion

This research advances the theoretical comprehension of digital entrepreneurial intention by integrating AI literacy with established entrepreneurial cognition frameworks and individual-level moderating factors, specifically self-efficacy and risk propensity. Through empirical validation of a structural model utilizing PLS-SEM and the disjoint two-stage approach, the study offers novel insights into how cognitive capabilities and psychological traits collectively influence entrepreneurial intentions within AI-driven environments.

6-1- Theoretical Implications

Our study provides robust empirical evidence extending entrepreneurial cognition theory into the digital transformation era. Drawing upon the Theory of Planned Behavior and cognition-based frameworks, we demonstrate that AI literacy functions not merely as a technical skill but as a crucial cognitive capability that directly and indirectly fosters digital entrepreneurial intention via perceived feasibility and opportunity.

AI literacy emerged as a significant positive predictor of Digital Entrepreneurial Intention ($\beta = 0.216$, $p < 0.001$), thereby confirming H1. This finding highlights the crucial role of understanding, utilizing, evaluating, and ethically applying AI tools for digital entrepreneurs. This perspective is reinforced by recent systematic reviews indicating that Large Language Models enhance self-efficacy, cognitive engagement, and creative problem-solving in entrepreneurship education, despite concerns about over-reliance and ethical implications [33]. AI literacy lowers cognitive barriers to entrepreneurial action and fosters entrepreneurial identity aspirations [5, 6]. Collectively, these studies support the argument that AI literacy serves as a strategic resource in entrepreneurship, enabling individuals to navigate increasingly technology-intensive environments. The observed effects of AI literacy on DEI are consistent with evidence suggesting that digital entrepreneurship flourishes in contexts with robust digital infrastructure, strong IT competencies, and brand-centric community models [30]. Furthermore, AI literacy significantly strengthened perceived feasibility ($\beta = 0.412$, $p < 0.001$) and perceived opportunity ($\beta = 0.368$, $p < 0.001$), thus supporting H2 and H3. These results suggest that AI literacy not only directly stimulates entrepreneurial intention but also reinforces the cognitive belief structures foundational to entrepreneurial decision-making. Perceived feasibility and opportunity as key mediators between intention and behavior, extending their model by positioning AI literacy as a primary antecedent [20]. Similarly, digital literacy enhances opportunity perception in uncertain markets, providing cross-contextual support for our evidence that literacy acts as a catalyst for both feasibility and opportunity appraisals [27].

Both perceived feasibility ($\beta = 0.298$, $p < 0.001$) and perceived opportunity ($\beta = 0.341$, $p < 0.001$) demonstrated significant positive effects on digital entrepreneurial intention, thereby supporting Hypotheses 4 and 5. This aligns with the Theory of Planned Behavior's emphasis on belief-based determinants of intention. Feasibility and opportunity perceptions translate cognitive evaluations into entrepreneurial intent [20]. It also resonates with the previous work, which indicated that financial and technological literacy enhance entrepreneurial intention through efficacy beliefs and outcome expectations [21]. Consequently, these results underscore the theoretical centrality of feasibility and opportunity within entrepreneurial cognition models. Consistent with TPB, our findings suggest that PF and PO transmit capability cues from AI literacy to DEI, which is in line with prior evidence that belief structures are proximal drivers of intention in digital entrepreneurship contexts [39].

Mediation analysis indicated that perceived feasibility ($\beta = 0.123$, $p < 0.001$) and perceived opportunity ($\beta = 0.126$, $p < 0.001$) partially mediated the relationship between AI literacy and digital entrepreneurial intention. This finding supports hypotheses H6 and H7, suggesting a complementary mediation pattern. The direct effect of AI literacy on digital entrepreneurial intention remained significant, which further reinforces the robustness of the model. These results align with previous research indicating that AI literacy affects entrepreneurial outcomes through self-efficacy and identity aspirations [6, 34]. Collectively, these results clarify that perceived feasibility and perceived opportunity serve as crucial cognitive channels through which AI literacy translates into entrepreneurial intention within AI-driven contexts.

