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Determinants of Artificial Intelligence (AI) Adoption in Green Entrepreneurship: An Integrated Framework of UTAUT and VBN Theory

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Abstract

With the rapid development of artificial intelligence (AI) technologies, their potential in green entrepreneurship has become increasingly evident, particularly in achieving sustainable development goals. Although AI can support green entrepreneurship by optimizing resource management, reducing energy consumption, and lowering emissions, its adoption faces numerous challenges. This paper aims to explore the application of AI in green entrepreneurship, focusing on the factors influencing the formation of Green Entrepreneurial Intention (GEI). By integrating the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Value-Belief-Norm (VBN) theory, we construct an integrated framework to examine how performance expectancy, effort expectancy, social influence, facilitating conditions, and pro-environmental personal norms collectively influence entrepreneurs' decisions to adopt AI. Using survey data from 260 green entrepreneurs in Beijing, we applied Partial Least Squares Structural Equation Modeling (PLS-SEM) for analysis. The results show that all five factors significantly positively affect GEI, with pro-environmental personal norms having the strongest influence. This study offers a new theoretical perspective on green entrepreneurship and provides practical recommendations for policymakers, entrepreneurs, and AI technology providers in promoting the adoption of sustainable technologies.

Keywords: *Artificial Intelligence (AI);Green Entrepreneurship;Technology Acceptance; Value-Belief-Norm (VBN) Theory; Unified Theory of Acceptance and Use of Technology (UTAUT)*

1. Introduction

Artificial intelligence (AI) is widely regarded as a transformative technology that empowers systems with capabilities such as machine learning, autonomous decision-making, and human–machine collaboration (Duraimutharasan et al., 2025; Khosravy et al., 2023). Within the context of sustainable development, AI plays a pivotal role in addressing environmental challenges by optimizing energy usage, reducing emissions, and enabling intelligent resource management (Vinuesa et al., 2020; Wamba et al., 2021). In green entrepreneurship, AI assists entrepreneurs in identifying eco-friendly opportunities, automating sustainability assessments, and designing low-impact business models (Jöhnk et al., 2021). For instance, AI-powered tools can predict demand for sustainable materials, streamline logistics for reduced carbon footprints, and support closed-loop production systems (Dwivedi et al., 2021). These applications support the prevailing belief that technological innovation—particularly through AI—can align economic development with ecological preservation (Vinuesa et al., 2020; United Nations, 2015). International organizations have echoed this optimism: the UN's Sustainable Development Goals (SDGs) report that AI could positively contribute to over 93% of environment-related targets (Jöhnk et al., 2021), reinforcing its potential as a catalyst for green transformation.

Despite these advantages, the adoption of AI in green entrepreneurship is not without tension. On one hand, AI enhances productivity, reduces uncertainty, and improves decision-making in environmentally oriented ventures (Venkatesh et al., 2003). On the other hand, AI systems—particularly those requiring high computational power—can significantly increase energy consumption, thereby producing unintended environmental burdens that may counteract their green potential (Strubell et al., 2019). Furthermore, the complexity and cost of AI tools pose adoption barriers for small- and medium-sized entrepreneurs, especially in resource-constrained contexts (Gast et al., 2017). These issues raise a crucial paradox: while AI is promoted as a solution for environmental sustainability, its actual ecological footprint and accessibility constraints remain underexplored in entrepreneurial settings. This duality suggests that merely promoting AI adoption may not guarantee green outcomes. Understanding how entrepreneurs perceive and integrate AI into their value creation processes—both technologically and normatively—is therefore essential.

Building on this tension, this study focuses on entrepreneurs—particularly those from digitally native cohorts such as Generation Z and Millennials—who demonstrate heightened awareness of environmental issues and increasing reliance on intelligent technologies in business (Stern, 2000). Although these entrepreneurs are at the forefront of AI-driven green ventures, existing research has not adequately examined the mechanisms shaping their green entrepreneurial intentions (Ajzen, 1991). Specifically, few studies have empirically investigated how cognitive evaluations of AI (e.g., performance expectancy, effort expectancy) interact with value-based personal norms (e.g., ecological responsibility, pro-environmental moral obligation) to influence sustainable entrepreneurial behavior. To address this theoretical gap, we propose an integrated framework combining the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Value-Belief-Norm (VBN) theory. This model captures the technological and normative determinants of green entrepreneurial intention. Drawing on data from early-stage entrepreneurs, the study contributes by offering new insights into how AI can be leveraged to foster environmentally responsible entrepreneurship through a dual lens of innovation acceptance and value-driven sustainability motivation.

