Original Article

AI Literacy and digital green entrepreneurship among university students: roles of support and expectancy

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ABSTRACT

This study examines how artificial intelligence (AI) literacy shapes university students' digital-oriented green entrepreneurial intention (DGEI). Drawing on Stimulus–Organism–Response theory, Social Cognitive Career Theory, and the Entrepreneurial Event Model, the study develops a moderated serial mediation model linking AI literacy to DGEI through green entrepreneurial self-efficacy (GESE), green entrepreneurial fear of failure (GEFF), perceived feasibility (PF), and perceived desirability (PD). The model also investigates the moderating roles of performance expectancy of AI solutions (PEAIS), external institutional support (EIS), and family support (FS). Data were collected from 539 Vietnamese university students. After data screening, 500 valid responses were retained and analyzed using PLS-SEM. The findings show that AI literacy positively influences DGEI and GESE, while negatively affecting GEFF. GESE increases PF, PD, and DGEI, whereas GEFF reduces these entrepreneurial appraisals and intentions. PF and PD both positively predict DGEI. This study contributes to AI literacy and green entrepreneurship research by explaining how AI capability, psychological readiness, venture appraisal, and contextual support jointly shape students' intention to pursue digital-oriented green ventures.

Keywords: AI literacy, Green entrepreneurial self-efficacy, Green entrepreneurial fear of failure, Digital-oriented green entrepreneurial intention, University students

Introduction

Green entrepreneurship has become an important mechanism for aligning entrepreneurial activity with environmental sustainability. Unlike conventional entrepreneurship, green entrepreneurship emphasizes the creation of ventures that address ecological problems through sustainable products, low-carbon services, cleaner technologies, and environmentally responsible business models. This orientation is especially relevant in emerging economies, where economic expansion often occurs alongside resource depletion, pollution, and institutional pressure for greener development [1, 2]. Universities play a central role in this transition because students represent a key group of potential entrepreneurs who are exposed to sustainability education, digital transformation, and career exploration before entering the labor market [3, 4]. However, students may still perceive green entrepreneurship as uncertain, risky, and resource-demanding. Their intention to create green ventures, therefore, depends not only on environmental concern but also on their confidence, perceived opportunity, support systems, and ability to use emerging technologies.

Artificial intelligence (AI) has recently become one of the most influential technologies in entrepreneurial contexts [5, 6]. AI tools can support business idea generation, market analysis, customer profiling, decision-making, and opportunity evaluation [7, 8]. Generative artificial intelligence (GenAI) has further

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expanded these possibilities by enabling students and entrepreneurs to generate content, simulate business ideas, search for information, and develop preliminary venture solutions [9-12]. These functions are relevant to green entrepreneurship because sustainable ventures often require integrating environmental knowledge, digital data, and innovative problem-solving [13, 14]. Prior studies have shown that AI adoption and GenAI incorporation can improve entrepreneurial self-efficacy, innovation, and entrepreneurial intention [15, 16]. Other evidence suggests that AI can support green knowledge management, green innovation, and sustainable business performance [8, 17]. These studies indicate that AI can shape how potential entrepreneurs interpret opportunities, evaluate risks, and imagine future ventures [18, 19].

AI literacy provides a useful construct for examining this process among university students. AI literacy reflects an individual's ability to understand, use, evaluate, and ethically engage with AI technologies. Recent research has conceptualized AI literacy as a higher-order construct comprising AI awareness, AI use, AI evaluation, and AI ethics [20, 21]. This multidimensional structure is important because students need more than technical familiarity with AI. They also need to judge the quality of AI outputs, understand ethical implications, and apply AI responsibly in entrepreneurial tasks. In the context of green entrepreneurship, these abilities may help students identify environmental problems, design digital solutions, and assess the viability of sustainability-oriented ventures. In this study, digital-oriented green entrepreneurial intention (DGEI) is adapted from digital-oriented sustainable entrepreneurial intention literature [22]. It refers to students' intention to create environmentally oriented ventures by using digital technologies, platforms, or AI-enabled tools. This construct is relevant because digital entrepreneurship relies on digital technologies to pursue and transform business opportunities, while green entrepreneurial intention reflects a commitment to engage in environmentally sustainable entrepreneurial activities [23, 24].

Although recent studies have advanced understanding of AI-enabled entrepreneurship, the literature still provides a fragmented explanation of how AI literacy contributes to DGEI. AI literacy has been shown to shape students' entrepreneurial cognition, self-efficacy, and digital entrepreneurial intention in e-entrepreneurship and digital entrepreneurship settings [18, 25]. Green entrepreneurship research, in contrast, has mainly emphasized sustainability education, environmental awareness, university support, and green entrepreneurial self-efficacy [3, 26]. These streams have developed in parallel. As a result, limited evidence exists on whether AI literacy helps students form intentions toward ventures that are simultaneously digitally enabled and environmentally oriented. This gap is important because DGEI requires students to combine digital opportunity creation with environmental value creation.

A further limitation concerns the internal process through which AI literacy operates. Prior work often presents AI as an enabling resource that improves confidence, opportunity evaluation, and entrepreneurial capability [16, 27]. This view is useful, but it underplays the ambivalent nature of AI-enabled entrepreneurship. AI literacy may increase students' confidence in using AI to search for information, evaluate markets, and design green solutions. It may also make them more aware of technological uncertainty, ethical risks, competitive pressure, and the possibility of failure. Research on technology-enabled entrepreneurship suggests that digital technologies can generate both enabling and constraining responses. Especially when individuals face technostress, uncertainty, or complex digital tasks [28, 29]. Therefore, green entrepreneurial self-efficacy and green entrepreneurial fear of failure should be examined together as contrasting psychological mechanisms rather than as isolated antecedents.

Besides, although perceived feasibility and perceived desirability are central to the Entrepreneurial Event Model (EEM), their antecedents remain underdeveloped in AI-enabled research on green entrepreneurship. The EEM explains entrepreneurial intention by examining individuals' evaluations of the feasibility and attractiveness of venture creation [30, 31]. Recent studies have applied this logic to digital and AI-enabled entrepreneurship by linking AI literacy, the incorporation of GenAI, perceived feasibility, perceived desirability, and entrepreneurial intention [32, 33]. However, these studies mainly explain how feasibility and desirability transmit the effect of AI-related capabilities, rather than what psychological states shape these appraisals. This limitation matters because green venture formation requires students to evaluate both their capability to mobilize AI-enabled resources and the personal value of pursuing environmental goals.

In addition, the boundary conditions of this process also remain underdeveloped. Recent studies call for greater attention to moderators, contextual factors, technological support, institutional conditions, and access to resources in AI-driven models of entrepreneurial intention [25, 32]. This issue is consequential because AI literacy is unlikely to affect all students equally. Yet limited research has examined how these boundary conditions operate across different stages of the AI literacy and DGEI process.

To address these gaps, this study integrates Stimulus-Organism-Response theory (SOR), Social Cognitive Career Theory (SCCT), and the Entrepreneurial Event Model (EEM). This theoretical integration is suitable for the present model because it links AI literacy, psychological readiness, venture appraisal, and intention within a single staged framework. Specifically, this study develops a moderated serial mediation model in which AI literacy influences DGEI through green entrepreneurial self-efficacy (GESE), green entrepreneurial fear of failure (GEFF), perceived feasibility (PF), and perceived desirability (PD). It further examines whether performance expectancy of AI solutions (PEAIS), family support (FS), and external institutional support (EIS) moderate different stages of this process. The study addresses two research questions.

RQ1. What is the relationship between AI literacy, GESE, GEFF, PF, PD, and DGEI?

RQ2. Do performance expectancy of AI solutions, family support, and external institutional support moderate different stages of the AI literacy and DGEI process?

By answering these questions, this study contributes to the literature in three ways. It extends AI literacy research into the context of digital-oriented green entrepreneurship. It explains the link between AI literacy and green entrepreneurial intention through both positive and negative psychological pathways. It also clarifies how technological, family, and institutional supports shape the conversion of AI literacy into green entrepreneurial intention.

Theoretical background and hypotheses development

Stimulus–organism–response (SOR) theory

The SOR model developed by Mehrabian and Russell [34] explains how external stimuli shape individuals' internal cognitive or affective states, which then influence behavioral responses. In entrepreneurship research, SOR has been used to show that digital and artificial intelligence-related stimuli can affect entrepreneurial self-efficacy, identity aspiration, perceived feasibility, perceived desirability, and entrepreneurial intention [20, 25, 35]. Recent studies further suggest that generative artificial intelligence incorporation and artificial intelligence literacy can reshape how students evaluate digital venture opportunities [32, 36]. In this study, AI literacy is treated as a digital stimulus that activates students' GESE, GEFF, PF, and PD. These organismic states explain how AI literacy is translated into DGEI.

Social cognitive career theory (SCCT)

SCCT, developed by Lent, Brown [37], explains how career interests, goals, and choices are shaped by self-efficacy, outcome expectations, and contextual supports or barriers. This theory is relevant to entrepreneurship because entrepreneurial intention can be viewed as a career-related goal that depends on individuals' perceived capability and the conditions surrounding their career choice. Prior studies have used SCCT-related logic to explain how self-efficacy and support systems influence green or sustainability-oriented entrepreneurial intention among students [3, 38]. Similar mechanisms have also been observed in AI-enabled and digital entrepreneurship, where ChatGPT adoption, generative AI incorporation, and digital entrepreneurial self-efficacy shape entrepreneurial intention under enabling or constraining conditions [28, 36]. In this study, SCCT explains how AI literacy shapes GESE and GEFF. It also supports the moderating roles of PEAISS, FS, and EIS as contextual conditions.