The moderation analysis confirmed that self-efficacy significantly influenced the relationship between AI literacy and perceived feasibility ($\beta = 0.231$, $p < 0.01$), thereby supporting Hypothesis 8. This implies that individuals with heightened self-confidence are more inclined to translate their AI literacy into stronger perceptions of feasibility. This finding corroborates the work of Pham et al. (2025), who established that self-efficacy enhances the effects of technological and financial literacy on entrepreneurial intention [21]. Conceptually, this underscores the role of self-efficacy as a boundary condition within cognition theory, indicating that the impact of literacy is amplified when supported by robust efficacy beliefs. In contrast, risk propensity did not significantly moderate the link between perceived opportunity and digital entrepreneurial intention ($\beta = 0.041$, $p = 0.411$), consequently failing to support Hypothesis 9. This result deviates from earlier research suggesting that highly risk-tolerant individuals are more prone to convert opportunity recognition into concrete entrepreneurial intentions [23, 24]. The evidence implies that in AI-intensive and rapidly evolving environments, intrinsic risk tolerance may hold less sway, given that uncertainty is inherently woven into the technology itself. Instead, cognitive capacities such as literacy and efficacy beliefs appear to be more instrumental in transforming opportunity recognition into entrepreneurial commitment. This interpretation aligns with Husnah's observation that in highly uncertain contexts, literacy and opportunity perception are stronger drivers of entrepreneurial behavior than risk attitudes.

This research significantly enriches the literature on entrepreneurship and digital transformation. Firstly, it extends entrepreneurial cognition theory by demonstrating that AI literacy not only directly influences digital entrepreneurial intention but also indirectly through perceived feasibility and opportunity. This positions AI literacy as a critical cognitive capability rather than merely a technical skill, aligning with calls to integrate domain-specific literacies into entrepreneurial models [27]. Secondly, the study clarifies the mediating roles of feasibility and opportunity perceptions in the relationship between AI literacy and entrepreneurial aspirations. Our findings indicate that these constructs act as complementary mediators, translating AI literacy into concrete entrepreneurial action, thereby addressing a gap in prior research that often linked AI literacy solely to identity or self-efficacy [6]. Thirdly, the study contributes to the understanding of boundary conditions in entrepreneurship. By revealing that self-efficacy moderates the relationship between AI literacy and perceived feasibility, the findings confirm that the impact of literacy is amplified under high self-efficacy, extending this concept to digital entrepreneurship [23, 24].

Conversely, the non-significant moderating effect of risk propensity on the perceived opportunity-digital entrepreneurial intention relationship challenges the traditional assumption that risk-taking is universally central to entrepreneurship. This suggests that in technology-intensive, uncertain contexts, literacy and cognitive evaluations may be more influential than dispositional risk tolerance, contributing to the debate on whether entrepreneurship is primarily trait-based or competence-driven. Finally, by integrating AI literacy into established intention models, this study proposes a novel conceptual extension of the Theory of Planned Behavior within digital contexts. This framework positions AI literacy as an antecedent to belief structures, which subsequently shape entrepreneurial intention, providing a theoretically grounded pathway for future research to explore other technology-specific literacies as precursors to entrepreneurial cognition and action. While AI literacy offers notable advantages, it also presents potential disadvantages, including heightened confidence in automated outcomes, reliance on automated processes, and blind spots regarding ethical implications. These factors could potentially impede rigorous opportunity evaluation. Although not investigated in the current study, these counteracting mechanisms necessitate explicit theoretical development and empirical investigation in subsequent research, particularly to explore potential curvilinear or suppressor effects. Addressing these limitations would significantly enhance entrepreneurial cognition theory by elucidating not only the facilitative role of literacy in entrepreneurial cognition but also the circumstances under which it might inadvertently compromise judicious decision-making in AI-augmented contexts.