2. Literature Review

2.1 Artificial Intelligence Technologies: Evolution and Entrepreneurial Application

This study focuses on artificial intelligence (AI) technologies that support entrepreneurs in enhancing operational efficiency, environmental awareness, and sustainable innovation. With the advancement of algorithms, deep learning, and computing power, AI has evolved from rule-based automation tools to intelligent systems capable of perception, prediction, and autonomous decision-making (Jordan & Mitchell, 2015; Lecun, Bengio, & Hinton, 2015). Existing literature indicates that AI technologies have been widely applied in sectors such as smart retail, digital marketing, green logistics, and sustainable energy management—areas highly relevant to emerging green entrepreneurial practices (Kshetri, 2018; Wamba et al., 2021). In particular, three categories of AI technologies have shown strong integration into entrepreneurial activities: (1) intelligent voice assistants for business coordination and energy control (Hoy, 2018); (2) AI-based energy management systems in smart offices and green buildings (Ahmad et al., 2021); and (3) recommendation engines used by green platforms to guide sustainable consumer choices (Chen et al., 2021). These applications not only enhance productivity and reduce operational costs but also enable eco-conscious business models, providing a solid contextual foundation for this study.

2.2 AI and the Pathway to Green Entrepreneurship

Meanwhile, sustainable development has become a central concern in both academic and policy domains worldwide. Existing research suggests that achieving goals such as environmental protection, green transformation, and low-carbon development requires not only institutional arrangements and public policies but increasingly depends on the behavioral shift enabled by digital technologies (Vinuesa et al., 2020). AI, in particular, is considered a transformative enabler for ecological transition, especially in carbon-intensive sectors such as agriculture (Murugan et al., 2022), energy systems (Ahmad et al., 2021), and transportation (Zhao et al., 2020). Studies have shown that AI can enhance energy efficiency through intelligent control and predictive optimization (Frank, 2021) and can also drive green innovation in business models through data-enabled redesign (Bao & Xie, 2022; Jöhnk et al., 2021). In this regard, placing AI technologies within the context of green entrepreneurship offers a valuable lens to examine how intelligent systems influence entrepreneurs' sustainability-oriented intentions and decisions. Such an approach bridges individual-level technology adoption with macro-level ecological transitions and provides theoretical and practical insights into digital sustainability pathways.

2.3 Integrating UTAUT and VBN to Explain Green Entrepreneurial Intentions

To better understand how individuals form green entrepreneurial intentions (GEI) when engaging with AI products, this study adopts an integrated perspective combining the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Value-Belief-Norm (VBN) theory.

The UTAUT framework identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as central factors shaping technology adoption (Venkatesh et al., 2003; Venkatesh, Thong, & Xu, 2012). These constructs offer a useful lens for explaining how entrepreneurs assess the commercial and environmental potential of AI technologies in their decision-making processes (Dwivedi et al., 2021).

The VBN framework extends the analysis by emphasizing the pro-environmental personal norm (PPN) as a reflection of deeply held values, which can activate environmental responsibility and moral obligation (Stern, 2000; Steg & Vlek, 2009). This value-based orientation creates a normative foundation through which pro-environmental beliefs translate into concrete entrepreneurial behaviors (Kaiser et al., 2005).

By linking UTAUT and VBN, the proposed model captures the interplay between technological acceptance and normative value commitments, offering a multi-layered explanation of why environmentally conscious entrepreneurs are more likely to integrate AI into green business models. This integrated approach also addresses the lack of cross-theoretical perspectives in the current literature on sustainable entrepreneurship (Kirkwood & Walton, 2010; Hsu et al., 2017).

3. Research Model and Hypotheses Development

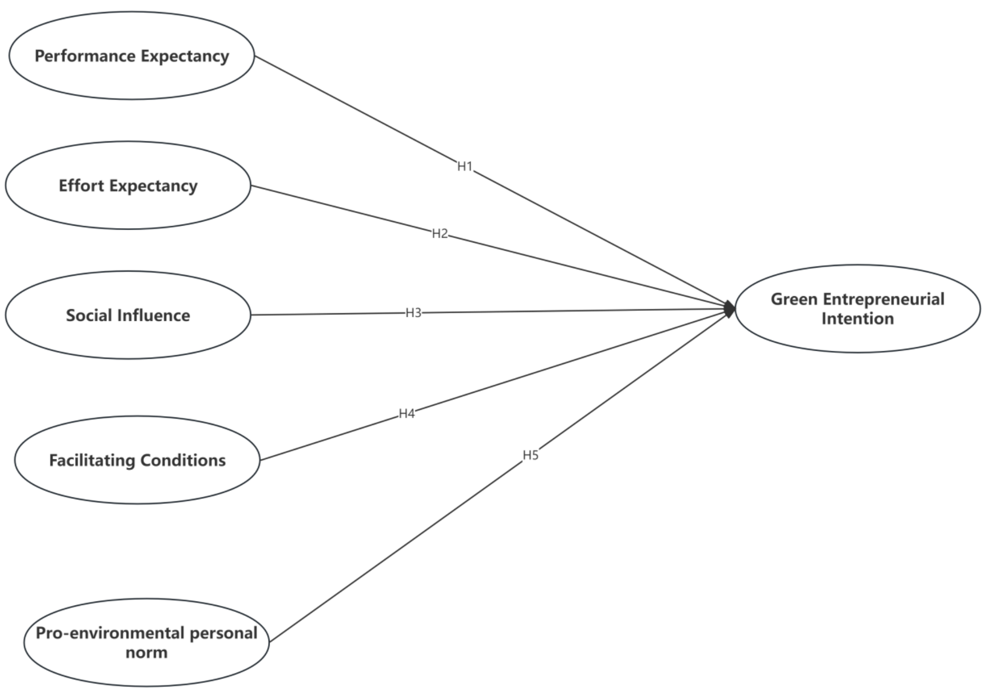
This study integrates two prominent theoretical perspectives—the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Value-Belief-Norm (VBN) theory—to examine the drivers of AI-enabled green entrepreneurial intention (GEI). GEI refers to the commitment and readiness of entrepreneurs to establish ventures that prioritize environmental sustainability through the use of artificial intelligence (AI) technologies.