Entrepreneurial event model (EEM)

The EEM proposed by Shapero and Sokol [31] explains entrepreneurial intention as a function of perceived feasibility, perceived desirability, and propensity to act. EEM has been widely used to explain entrepreneurial intention because it focuses on the subjective appraisal of venture creation rather than only on attitudes or social pressure [33, 39]. Recent studies have extended EEM to digital and artificial intelligence-enabled entrepreneurship, showing that artificial intelligence literacy and the incorporation of generative artificial intelligence can influence entrepreneurial intention through perceived feasibility and perceived desirability [32, 40]. In this study, EEM explains the final appraisal stage through which green entrepreneurial self-efficacy and green entrepreneurial fear of failure are translated into digital-oriented green entrepreneurial intention. Specifically, students are more likely to form such an intention when green venture creation is perceived as both feasible and desirable [41, 42].

Artificial intelligence literacy (AI literacy)

According to Wang, Rau [21] and Bewersdorff, Hornberger [43], AI literacy refers to individuals' capacity to identify, understand, use, evaluate, and engage with AI technologies in an ethically appropriate manner. In this study, AI literacy is conceptualized as students' capability to understand AI tools, use them for entrepreneurial tasks, critically evaluate AI-generated outputs, and apply AI responsibly in green venture-related decision-making. Based on research by Tran and Lam [22], digital-oriented green entrepreneurial intention (DGEI) refers to students' intention to create environmentally oriented ventures by using digital technologies, platforms, or AI-enabled tools. This construct is adapted from the literature on digital entrepreneurship and green entrepreneurial intention [14, 44]. Digital entrepreneurship emphasizes venture creation through digital technologies, online platforms, and data-driven tools, while green entrepreneurial intention reflects individuals' willingness to pursue ventures that create environmental value [2, 45]. AI literacy can make digital-oriented green venture creation more visible and accessible because AI-literate students are better able to search for information, analyze market data, develop ideas, evaluate alternatives, and communicate digitally. Prior studies show that AI literacy shapes e-entrepreneurial intention among university students [20, 25]. In green entrepreneurship, AI can also support green knowledge management, green innovation, and sustainable business performance by improving information processing and decision support [8, 17].

H1. AI literacy positively influences DGEI

Green entrepreneurial self-efficacy (GESE) is commonly understood as individuals' belief that they can contribute to environmental problem-solving through entrepreneurial action and develop environmentally oriented business ideas [3, 41]. This construct is grounded in SCCT, which argues that self-efficacy beliefs shape career interests, goals, and choices [37, 46]. AI literacy may strengthen GESE because AI-literate students can use AI tools to search for environmental information, compare alternative solutions, analyze digital data, and support opportunity-related tasks. These capabilities can reduce the perceived difficulty of green venture creation and increase students' confidence in performing entrepreneurial tasks. Prior green entrepreneurship studies show that GESE is an important antecedent of green entrepreneurial intention [3, 26]. Related e-entrepreneurship research also shows that AI literacy enhances e-entrepreneurial self-efficacy among university students [20, 25].

H2. AI literacy positively influences GESE.

Entrepreneurial fear of failure refers to a cognitive and emotional response to the anticipated negative consequences of failing in venture creation, including financial loss, social evaluation, shame, and psychological stress [47, 48]. In this study, green entrepreneurial fear of failure (GEFF) refers to students' concern about failing to launch or manage a venture that pursues environmental value creation. This contextualization is appropriate because green ventures often involve additional uncertainty related to regulation, environmental legitimacy, market acceptance, and the need to balance commercial and ecological outcomes [1, 49]. AI literacy may reduce GEFF by improving students' perceived control over early-stage venture tasks. Students who understand and use AI can collect information, evaluate market signals, compare possible solutions, and reduce ambiguity in green venture planning. It also aligns with recent evidence that generative AI can produce both enabling and fear-related pathways in sustainable entrepreneurship, depending on how students perceive and manage AI-enabled complexity [50].

H3. AI literacy negatively influences GEFF.

Green entrepreneurial self-efficacy (GESE)

Perceived feasibility (PF) refers to individuals' belief that starting and running a venture is achievable, given their capability, skills, and resources [39]. In digital entrepreneurship, PF captures whether students feel able to start and manage a technology-enabled venture [32, 33]. In this study, PF refers to students' belief that creating a digital-oriented green venture is practically attainable. GESE reflects students' confidence in performing green entrepreneurial tasks. Hence, students with stronger GESE should therefore perceive digital-oriented green entrepreneurship as more feasible because they feel more capable of identifying green opportunities, developing sustainable solutions, and managing entrepreneurial tasks [3, 26].

H4. GESE positively influences PF.

Perceived desirability (PD) refers to the extent to which venture creation is viewed as attractive, personally rewarding, and worth pursuing [31, 39]. In digital entrepreneurship, PD captures the motivational appeal of creating a technology-enabled venture and predicts students' entrepreneurial intention [33]. In AI-driven digital social entrepreneurship, PD is linked to emotional resonance, mission commitment, and the perceived value of addressing social problems through digital technologies [18, 51]. In the green context, PD also reflects environmental values, sustainability aspirations, and the perceived meaning of creating ecological value [52, 53]. Therefore, students with stronger GESE are more likely to view digital-oriented green entrepreneurship as desirable because they feel capable of applying their abilities to meaningful sustainability goals.

H5. GESE positively influences PD.

Recent research shows that digital competencies and environmental values shape students' digital-oriented sustainable entrepreneurial intention [22]. Hence, GESE increases DGEI because students who believe they can identify green opportunities and develop sustainability-oriented solutions are more likely to form entrepreneurial intentions. It is consistent with SCCT, which treats self-efficacy as a core driver of career goals [37]. Empirical studies also show that self-efficacy predicts entrepreneurial intention in AI-enabled, digital, and green entrepreneurship contexts [3, 28, 41, 54]. Therefore, students with stronger GESE are expected to report stronger DGEI.

H6. GESE positively influences DGEI.

Green entrepreneurial fear of failure (GEFF)

GEFF can reduce PF because fear makes students focus on uncertainty, possible loss, and barriers to venture creation. In sustainable entrepreneurship, entrepreneurial fear is linked to failure, perceived hazards, financial risk, market uncertainty, and the high cost of sustainable technologies [55]. Recent e-entrepreneurship research also shows that loss aversion and fear of loss can make students overestimate risks, avoid uncertain projects, and perceive online ventures as less feasible [56, 57]. It is relevant to digital-oriented green entrepreneurship because students must evaluate both technological uncertainty and environmental value creation. Specifically, perceived risk and risk aversion also shape students' intentions, as sustainable ventures are often associated with regulatory, technological, and market uncertainty [49]. Therefore, a stronger GEFF should weaken students' PF.

H7. GEFF negatively influences PF.

Entrepreneurial intention requires commitment to a future venture path, whereas fear of failure increases avoidance, hesitation, and perceived barriers. Recent entrepreneurship research shows that fear of failure can widen the attitude-intention-behavior gap and weaken the translation of entrepreneurial motivation into action [58]. Student-based evidence also indicates that fear of failure is relevant to the formation of entrepreneurial intention across educational contexts [59]. In sustainable entrepreneurship, entrepreneurial fear has been examined as a key boundary condition in students' sustainable entrepreneurial intention, especially when sustainability and AI-related learning are considered together [55]. Since digital-oriented green entrepreneurship requires students to manage technological uncertainty, commercial viability, and environmental value creation, a stronger GEFF should weaken DGEI.

H8. GEFF negatively influences DGEI.

Fear of failure can lower PD by making green venture creation appear emotionally costly and less personally rewarding. When students associate entrepreneurship with financial loss, social judgment, technical difficulty, or reputational risk, the motivational appeal of venture creation declines [48, 60]. Recent evidence also shows that fear of failure can suppress entrepreneurial intention by encouraging avoidance and defensive responses, particularly in student and sustainability-oriented contexts [58, 59]. This mechanism is relevant to green entrepreneurship because students must evaluate commercial risk together with regulatory uncertainty, technological complexity, and sustainability-related demands [49, 55].

H9. GEFF negatively influences PD.

Perceived feasibility (PF)

The EEM treats PF as a core appraisal through which individuals judge whether venture creation is achievable and within their capability [31, 39]. In e-entrepreneurship, PF also involves students' assessment of market demand, scalability, competition, and their ability to manage technology-enabled ventures [56, 61]. Recent research further shows that feasibility appraisals shape intention when students perceive digital technologies as useful for venture creation and social value generation [33, 35]. In digital-oriented green entrepreneurship, PF is particularly relevant because students must evaluate both venture viability and environmental value creation [53].

H10. PF positively influences DGEI.

Perceived desirability (PD)

Recent digital entrepreneurship research shows that PD increases students' intention when venture creation aligns with personal goals, intrinsic motivation, and future identity [33, 62]. In sustainable entrepreneurship, desirability is closely linked to environmental values, entrepreneurial passion, and the perceived meaning of solving ecological problems [53, 63]. Thus, students who view DGE as attractive and meaningful are more likely to form stronger DGEI.