6-2- Managerial and Practical Implications

The findings of this study offer several actionable insights for policymakers, educational institutions, and entrepreneurship support organizations aiming to cultivate robust digital entrepreneurial ecosystems in the era of artificial intelligence. Primarily, enhancing AI literacy should be prioritized as a foundational capability. Our research indicates that AI literacy not only directly stimulates entrepreneurial intent but also indirectly reinforces evaluations of feasibility and opportunity. For educators, this underscores the necessity of integrating AI literacy into entrepreneurship curricula, emphasizing technical proficiency, critical assessment, ethical awareness, and problem-solving using AI tools. Policymakers can further advance this agenda by investing in national digital literacy frameworks, establishing certification programs, and creating open-access training platforms to democratize AI knowledge for young individuals and aspiring entrepreneurs. Secondly, training initiatives must explicitly foster skills in feasibility and opportunity recognition. Given that perceived feasibility and perceived opportunity emerged as crucial mediators, entrepreneurship support agencies should develop experiential learning interventions, such as hackathons, AI-enabled business simulations, and incubation challenges.

These initiatives would enable participants to apply AI tools to authentic business problems, thereby making opportunities more apparent and feasibility assessments more realistic, ultimately bridging the gap between literacy and entrepreneurial action. Thirdly, nurturing self-efficacy is vital for maximizing the benefits of AI literacy. The significant moderating effect of self-efficacy suggests that even highly literate individuals may not perceive entrepreneurial ventures as feasible if they lack confidence. Consequently, universities and incubators should incorporate mentoring schemes, peer role-modeling, and mastery-based learning approaches to bolster entrepreneurial self-belief. Governments and development agencies can supplement these efforts by offering micro-grants, sandbox experiments, or low-stakes pilot opportunities, which can reduce the fear of failure and enable entrepreneurs to progressively build their confidence. Fourthly, the limited influence of risk propensity signals a need to recalibrate policy and training interventions.

In contrast to traditional entrepreneurial contexts where risk-taking is often lauded, our results indicate that in AI-intensive environments, literacy and efficacy are more influential than dispositional risk tolerance. Rather than promoting risk-taking as a general trait, support initiatives should concentrate on structured risk management. This involves equipping entrepreneurs with AI-enabled predictive analytics, scenario planning, and data-driven decision-making techniques, thereby shifting the focus from personality-based risk-taking to competence-based risk navigation. Lastly, ecosystem-level interventions are indispensable. Digital entrepreneurship cannot thrive in isolation; it requires supportive environments that provide legitimacy, access, and collaborative opportunities. Policymakers should therefore encourage open innovation initiatives, AI-powered co-working hubs, and public-private partnerships where entrepreneurs can exchange knowledge, validate opportunities, and co-create solutions. Embedding AI literacy within community-level structures ensures equitable dissemination, particularly in developing economies where digital disparities persist. Such systemic interventions can accelerate not only individual entrepreneurial outcomes but also the collective capacity of societies to leverage AI for inclusive and sustainable growth. The socio-cultural milieu of Thailand, characterized by high uncertainty avoidance and collectivist orientations, is likely to significantly influence entrepreneurial engagement with artificial intelligence. Prospective entrepreneurs within this context may exhibit a preference for structured guidance and social endorsement prior to embarking on AI-centric ventures, thereby underscoring the necessity for collaborative and risk-attenuating entrepreneurial programs. The implications for global entrepreneurship education are significant, underscoring the imperative to integrate AI literacy, robust opportunity recognition, and efficacy development within a unified pedagogical framework. Educational programs should evolve beyond mere technical instruction, embedding AI-specific knowledge and ethical considerations directly into practical entrepreneurial endeavors, such as prototyping and market analysis. Crucially, learning experiences must be designed to enhance participants' abilities in feasibility assessment and opportunity identification, thereby enabling the effective application of AI tools in developing sustainable business models. Moreover, pedagogical strategies should actively foster confidence and adaptability, leveraging mentorship, experiential learning, and iterative experimental approaches. To ensure cross-cultural applicability, educators are advised to adapt program implementation to local contexts, especially within cultures exhibiting high uncertainty avoidance. This adaptation should prioritize structured analytical processes and scenario-based learning over approaches that emphasize individual risk-taking propensities.