H11. PD positively influences DGEI.

Performance expectancy of AI solutions (PEAISS) as a moderator

PEAIS refers to the extent to which students believe that AI can improve business-related tasks through greater efficiency, speed, and effectiveness. The construct is rooted in technology acceptance research and has been adapted to entrepreneurship to capture the perceived business value of AI solutions [64, 65]. In digital entrepreneurship, PEAIS strengthens the role of digital competencies in entrepreneurial intention because students are more likely to act on their abilities when they perceive AI as useful for venture creation [66].

Meanwhile, AI literacy enables students to understand, evaluate, and use AI. This capability becomes more empowering when students believe that AI can support market analysis, business planning, idea development, and decision-making. In AI-enabled entrepreneurship, technological support can strengthen the effect of AI-related capability on feasibility-related appraisals [32]. Therefore, AI literacy should translate more strongly into GESE when PEAIS is high.

H12a. PEAIS moderates the relationship between AI literacy and GESE

Moreover, AI literacy equips students with the knowledge and skills to recognize how AI can support green venture creation. However, this literacy is more likely to become entrepreneurial intention when students believe that AI can generate practical business value. When PEAIS is high, students may view AI-enabled green entrepreneurship as more efficient, actionable, and strategically valuable. Prior digital entrepreneurship research shows that perceived AI usefulness can reinforce the effect of digital capability on entrepreneurial intention [66]. Therefore, AI literacy should have a stronger positive effect on DGEI when PEAIS is high.

H12b. PEAIS moderates the relationship between AI literacy and DGEI.

In addition, AI-literate students may still feel fear if they doubt AI's practical value for entrepreneurship. When students believe that AI can reduce time costs, improve efficiency, and support decision-making, AI literacy is more likely to reduce perceived difficulty and failure-related concerns. It aligns with research showing that AI tools support entrepreneurial learning, idea development, and planning [16, 36].

H12c. PEAIS moderates the relationship between AI literacy and GEFF.

External institutional support (EIS) as a moderator

EIS refers to the extent to which government agencies, public institutions, and related support organizations provide policy, regulatory, technical, financial, informational, and advisory assistance that facilitates entrepreneurial activity [2, 67, 68]. In green entrepreneurship, EIS is particularly important because green ventures often depend on regulatory clarity, environmental legitimacy, technology information, licensing assistance, subsidies, and access to sustainability-oriented programs [69, 70]. Recent sustainable entrepreneurship research further suggests that institutional support can reduce uncertainty and strengthen entrepreneurial competence, thereby helping entrepreneurs convert available resources into sustainable entrepreneurial action [71, 72].

PF is a reflection of students' confidence in the viability of creating green ventures with a digital focus. However, when the institutional environment is seen as weak or ambiguous, feasibility might not become intention. Strong EIS can provide policy signals, startup programs, public information, financial incentives, and green entrepreneurship initiatives that reduce external barriers and make feasibility judgments more actionable [1, 2, 69]. Thus, students who perceive green venture creation as feasible are more likely to form stronger DGEI when EIS is high.

H13a. EIS moderates the relationship between PF and DGEI.

Fear of failure can discourage entrepreneurial intention by increasing avoidance, hesitation, and perceived barriers [58, 59]. In sustainable entrepreneurship, this fear is salient because students may worry about financial risk, market uncertainty, technological difficulty, and the high cost of sustainable solutions [55]. Strong EIS can buffer these concerns by providing financial backing, regulatory guidance, legitimacy, and access to green entrepreneurship programs. Prior green entrepreneurship research shows that institutional support can reduce barriers, help entrepreneurs identify green opportunities, and facilitate the movement from intention to action, especially when perceived risks and resource constraints are [1, 2, 69]. Therefore, the negative effect of GEFF on DGEI should be weaker when EIS is high.

H13b. EIS moderates the relationship between GEFF and DGEI.

Family support as a moderator

FS refers to tangible and intangible resources provided by family members, including approval, encouragement, emotional backing, advice, role modeling, social connections, and possible financial resources for venture creation [73, 74]. In student entrepreneurship, family influence is salient because students often depend on parental approval, social legitimacy, and early-stage resources before committing to an entrepreneurial career [75, 76]. In digital entrepreneurship, FS is also relevant because family approval and access to resources can help students manage the uncertainty of technology-enabled venture creation [33, 77]. In digital-oriented green entrepreneurship, PD may remain psychologically weak if students perceive limited family approval. Supportive families can make green venture creation more socially acceptable, emotionally secure, and personally meaningful. Prior research shows that family support can increase the appeal of entrepreneurship and strengthen the effect of PD on digital entrepreneurial intention [33, 78]. Green entrepreneurship research also suggests that social support helps translate green entrepreneurial intention into action, especially when students pursue sustainability-oriented ventures [79]. Thus, the positive relationship between PD and DGEI can be stronger when FS is high.

H14a. FS moderates the relationship between PD and DGEI.

Moreover, GESE may be more likely to become intentional when students receive family approval, encouragement, and resource support. FS can foster psychological safety and reduce the perceived burden of pursuing an uncertain venture. Prior studies show that family support enhances entrepreneurial intention through self-efficacy and can strengthen the conversion of self-efficacy into entrepreneurial intention [80, 81]. In digital entrepreneurship, Nguyen and Nguyen [33] also found that FS strengthens the relationship between self-efficacy and digital entrepreneurial intention. Therefore, the higher the FS, the stronger the positive impact of GESE on DEGI will be.

H14b. FS moderates the relationship between GESE and DGEI.

Figure 1 illustrates the proposed research model.

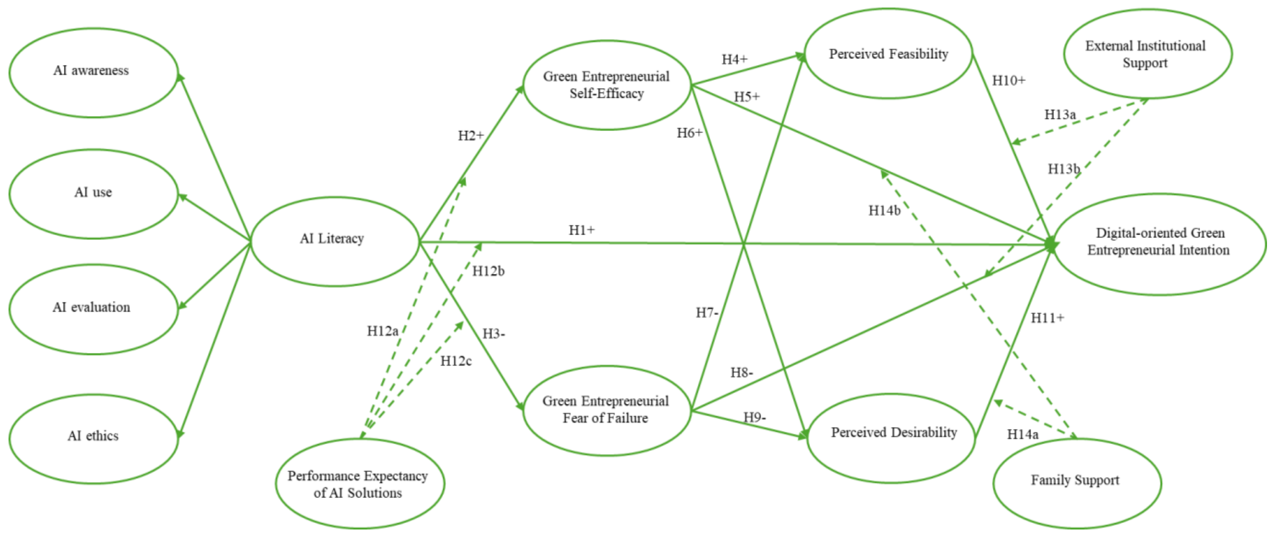

Figure 1. Research model

Materials and Methods

Research design

This study employed a quantitative research design to examine the relationships among AI literacy, green entrepreneurial self-efficacy, green entrepreneurial fear of failure, perceived feasibility, perceived desirability, contextual support factors, and digital-oriented green entrepreneurial intention among university students in Vietnam **(Figure 1)**. A structured survey was considered appropriate because the study aims to test a theory-driven model involving direct, mediating, and moderating relationships.

Data collection

The target population consisted of Vietnamese university students who had basic familiarity with AI tools and were able to evaluate entrepreneurship-related issues. This group was suitable for the study because students are potential early-stage entrepreneurs and are increasingly exposed to AI applications, digital learning environments, and sustainability-oriented career choices. To make sure that respondents were pertinent to the study setting, a purposive sampling strategy was employed. The survey was disseminated using online resources and university networks.Before answering the main items, respondents were informed about the purpose of the study and were assured that their responses would remain anonymous and confidential. A total of 539 questionnaires were collected. After data screening, 39 responses were removed because of incomplete answers, inconsistent response patterns, or failure to satisfy the required response quality criteria. The final valid sample included 500 responses, representing an effective response rate of 92.8%.

Table 1 shows that female respondents accounted for a larger proportion of the sample (60.8%) than male respondents (39.2%). Regarding study year, third-year students formed the largest group (31.0%), followed by second-year students (26.2%), fourth-year students (18.4%), first-year students (17.0%), and postgraduate students (7.4%). The respondents came from diverse academic backgrounds, with Business/Management representing the largest group (36.2%), followed by Information Technology (20.0%), Economics/Finance (16.8%), Engineering (10.6%), Tourism/Hospitality (10.0%), and other majors (6.4%). This distribution is suitable for the present research context because digital-oriented green entrepreneurship is closely related to business, technology, innovation, and sustainability-oriented career development. Geographically, respondents were distributed across Northern Vietnam (28.0%), Central Vietnam (21.0%), and Southern Vietnam (51.0%)

Table 1. Sample characteristics of respondents.

Categories	Sub-categories	Frequency	Percentage
Gender	Male	196	39.2
	Female	304	60.8
Study year	Year 1	85	17.0
	Year 2	131	26.2
	Year 3	155	31.0
	Year 4	92	18.4
	Postgraduate	37	7.4
Major group	Business/Management	181	36.2
	Economics/Finance	84	16.8
	Information Technology	100	20.0
	Engineering	53	10.6
	Tourism/Hospitality	50	10.0
	Other	32	6.4
Geographical area	Northern Vietnam	140	28.0
	Central Vietnam	105	21.0
	Southern Vietnam	255	51.0

Scale development

The measurement items were adapted from established scales in prior studies and modified to fit the context of digital-oriented green entrepreneurship among university students. All constructs were measured using a five-point Likert scale ranging from 1 = "strongly disagree" to 5 = "strongly agree". AW, US, EV, and ET scale were adapted from [40]. GESE, GEFF, and FS were adapted from Kong, Hu [50]. PF and PD were adapted from Nguyen and Nguyen [33]. PEAIS was adapted from Duong, Le [66]. EIS was adapted from Yi [2]. DGEI was adapted from Tran and Lam [22].

The original questionnaire was developed in English and then translated into Vietnamese to ensure respondents' comprehension. A back-translation procedure was applied to check semantic consistency between the English and Vietnamese versions. Minor wording adjustments were made to improve clarity and contextual relevance. A pilot check (Cronbach's alpha > 0.7) was also conducted before the main survey to ensure that the items were understandable and suitable for the target respondents.

Data analysis

The proposed model was analyzed using partial least squares structural equation modeling (PLS-SEM). This method was selected because the study includes a complex research model with multiple mediating paths, moderating effects, and a higher-order construct [82]. PLS-SEM is also appropriate for prediction-oriented research and for examining models that integrate psychological, technological, and contextual factors [83].

Results and Discussion

Common method bias (CMB)

CMB was checked using procedural and statistical remedies. The survey ensured anonymity, reduced evaluation apprehension, and separated predictors, mediators, moderators, and outcome variables into different sections [84]. Statistically, Harman's single-factor test showed that the first factor explained 34.109% of the total variance, which was < 50% [85]. In addition, all full collinearity VIF values were < 3.3 [86]. These results suggest that CMB was not a serious threat to this study.

Measurement model

Table 2 reports the reliability and validity statistics of the measurement model. The outer loadings of all observed indicators ranged from 0.819 to 0.921, exceeding the recommended threshold of 0.70. This indicates that the indicators adequately represented their respective latent constructs. Cronbach's alpha values ranged from 0.863 to 0.939, while composite reliability values ranged from 0.916 to 0.951. These findings show that all constructs have enough internal consistency and dependability. In addition, the average variance extracted values ranged from 0.744 to 0.833, all of which were higher than the recommended minimum of 0.50. Therefore, the constructs achieved adequate convergent validity. For the higher-order construct, AI literacy also showed strong reliability and validity, with Cronbach's alpha of 0.912, composite reliability of

0.938, and AVE of 0.791. Overall, the measurement model met the criteria for reliability and convergent validity, supporting the suitability of the scales for subsequent structural modeling [87].

Table 2. Measurement model

Constructs/Variables	Outer loadings	Cronbach's alpha	Composite reliability	AVE
AI literacy (Second order)		0.912	0.938	0.791
AI awareness (First order)		0.896	0.935	0.827
AW1	0.904			
AW2	0.910			
AW3	0.915			
AI use (First order)		0.899	0.937	0.833
US1	0.919			
US2	0.907			
US3	0.911			
AI evaluation (First order)		0.889	0.931	0.818
EV1	0.903			
EV2	0.914			
EV3	0.896			
AI ethics (First order)		0.899	0.937	0.833
ET1	0.898			
ET2	0.921			
ET3	0.918			
Digital-oriented green entrepreneurial intention		0.922	0.942	0.763
DGEI1	0.897			
DGEI2	0.862			
DGEI3	0.872			
DGEI4	0.874			
DGEI5	0.863			
Green entrepreneurial self-efficacy		0.863	0.916	0.785
GESE1	0.897			
GESE2	0.878			
GESE3	0.884			
Green entrepreneurial fear of failure		0.921	0.940	0.759
GEFF1	0.870			
GEFF2	0.876			
GEFF3	0.858			
GEFF4	0.874			
GEFF5	0.880			
Perceived feasibility		0.914	0.936	0.744
PF1	0.874			
PF2	0.862			
PF3	0.856			
PF4	0.858			
PF5	0.861			
Perceived desirability		0.864	0.917	0.786
PD1	0.889			
PD2	0.871			
PD3	0.899			
Performance expectancy of AI solutions		0.898	0.929	0.766
PEAIS1	0.884			
PEAIS2	0.870			
PEAIS3	0.860			
PEAIS4	0.886			
External institutional support		0.893	0.923	0.749
EIS1	0.819			
EIS2	0.892			
EIS3	0.880			
EIS4	0.871			
Family support		0.939	0.951	0.762
FS1	0.879			
FS2	0.900			
FS3	0.859			
FS4	0.861			
FS5	0.867			
FS6	0.872			

Table 3 confirms discriminant validity. All HTMT values ranged from 0.050 to 0.720, which were < 0.85. Thus, the constructs were sufficiently distinct [88]. The Fornell–Larcker criterion was also satisfied because each diagonal value, i.e., √AVE = 0.862–0.889, was above its corresponding inter-construct correlations [89]. Overall, the results indicate no discriminant validity concern.

Table 3. Discriminant validity

Heterotrait-monotrait ratio (HTMT)									
	AIL	DGEI	EIS	FS	GEFF	GESE	PD	PEAIS	**PF**
AIL									
DGEI	0.633								
EIS	0.176	0.144							
FS	0.144	0.107	0.226						
GEFF	0.561	0.578	0.171	0.180					
GESE	0.618	0.690	0.175	0.120	0.495				
PD	0.547	0.627	0.154	0.195	0.557	0.624			
PEAIS	0.348	0.297	0.180	0.222	0.295	0.386	0.374		
PF	0.565	0.642	0.174	0.050	0.608	0.720	0.509	0.306	
Fornell–Larcker									
	AIL	DGEI	EIS	FS	GEFF	GESE	PD	PEAIS	PF
AIL	0.889								
DGEI	0.581	0.874							
EIS	0.170	0.143	0.866						
FS	0.139	0.107	0.205	0.873					
GEFF	-0.515	-0.534	-0.158	-0.172	0.871				
GESE	0.549	0.617	0.160	0.111	-0.442	0.886			
PD	0.486	0.561	0.142	0.176	-0.497	0.539	0.887		
PEAIS	0.316	0.272	0.160	0.205	-0.269	0.341	0.330	0.875	
PF	0.516	0.590	0.166	0.036	-0.558	0.641	0.452	0.277	0.862

Note(s): AI literacy – AIL; Digital-oriented green entrepreneurial intention – DGEI; Green entrepreneurial self-efficacy – GESE; Green entrepreneurial fear of failure – GEFF; Perceived feasibility – PF; Perceived desirability – PD; Performance expectancy of AI solutions – PEAIS; External institutional support – EIS; Family support – FS.

Structural model

Table 4 and **Figure 2** present the results of the structural model assessment. All hypothesized paths were statistically significant and supported. AIL positively influenced DGEI ($\beta = 0.229$), supporting H1. AIL also positively influenced GESE ($\beta = 0.489$) and negatively influenced GEFF ($\beta = -0.477$), supporting H2 and H3. These findings suggest that students with stronger AILs are more likely to feel capable of engaging in green entrepreneurship and less likely to fear failure in this context.

The results further show that GESE positively affected PF ($\beta = 0.490$), PD ($\beta = 0.397$), and DGEI ($\beta = 0.186$), supporting H4, H5, and H6. In contrast, GEFF negatively affected PF ($\beta = -0.341$), DGEI ($\beta = -0.114$, $t = 3.107$), and PD ($\beta = -0.322$), supporting H7, H8, and H9. These findings indicate that GESE and GEFF operate as contrasting psychological mechanisms in the formation of DGEI.

PF and PD were also significant predictors of DGEI. Specifically, PF positively influenced DGEI ($\beta = 0.181$), supporting H10, while PD also positively influenced DGEI ($\beta = 0.187$), supporting H11. These results confirm the relevance of feasibility and desirability appraisals in explaining students' intention to pursue digital-oriented green entrepreneurship .

The moderation results were also significant. The PEAIS strengthened the relationships between AIL and GESE ($\beta = 0.199$) and between AIL and DGEI ($\beta = 0.157$), supporting H12a and H12b. It also significantly moderated the relationship between AIL and GEFF ($\beta = -0.131$), supporting H12c. This indicates that when students perceive AI solutions as useful and performance-enhancing, AI literacy becomes more effective in increasing entrepreneurial confidence, strengthening intention, and reducing fear of failure.