7- Conclusion

This study presents an empirically validated, comprehensive framework detailing how AI literacy influences digital entrepreneurial intention. It highlights the mediating roles of perceived feasibility and perceived opportunity, along with the moderating effects of self-efficacy and risk propensity. Integrating entrepreneurial cognition theory with the Theory of Planned Behavior (TPB), the findings demonstrate that AI literacy directly boosts entrepreneurial intention and indirectly fosters it through evaluations of feasibility and opportunity. Specifically, AI literacy significantly drives both feasibility and opportunity perceptions, confirming its strategic cognitive importance in digital entrepreneurship. Mediation analysis revealed that perceived feasibility and perceived opportunity function as partial mediators, indicating that AI literacy not only provides technical knowledge but also reinforces the belief systems essential for translating intentions into action. Crucially, the moderating results showed an asymmetry: self-efficacy amplified the pathway from AI literacy to feasibility, whereas risk propensity did not significantly alter the relationship between perceived opportunity and digital entrepreneurial intention. These findings refine existing models by suggesting that confidence in one's capabilities is more impactful than dispositional risk attitudes in AI-driven entrepreneurial contexts. Theoretically, this research extends entrepreneurial cognition theory by positioning AI literacy as a critical antecedent of cognitive evaluations, thereby broadening the explanatory power of the Theory of Planned Behavior within digital transformation settings. It also contributes to the literature on individual differences by clarifying that self-efficacy conditions how literacy translates into feasibility perceptions, while risk tolerance may become less salient in contexts marked by technological uncertainty. Practically, the study underscores AI literacy as both a direct enabler and an indirect catalyst for entrepreneurial action, reinforcing its importance as a policy and educational priority for cultivating digital entrepreneurship in emerging economies.

Despite its valuable contributions, this investigation possesses inherent limitations, thereby presenting numerous avenues for subsequent research. While the proposed theoretical model is robust, its cross-sectional design inherently restricts the capacity for causal inference, as it precludes the establishment of temporal precedence and the control of time-varying confounding variables. Consequently, the observed relationships should be interpreted as associations rather than definitive causal links. Future longitudinal panel studies or randomized interventional learning strategies, such as AI literacy bootcamps, could effectively monitor intra-individual variations in AI Literacy, perceived feasibility and opportunity assessments, and Digital Entrepreneurial Intention to ascertain temporal ordering and bolster causal claims. Furthermore, the reliance on self-reported measures, although prevalent in behavioral research, introduces a potential for bias. Subsequent investigations could mitigate this by employing data triangulation methodologies, incorporating objective metrics such as actual entrepreneurial engagement or AI utilization analytics, to augment validity. Additionally, this study's execution within the specific context of Thailand, an emerging economy characterized by distinctive socio-cultural attributes, may constrain the generalizability of its findings. Therefore, comparative research across diverse cultural and economic environments is strongly encouraged to ascertain cross-contextual applicability. Descriptive analyses indicated generally comparable mean levels of AIL and DEI across gender cohorts; however, given the circumscribed scope of this study's design, these findings necessitate cautious interpretation. Future research should implement multi-group measurement invariance analyses and multi-group comparative approaches to rigorously assess potential structural discrepancies. Finally, while this inquiry primarily focused on pivotal cognitive and psychological antecedents of digital entrepreneurial intention, specifically perceived feasibility, perceived opportunity, self-efficacy, and risk propensity, future explorations could broaden the conceptual framework by integrating additional constructs such as entrepreneurial identity, creativity, and institutional support, alongside ecosystem-level facilitators like policy incentives and AI infrastructure.

8- Declarations

8-1- Author Contributions

Conceptualization, D.H. and S.T.; methodology, D.H. and S.T.; software, S.T.; validation, D.H.; formal analysis, S.T.; investigation, S.T.; resources, D.H. and S.T.; data curation, D.H.; writing—original draft preparation, D.H. and S.T.; writing—review and editing, D.H. and S.T.; visualization, D.H. and S.T.; supervision, D.H.; project administration, S.T.; funding acquisition, D.H. and S.T. All authors have read and agreed to the published version of the manuscript.

8-2- Data Availability Statement

The datasets generated during and/or analyzed during the current study are not publicly available due to IRB stipulations, but are available from the corresponding author upon reasonable request.

8-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

8-4- Institutional Review Board Statement

This study was approved by the Ethics Committee for Human Research of Bangkok University (Ref. No. 416812092).

8-5- Informed Consent Statement

Not applicable.

8-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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