EIS positively moderated the relationship between PF and DGEI ($\beta = 0.141$), supporting H13a. It also moderated the relationship between GEFF and DGEI ($\beta = 0.134$, $t = 3.615$, $p < 0.001$), supporting H13b. Given the negative direct effect of GEFF on DGEI, the positive interaction coefficient suggests that EIS buffers the adverse effect of GEFF. Finally, FS strengthened the effects of PD ($\beta = 0.138$) and GESE ($\beta = 0.081$) on DGEI, supporting H14a and H14b. Overall, the structural model provides full empirical support for the proposed hypotheses.

The model best explains DGEI (0.614) and PF (0.502), accounting for 61.4% and 50.2% of their respective variances. Moreover, PD (0.371), GESE (0.367), and GEFF (0.290) have lower adjusted values. This indicates that the current model only explains about 29% to 37% of their changes, suggesting that other external factors heavily influence these three variables **(Table 5)**.

Table 4. Path coefficients

Path	Original sample (β)	Standard deviation	t-value	p-value	Decision
AIL → DGEI = H1	0.229	0.037	6.268	0.000	Accepted
AIL → GESE = H2	0.489	0.035	13.922	0.000	Accepted
AIL → GEFF = H3	-0.477	0.037	12.789	0.000	Accepted
GESE → PF = H4	0.490	0.031	15.793	0.000	Accepted
GESE → PD = H5	0.397	0.037	10.707	0.000	Accepted
GESE → DGEI = H6	0.186	0.041	4.524	0.000	Accepted
GEFF → PF = H7	-0.341	0.034	10.079	0.000	Accepted
GEFF → DGEI = H8	-0.114	0.037	3.107	0.002	Accepted
GEFF → PD = H9	-0.322	0.038	8.524	0.000	Accepted
PF → DGEI = H10	0.181	0.040	4.499	0.000	Accepted
PD → DGEI = H11	0.187	0.039	4.855	0.000	Accepted
PEAIS × AIL → GESE = H12a	0.199	0.033	6.041	0.000	Accepted
PEAIS × AIL → DGEI = H12b	0.157	0.027	5.860	0.000	Accepted
PEAIS × AIL → GEFF = H12c	-0.131	0.037	3.566	0.000	Accepted
EIS × PF → DGEI = H13a	0.141	0.033	4.325	0.000	Accepted
EIS × GEFF → DGEI = H13b	0.134	0.037	3.615	0.000	Accepted
FS × PD → DGEI = H14a	0.138	0.036	3.834	0.000	Accepted
FS × GESE → DGEI = H14b	0.081	0.033	2.439	0.015	Accepted

Note(s): AI literacy – AIL; Digital-oriented green entrepreneurial intention – DGEI; Green entrepreneurial self-efficacy – GESE; Green entrepreneurial fear of failure – GEFF; Perceived feasibility – PF; Perceived desirability – PD; Performance expectancy of AI solutions – PEAIS; External institutional support – EIS; Family support – FS.

Table 5. R-square adjusted

	R-square	R-square adjusted
DGEI	0.624	0.614
GEFF	0.294	0.290
GESE	0.371	0.367
PD	0.374	0.371
PF	0.504	0.502

Note(s): Digital-oriented green entrepreneurial intention – DGEI; Green entrepreneurial self-efficacy – GESE; Green entrepreneurial fear of failure – GEFF; Perceived feasibility – PF; Perceived desirability – PD.

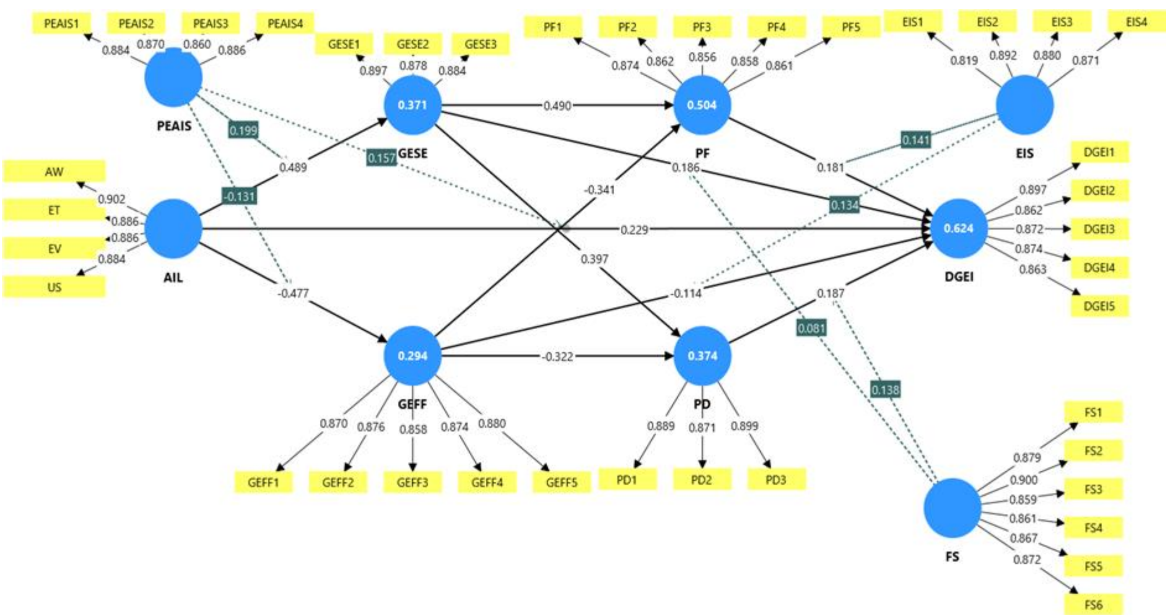

Figure 2. Structural model

This study provides empirical evidence on how AIL shapes students' DGEI through psychological, appraisal-based, and contextual mechanisms. Overall, all proposed hypotheses were supported. The results confirm that AIL is not merely a technical competence but also an entrepreneurial stimulus that influences students' confidence, fear-related cognition, feasibility/desirability appraisals, and intention to pursue digital-oriented green entrepreneurship. This is consistent with the SOR logic, which suggests that technology-related stimuli can activate internal cognitive and affective states before shaping behavioral responses [20, 25, 34, 90]. It also supports the integration of SCCT and EEM, as entrepreneurial intention is jointly shaped by self-efficacy, contextual support, PF, and PD [30, 31, 37]

First, AIL positively influences DGEI (β = 0.229), supporting H1. This finding suggests that students who can understand, use, evaluate, and ethically engage with AI are more likely to develop intentions to create environmentally oriented ventures using digital technologies. This result is consistent with prior studies showing that AIL and GenAI incorporation can enhance entrepreneurial cognition, digital entrepreneurial self-efficacy, and entrepreneurial intention [20, 25, 32, 36]. It also aligns with research suggesting that AI tools can support opportunity recognition, market analysis, idea development, and decision-making in entrepreneurial contexts [7, 8, 16]. However, this study extends previous work by showing that AIL is also relevant to green entrepreneurship, where students must combine digital opportunity creation with environmental value creation [7, 13, 14].

Second, AIL positively influenced GESE (β = 0.489) and negatively influenced GEFF (β = -0.477), supporting H2 and H3. These results confirm the dual psychological role of AI literacy. On the enabling side, AI-literate students may feel more capable of identifying environmental problems, evaluating sustainable business ideas, and using AI tools to support green entrepreneurial tasks. This is consistent with SCCT, which views self-efficacy as a key determinant of career goals and entrepreneurial action [37, 46]. It also supports prior green entrepreneurship studies, which show that GESE is a central antecedent of green entrepreneurial intention [3, 26, 41]. On the constraining side, the negative effect of AI literacy on GEFF indicates that AIL may reduce uncertainty and perceived difficulty in green venture creation. This is consistent with studies suggesting that technology-related competence can reduce ambiguity and strengthen perceived control in entrepreneurial decision-making [20, 28]. Compared with studies that primarily view AI as an enabling resource [16, 27], this study offers a more balanced account by showing that AI literacy simultaneously increases confidence and reduces fear of failure [91-95].

Third, GESE positively affected PF (β = 0.490), PD (β = 0.397), and DGEI (β = 0.186), supporting H4, H5, and H6. These findings indicate that students who believe they can perform green entrepreneurial tasks are more likely to perceive digital-oriented green entrepreneurship as feasible, desirable, and worth pursuing. This result is consistent with SCCT, which argues that self-efficacy shapes career interest and goal formation [37], and with green entrepreneurship research emphasizing the role of GESE in strengthening entrepreneurial intention [3, 26, 41]. The finding also extends EEM-based research by showing that self-efficacy is an important antecedent of both perceived feasibility and perceived desirability rather than only a direct predictor of intention [31, 33, 39].

Fourth, GEFF negatively affected PF (β = -0.341), DGEI (β = -0.114), and PD (β = -0.322), supporting H7, H8, and H9. These findings show that fear of failure remains a critical psychological barrier in digital-oriented green entrepreneurship. Students who worry about failure may perceive green venture creation as less achievable and less attractive, thereby weakening their entrepreneurial intention. This is consistent with entrepreneurship research showing that fear of failure can create avoidance, hesitation, and risk-focused cognition [29, 47, 48, 58]. The result is also relevant to sustainable entrepreneurship because green ventures often involve additional uncertainty related to technology, regulation, environmental legitimacy, and market acceptance [1, 49, 55]. Therefore, the study adds to the literature by demonstrating that fear of failure not only directly reduces intention but also weakens the two key EEM appraisals, feasibility and desirability.

Fifth, PF and PD positively influenced DGEI, supporting H10 and H11. Specifically, PF positively influences DGEI (β = 0.181), while PD also positively influences DGEI (β = 0.187). These results confirm the relevance of the Entrepreneurial Event Model in explaining digital-oriented green entrepreneurial intention. Students are more likely to form entrepreneurial intention when they perceive green venture creation as both practically attainable and personally attractive [30, 31, 39]. This finding is consistent with recent digital and AI-enabled entrepreneurship studies showing that PF and PD transmit the effect of AI-related capability on entrepreneurial intention [32, 33, 40].

Sixth, PEAIS significantly moderated the effects of AIL on GESE, DGEI, and GEFF, supporting H12a, H12b, and H12c. The positive interaction between PEAIS and AIL on GESE (β = 0.199) and DGEI (β = 0.157) indicates that AIL becomes more influential when students believe that AI solutions can improve entrepreneurial performance. This is in line with research on technology acceptance, which indicates that a key factor influencing technology-related intention and behaviour is performance expectancy [64, 65]. The negative interaction effect on GEFF (β = -0.131) further indicates that performance expectancy strengthens AIL's fear-reducing function. This finding is similar to AI adoption studies showing that the perceived usefulness and strategic value of AI can strengthen the conversion of technological capability into favorable outcomes [96-98]. However, unlike firm-level AI adoption studies that focus on organizational outcomes such as innovation, competitive advantage, and performance, the present study shows that performance expectancy also operates at the individual student level, strengthening confidence, intention, and reducing fear.

Seventh, EIS positively moderated the PF–DGEI relationship (β = 0.141) and the GEFF–DGEI relationship (β = 0.134), supporting H13a and H13b. The first result suggests that when students perceive stronger institutional support, feasibility judgments are more likely to become entrepreneurial intention. This is consistent with studies showing that institutional support, government policies, financial incentives, and advisory programs can reduce uncertainty and facilitate entrepreneurship or technology adoption [2, 67-69]. The second result is particularly meaningful because GEFF negatively influences DGEI. The positive interaction coefficient indicates that EIS buffers the harmful effect of fear of failure on intention. This finding is consistent with AI adoption research in Vietnam, where government support reduces risk, improves organizational readiness, and facilitates deeper AI adoption [96]. Nevertheless, this study differs from prior firm-level research by showing that institutional support not only enables technology adoption but also protects students from the discouraging effects of entrepreneurial fear.

Finally, FS strengthened the effects of PD and GESE on DGEI, supporting H14a and H14b. Specifically, family support intensified the relationship between PD and DGEI ($\beta = 0.138$) and between GESE and DGEI ($\beta = 0.081$). These findings confirm the importance of the family environment in student entrepreneurship. When students receive approval, encouragement, emotional support, advice, and potential resources from family members, their perceived desirability and self-efficacy are more likely to become entrepreneurial intention. This result is consistent with family embeddedness research, which argues that family support provides social legitimacy, emotional security, and access to resources for entrepreneurial action [73, 75, 76]. It also aligns with studies showing that family support strengthens entrepreneurial intention through self-efficacy and perceived desirability [33, 74, 81].

Conclusion

Theoretical contributions

This study contributes to the literature by extending AI literacy research into the context of digital-oriented green entrepreneurship. While prior studies have mainly examined AI literacy in general digital entrepreneurship or e-entrepreneurship contexts [20, 25, 40], this study shows that AI literacy also explains students' intention to create environmentally oriented ventures through digital and AI-enabled tools. The findings address the limited integration between AI-enabled entrepreneurship and green entrepreneurship by demonstrating that AI literacy is a key digital capability for translating technological understanding into green-oriented entrepreneurial intention. The study also advances the theoretical integration of SOR, SCCT, and EEM. AI literacy is positioned as a digital stimulus that activates students' internal psychological states, while GESE and GEFF explain the enabling and inhibiting mechanisms through which AI literacy shapes entrepreneurial appraisal and intention [31, 34, 37]. By confirming the roles of PF and PD, the study extends EEM by showing that feasibility and desirability are not only direct antecedents of intention but also appraisal mechanisms shaped by AI-driven psychological readiness. Moreover, the moderator role of PEAIS, EIS, and FS clarifies when AI literacy, feasibility, desirability, self-efficacy, and fear of failure become more or less influential. This extends existing theory by showing that DGEI emerges from the interaction between AI capability, psychological readiness, venture appraisal, and contextual support.

Practical contributions

The findings provide practical implications for universities, entrepreneurship educators, AI training providers, policymakers, and families. Since AI literacy positively affects DGEI through both GESE and GEFF, universities should not treat AI training as a purely technical subject. Instead, AI-related entrepreneurship education should develop students' AI awareness, use, evaluation, and ethics through green venture simulations, AI-assisted opportunity recognition, sustainability problem-solving tasks, and responsible AI decision-making exercises. Such activities can help students use AI to identify environmental problems, test green business ideas, evaluate market information, and reduce uncertainty in early-stage venture creation. The significant effects of GESE and GEFF indicate that practical training should simultaneously strengthen students' confidence and reduce fear of failure. Entrepreneurship programs should include mentoring, prototype development, pitching activities, failure-learning workshops, and case-based discussions on green startups. These activities can make digital-oriented green entrepreneurship appear more feasible and desirable, thereby increasing students' intention to pursue it. Because PF and PD both predict DGEI, educators should design learning activities that show students not only how green ventures can be practically implemented but also why they are personally meaningful, socially valuable, and environmentally relevant. The moderating role of PEAIS suggests that students benefit more from AI literacy when they believe AI solutions can improve entrepreneurial performance. The application of AI in company planning, consumer analysis, content creation, cost estimation, green product development, and sustainability communication should therefore be amply demonstrated in AI trainingWhen students perceive AI as efficient, actionable, and valuable for venture creation, AI literacy is more likely to translate into entrepreneurial confidence and intention. The moderating role of EIS implies that institutional actors should provide visible and accessible support for student green entrepreneurship. Government agencies, universities, incubators, and sustainability organizations should offer green startup competitions, AI-based entrepreneurship labs, seed funding, policy guidance, expert consultation, and access to sustainability networks. Such support can strengthen the conversion of perceived feasibility into intention and buffer the negative effect of fear of failure. In addition, the significant role of FS indicates that families should be included in the entrepreneurial support ecosystem. Universities can involve parents or family members through orientation sessions, startup showcases, and communication activities that emphasize the career value, social legitimacy, and future potential of digital-oriented green entrepreneurship.

Limitations and future research

This study has several limitations that open directions for future research. The data were collected from Vietnamese university students using a non-probability sampling approach; therefore, future studies should apply probability sampling or compare samples across different countries, regions, and educational systems to improve generalizability. Because the study used cross-sectional survey data, future research should employ longitudinal or experimental designs to examine how AIL shapes DGEI over time and whether AI-based training interventions can increase GESE, reduce GEFF, and strengthen DGEI. The study focused on selected psychological and contextual mechanisms, including GESE, GEFF, PF, PD, PEAIS, EIS, and FS. Future research can extend the model by adding other mechanisms such as green opportunity recognition, environmental passion, perceived risk, entrepreneurial resilience, green creativity, digital innovation capability, or trust in AI. Future studies may also examine other boundary conditions, such as AI anxiety, algorithmic distrust, green skepticism, university entrepreneurial support, peer influence, cultural values, and prior startup experience. Although AI literacy was treated as a higher-order construct, future research could compare the distinct effects of AI awareness, AI use, AI evaluation, and AI ethics to identify which dimension contributes most strongly to green entrepreneurial cognition and intention. In addition, future studies should move beyond intention and examine actual entrepreneurial behavior, such as participation in green startup projects, prototype development, crowdfunding attempts, or venture creation. This would provide stronger evidence on how AI literacy is translated into real, digital-oriented green entrepreneurial action.

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References

1. Ip CY. From green entrepreneurial intention to behaviour: the role of environmental knowledge, subjective norms, and external institutional support. Sustain Futures. 2024;8:100331.
2. Yi G. From green entrepreneurial intentions to green entrepreneurial behaviors: the role of university entrepreneurial support and external institutional support. Int Entrep Manag J. 2021;17(2):963-79.
3. Mambali ER, Kapipi MS, Changalima IA. Entrepreneurship education and business and science students' green entrepreneurial intentions: the role of green entrepreneurial self-efficacy and environmental awareness. Int J Manag Educ. 2024;22(2):100987.
4. Soonsan N, Prasankarn H, Tanticharatwarodom P, Prasankarn J, Jumani ZA. University entrepreneurial support and green entrepreneurial behavior: a quantitative serial mediation. J Innov Entrep. 2025;14(1):54.
5. Chalmers D, MacKenzie NG, Carter S. Artificial intelligence and entrepreneurship: implications for venture creation in the fourth industrial revolution. Entrep Theory Pract. 2021;45(5):1028-53.
6. Giuggioli G, Pellegrini MM. Artificial intelligence as an enabler for entrepreneurs: a systematic literature review and an agenda for future research. Int J Entrep Behav Res. 2023;29(4):816-37.
7. Pietronudo MC, Croidieu G, Schiavone F. A solution looking for problems? A systematic literature review of the rationalizing influence of artificial intelligence on decision-making in innovation management. Technol Forecast Soc Change. 2022;182:121828.
8. Wang S, Zhang H. Green entrepreneurship success in the age of generative artificial intelligence: the interplay of technology adoption, knowledge management, and government support. Technol Soc. 2024;79:102744.
9. Dai CP, Ke F. Educational applications of artificial intelligence in simulation-based learning: a systematic mapping review. Comput Educ Artif Intell. 2022;3:100087.
10. Dwivedi YK. Generative artificial intelligence (GenAI) in entrepreneurial education and practice: emerging insights, the GAIN framework, and research agenda. Int Entrep Manag J. 2025;21(1):82.
11. Short CE, Short JC. The artificially intelligent entrepreneur: ChatGPT, prompt engineering, and entrepreneurial rhetoric creation. J Bus Ventur Insights. 2023;19:e00388.
12. Winkler C, Hammoda B, Noyes E, Van Gelderen M. Entrepreneurship education at the dawn of generative artificial intelligence. Entrep Educ Pedag. 2023;6(4):579-89.
13. George G, Merrill RK, Schillebeeckx SJ. Digital sustainability and entrepreneurship: how digital innovations are helping tackle climate change and sustainable development. Entrep Theory Pract. 2021;45(5):999-1027.
14. Gregori P, Holzmann P. Digital sustainable entrepreneurship: a business model perspective on embedding digital technologies for social and environmental value creation. J Clean Prod. 2020;272:122817.
15. Selvan AM, Susainathan S, George HJ, Parayitam S, Fazalbhoy S, Shaik SA. The synergy between artificial intelligence adoption and green entrepreneurship for sustainable business growth. Int J Inf Manage Data Insights. 2026;6(1):100389.

16. Xie Y, Wang S. Generative artificial intelligence in entrepreneurship education enhances entrepreneurial intention through self-efficacy and university support. Sci Rep. 2025;15(1):24079.
17. Tetteh FK, Obiri-Yeboah H, Owusu Kwateng K. Circular supply chain practices and sustainability performance: does AI capability and green entrepreneurial orientation matter? Bottom Line. 2026:1-26.
18. Duong CD. What makes for digital entrepreneurs? The role of AI-related drivers for nascent digital start-up activities. Eur J Innov Manag. 2025;28(7):2689-718.
19. Odugbesan JA, Tafamel AE, Akrawah DO. AI and the entrepreneurial mindset: mapping cognitive adaptability in the age of technological disruption. J Entrep Emerg Econ. 2026;18(1):212-36.
20. Duong CD. AI literacy and e-entrepreneurial intention: a serial mediation model of e-entrepreneurial self-efficacy and e-entrepreneurial identity aspiration. Int J Inf Manage Data Insights. 2025;5(2):100349.
21. Wang B, Rau PLP, Yuan T. Measuring user competence in using artificial intelligence: validity and reliability of the artificial intelligence literacy scale. Behav Inf Technol. 2023;42(9):1324-37.
22. Tran HY, Lam BQ. How education and institutional support shape university students' digital sustainable entrepreneurial intentions: the moderating role of sustainable development goals knowledge. Acta Psychol (Amst). 2026;266:106965.
23. Sitaridis I, Kitsios F. Digital entrepreneurship and entrepreneurship education: a review of the literature. Int J Entrep Behav Res. 2024;30(2-3):277-304.
24. Wang Y, Wang Q, Pan X, Mata MN. Green entrepreneurial intention, knowledge management process, and green entrepreneurial behaviour through a lens of transformative innovation. J Innov Knowl. 2024;9(4):100567.
25. Alkhalaileh MY, Qasim D. The impact of AI literacy on e-entrepreneurial intention: the mediating role of e-self-efficacy and innovation mindset. Entrep Educ. 2026:1-20.
26. Rahayu NS. Assessing the determinant factors affecting green entrepreneurial intention among female entrepreneurs in Indonesia. Cogent Bus Manag. 2024;11(1):2378919.
27. Sharma A, Goel A, Taneja U. AI adoption and digital entrepreneurial intentions: a theory of planned behaviour and technology acceptance model approach. Technol Soc. 2025;103137.
28. Bui HN, Duong CD. ChatGPT adoption in entrepreneurship and digital entrepreneurial intention: a moderated mediation model of technostress and digital entrepreneurial self-efficacy. Equilibrium. 2024;19(2):391-428.
29. Cacciotti G, Hayton JC. Fear and entrepreneurship: a review and research agenda. Int J Manag Rev. 2015;17(2):165-90.
30. Krueger NF Jr, Reilly MD, Carsrud AL. Competing models of entrepreneurial intentions. J Bus Ventur. 2000;15(5-6):411-32.
31. Shapero A, Sokol L. The social dimensions of entrepreneurship. In: University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship. 1982.
32. Ngo TV, Phan TT, Duong CD, Vu AT. Nurturing e-entrepreneurs with artificial intelligence: curvilinear effects of perceived desirability and perceived feasibility based on the entrepreneurial event model. Soc Sci Humanit Open. 2025;12:102180.
33. Nguyen PND, Nguyen HH. Examining the role of family in shaping digital entrepreneurial intentions in emerging markets. SAGE Open. 2024;14(1):21582440241239493.
34. Mehrabian A, Russell JA. An approach to environmental psychology. Cambridge (MA): MIT Press; 1974.
35. Duong CD, Nguyen TH. How AI-related drivers stimulate digital social entrepreneurship: an integrated framework of the entrepreneurial event model within stimulus-organism-response theory. Digit Bus. 2025;100142.
36. Duong CD, Vu TN. Entrepreneurial education and higher education students' e-entrepreneurial intention: a moderated mediation model of generative AI incorporation and e-entrepreneurial self-efficacy. High Educ Skills Work Based Learn. 2025;15(5):1024-48.
37. Lent RW, Brown SD, Hackett G. Toward a unifying social cognitive theory of career and academic interest, choice, and performance. J Vocat Behav. 1994;45(1):79-122.
38. Sharma L, Bulsara HP, Trivedi M, Bagdi H. An analysis of sustainability-driven entrepreneurial intentions among university students: the role of university support and SDG knowledge. J Appl Res High Educ. 2024;16(2):281-301.
39. Esfandiar K, Sharifi-Tehrani M, Pratt S, Altinay L.Understanding entrepreneurial intentions: a developed integrated structural model approach. J Bus Res. 2019;94:172-82.
40. Duong CD. Explore how AI literacy inspires higher education students' digital entrepreneurial intentions: the moderating role of technological support and educational support. Asian Educ Dev Stud. 2026:1-23.
41. Hockerts K. Determinants of social entrepreneurial intentions. Entrep Theory Pract. 2017;41(1):105-30.
42. Rajpal M, Singh B. How to drive sustainable entrepreneurial intentions: unraveling the nexus of entrepreneurship education ecosystem, attitude and orientation. Corp Soc Responsib Environ Manag. 2024;31(3):1705-21.
43. Bewersdorff A, Hornberger M, Nerdel C, Schiff DS. AI advocates and cautious critics: how AI attitudes, AI interest, use of AI, and AI literacy build university students' AI self-efficacy. Comput Educ Artif Intell. 2025;8:100340.
44. Holzmann P, Gregori P. The promise of digital technologies for sustainable entrepreneurship: a systematic literature review and research agenda. Int J Inf Manag. 2023;68:102593.

45. Nambisan S. Digital entrepreneurship: toward a digital technology perspective of entrepreneurship. Entrep Theory Pract. 2017;41(6):1029-55.
46. Bandura A. *Self-efficacy: the exercise of control*. New York: Freeman; 1997.
47. Cacciotti G, Hayton JC, Mitchell JR, Allen DG. Entrepreneurial fear of failure: scale development and validation. J Bus Ventur. 2020;35(5):106041.
48. Morgan J, Sisak D. Aspiring to succeed: a model of entrepreneurship and fear of failure. J Bus Ventur. 2016;31(1):1-21.
49. Al-Azab MR, Zaki HS. Towards sustainable development: antecedents of green entrepreneurship intention among tourism and hospitality students in Egypt. J Hosp Tour Insights. 2024;7(5):2883-902.
50. Kong W, Hu H, Wang Z, Qiao J, Liu J. The double-edged sword effect of generative AI adoption on students' sustainable entrepreneurship intentions. Behav Sci (Basel). 2025;15(12):1705.
51. Ghatak A, Chatterjee S, Bhowmick B. Intention towards digital social entrepreneurship: an integrated model. J Soc Entrep. 2023;14(2):131-51.
52. Thelken HN, De Jong G. The impact of values and future orientation on intention formation within sustainable entrepreneurship. J Clean Prod. 2020;266:122052.
53. Vuorio AM, Puumalainen K, Fellnhofer K. Drivers of entrepreneurial intentions in sustainable entrepreneurship. Int J Entrep Behav Res. 2018;24(2):359-81.
54. Tang L, Lin Q, Luo X, Li Y, Lu M. The role of AI and entrepreneurial ecosystem in shaping students' digital entrepreneurship intentions: evidence from a multi-group analysis. Asia Pac J Educ. 2025:1-25.
55. Asad M, Fryan LHA, Shomo MI. Sustainable entrepreneurial intention among university students: synergetic moderation of entrepreneurial fear and use of artificial intelligence in teaching. Sustainability (Basel). 2025;17(1):290.
56. Abdelfattah F, Al Halbusi H, Al-Brwani RM. Influence of self-perceived creativity and social media use in predicting e-entrepreneurial intention. Int J Innov Stud. 2022;6(3):119-27.
57. Chaudhary M, Biswas A. From mindset to market: unveiling the nexus of cognition, behavior and environment in igniting students' e-entrepreneurial intentions. Int J Educ Manag. 2024;38(7):1839-61.
58. Duong CD. Entrepreneurial fear of failure and the attitude-intention-behavior gap in entrepreneurship: a moderated mediation model. Int J Manag Educ. 2022;20(3):100707.
59. de Sousa-Filho JM, de Souza Lessa B, Garcia-Salirrosas EE, de Carvalho Castro JL. The role of fear of failure on students' entrepreneurial intentions in Latin America. Int J Manag Educ. 2023;21(3):100880.
60. Kautonen T, Van Gelderen M, Fink M. Robustness of the theory of planned behavior in predicting entrepreneurial intentions and actions. Entrep Theory Pract. 2015;39(3):655-74.
61. Martínez-González JA, Kobylinska U, García-Rodríguez FJ, Nazarko L.Antecedents of entrepreneurial intention among young people: model and regional evidence. Sustainability (Basel). 2019;11(24):6993.
62. Ambad SNA, Rafiki A. The roles of vocational interest and entrepreneurial event model in agropreneurship intention. J Entrep Emerg Econ. 2025;17(2):394-417.
63. Valencia-Arias A, Palacios-Moya L, Londoño-Celis W, Sanchez KI. Sustainable entrepreneurial intention: a research trends and agenda. Sustain Environ. 2024;10(1):2362512.
64. Dabbous A, Boustani NM. Digital explosion and entrepreneurship education: impact on promoting entrepreneurial intention for business students. J Risk Financ Manag. 2023;16(1):27.
65. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: toward a unified view. MIS Q. 2003;27(3):425-78.
66. Duong CD, Le TT, Dang NS, Do ND, Vu AT.Unraveling the determinants of digital entrepreneurial intentions: do performance expectancy of artificial intelligence solutions matter? J Small Bus Enterp Dev. 2024;31(7):1327-56.
67. Ishaq MI, Sarwar H, Aftab J, Franzoni S, Raza A. Accomplishing sustainable performance through leaders' competencies, green entrepreneurial orientation, and innovation in an emerging economy: moderating role of institutional support. Bus Strategy Environ. 2024;33(2):1515-32.
68. Li H, Atuahene-Gima K. Product innovation strategy and the performance of new technology ventures in China. Acad Manage J. 2001;44(6):1123-34.
69. Mawardi MK, Noor AY, Edityastono L, ‘Atikah Zulkiffli SN, Mashahadi F. Green entrepreneurship in the era of sustainability: the relationship between intent, institutional support, and student behavior. Cogent Bus Manag. 2025;12(1):2460625.
70. Zhao M, Liu J, Shu C. Pursuing sustainable development through green entrepreneurship: an institutional perspective. Bus Strategy Environ. 2021;30(8):4281-96.
71. Uddin MS, Kabir MM, Kabir AJ, Roshid MM. Bridging institutional support and entrepreneurial competence for sustainable entrepreneurship. Bus Strategy Dev. 2026;9(2):e70344.
72. Yang Y. Impact of institutional support and green knowledge transfer on university students' absorptive capacity and green entrepreneurial behavior: the moderating role of environmental responsibility. PLoS One. 2024;19(5):e0304070.
73. Aldrich HE, Cliff JE. The pervasive effects of family on entrepreneurship: toward a family embeddedness perspective. J Bus Ventur. 2003;18(5):573-96.
74. Baluku MM, Kikooma JF, Otto K, König CJ, Bajwa NU. Positive psychological attributes and entrepreneurial intention and action: the moderating role of perceived family support. Front Psychol. 2020;11:546745.

75. Lingappa AK, Shah A, Mathew AO. Academic, family, and peer influence on entrepreneurial intention of engineering students. SAGE Open. 2020;10(3):2158244020933877.
76. Mei H, Ma Z, Zhan Z, Ning W, Zuo H, Wang J, Huang Y. University students' successive development from entrepreneurial intention to behavior: the mediating role of commitment and moderating role of family support. Front Psychol. 2022;13:859210.
77. Soluk J, Kammerlander N, Darwin S. Digital entrepreneurship in developing countries: the role of institutional voids. Technol Forecast Soc Change. 2021;170:120876.
78. Ruiz-Palomino P, Martínez-Cañas R. From opportunity recognition to the start-up phase: the moderating role of family and friends-based entrepreneurial social networks. Int Entrep Manag J. 2021;17(3):1159-82.
79. Li C, Murad M, Ashraf SF. The influence of women's green entrepreneurial intention on green entrepreneurial behavior through university and social support. Sustainability (Basel). 2023;15(13):10123.
80. Ciuchta MP, Finch D. The mediating role of self-efficacy on entrepreneurial intentions: exploring boundary conditions. J Bus Ventur Insights. 2019;11:e00128.
81. Saoula O, Shamim A, Ahmad MJ, Abid MF. Do entrepreneurial self-efficacy, entrepreneurial motivation, and family support enhance entrepreneurial intention? The mediating role of entrepreneurial education. Asia Pac J Innov Entrep. 2023;17(1):20-45.
82. Hair JF, Risher JJ, Sarstedt M, Ringle CM. When to use and how to report the results of PLS-SEM. Eur Bus Rev. 2019;31(1):2-24.
83. Hair JF, Astrachan CB, Moisescu OI, Radomir L, Sarstedt M, Vaithilingam S, Ringle CM. Executing and interpreting applications of PLS-SEM: updates for family business researchers. J Fam Bus Strategy. 2021;12(3):100392.
84. Podsakoff PM, MacKenzie SB, Lee JY, Podsakoff NP. Common method biases in behavioral research: a critical review of the literature and recommended remedies. J Appl Psychol. 2003;88(5):879-903.
85. Cooper B, Eva N, Fazlelahi FZ, Newman A, Lee A, Obschonka M. Addressing common method variance and endogeneity in vocational behavior research: a review of the literature and suggestions for future research. J Vocat Behav. 2020;121:103472.
86. Kock N. Common method bias in PLS-SEM: a full collinearity assessment approach. Int J e-Collab. 2015;11(4):1-10.
87. Hair J, Alamer A. Partial least squares structural equation modeling (PLS-SEM) in second language and education research: guidelines using an applied example. Res Methods Appl Linguist. 2022;1(3):100027.
88. Henseler J, Ringle CM, Sarstedt M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. J Acad Mark Sci. 2015;43:115-35.
89. Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. J Mark Res. 1981;18(1):39-50.
90. Abbasi GA, Kumaravelu J, Goh YN, Dara Singh KS. Understanding the intention to revisit a destination by expanding the theory of planned behaviour (TPB). Span J Mark ESIC. 2021;25(2):282-311.
91. Alves R, Costa B, Martins H, Faria N. Federated learning framework for adverse drug reaction prediction from multi-institutional health records. Pharmacophore. 2026;17(1):1-11. doi:10.51847/f2RnAaSwj2
92. Petrov I, Ivanova O, Smirnov D. Predicting long-acting injectable release using polymer degradation, drug loading, and microsphere morphology. Pharmacophore. 2026;17(1):33-42. doi:10.51847/MT3QwGFdub
93. Ha MN, Thanh TL, Thanh VPT. Factors influencing retail customer satisfaction in mobile banking services: a case study of Sacombank-Hanoi branch. Ann Organ Cult Leadersh Extern Engagem J. 2025;6:41-50. doi:10.51847/0718r25rSv
94. Yilmaz D, Erkol C. Understanding and reducing alienation among assembly line workers: insights from leadership, compensation, and work formalisation. Ann Organ Cult Leadersh Extern Engagem J. 2025;6:56-72. doi:10.51847/FegO2CUoQF
95. Bona C, Lozano R. Delayed hematologic toxicities following axicabtagene ciloleucel and tisagenlecleucel CAR-T cell therapy: a retrospective analysis of lymphocytopenia, neutropenia, and thrombocytopenia. Asian J Curr Res Clin Cancer. 2024;4(2):1-4. doi:10.51847/13fIAq9Er0
96. Anh NT, Khoi BH, Thu NQ, Ghi TN. The role of the level of artificial intelligence adoption on business model innovation, sustainable competitive advantage, and firm performance: integrating the TOE framework and dynamic capabilities theory. Green Technol Sustain. 2026:100384.
97. Baabdullah AM, Alalwan AA, Slade EL, Raman R, Khatatneh KF. SMEs and artificial intelligence (AI): antecedents and consequences of AI-based B2B practices. Ind Mark Manag. 2021;98:255-70.
98. Hossain MA, Agnihotri R, Rushan MR, Rahman MS, Sumi SF. Marketing analytics capability, artificial intelligence adoption, and firms' competitive advantage: evidence from the manufacturing industry. Ind Mark Manag. 2022;106:240-55.