From the UTAUT framework, Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) represent core determinants of technology adoption intentions. These constructs explain how entrepreneurs evaluate the usefulness, ease of use, social endorsement, and available resources for AI adoption in green entrepreneurship (Venkatesh et al., 2003; Williams et al., 2015).

The VBN theory introduces Pro-environmental Personal Norm (PPN) as a value-oriented driver that reflects moral obligation and ecological responsibility in entrepreneurial decision-making (Stern, 2000). PPN emphasizes that deeply internalized values and moral commitments can strongly motivate entrepreneurs to pursue environmentally sustainable ventures.

In the proposed model, GEI serves as the sole endogenous construct, while five determinants (PE, EE, SI, FC, and PPN) are modeled as exogenous variables directly influencing GEI. The conceptual framework is illustrated in Figure 1.

Figure1 Research model



Performance Expectancy (PE) refers to the extent to which entrepreneurs believe that the use of AI technologies will enhance the effectiveness and outcomes of their green entrepreneurial efforts. Drawing on UTAUT, individuals who perceive AI as beneficial for improving business performance, resource efficiency, or innovation are more likely to form strong green entrepreneurial intentions (Venkatesh et al., 2003; Dwivedi et al., 2021).

H1: Performance expectancy has a significant positive effect on green entrepreneurial intention.

Effort Expectancy (EE) denotes the perceived ease of learning and operating AI technologies in the context of green entrepreneurship. When entrepreneurs find AI systems intuitive and less demanding, they are more likely to integrate them into their green innovation processes. Consistent with UTAUT, ease of use reduces adoption barriers (Venkatesh et al., 2003; Tamilmani et al., 2021).

H2: Effort expectancy has a significant positive effect on green entrepreneurial intention.

Social Influence (SI) captures the perceived pressure or encouragement from important referents—such as mentors, peers, or professional networks—to adopt AI for sustainable entrepreneurship. In socially visible domains like environmental entrepreneurship, normative influence is particularly salient (Ajzen, 1991; Dwivedi et al., 2019).

H3: Social influence has a significant positive effect on green entrepreneurial intention.

Facilitating Conditions (FC) refer to the availability of organizational, technical, and institutional resources needed to implement AI-enabled green entrepreneurship. This includes access to platforms, skills, support networks, and policy incentives. According to UTAUT, such conditions are pivotal for adoption intentions (Venkatesh et al., 2003; Williams et al., 2015).

H4: Facilitating conditions have a significant positive effect on green entrepreneurial intention.

Pro-environmental Personal Norm (PPN), derived from the VBN theory, represents an entrepreneur's intrinsic motivation and moral obligation to conserve energy and act sustainably. This value-driven norm is expected to positively shape green entrepreneurial intentions (Stern, 2000; Harland et al., 1999).

H5: Pro-environmental personal norm has a significant positive effect on green entrepreneurial intention.

4. Research methodology

4.1 Sampling and Data Collection

This study targeted green entrepreneurs in Beijing who are actively engaged in ventures with an environmental or sustainability focus and have experience with artificial intelligence (AI) technologies. Given the study's aim of understanding the determinants of AI-enabled green entrepreneurial intention, a purposive sampling approach was adopted to ensure that all respondents were actual users of AI tools in their entrepreneurial activities.

The survey was conducted between April and June 2025 using a structured questionnaire. Participants were recruited through entrepreneurial networks, incubators, and social media platforms related to green innovation. The questionnaire link was distributed via WeChat, email, and entrepreneurial forums. Before proceeding to the main survey, a screening question confirmed whether respondents had prior experience in applying AI technologies—such as predictive analytics, intelligent recommendation systems, or AI-enabled automation—within their business operations. Only those answering affirmatively were allowed to continue.

Out of 300 distributed questionnaires, 260 valid responses were retained after excluding incomplete and invalid entries, resulting in an effective response rate of 86.7%. This sample size exceeds the recommended minimum for PLS-SEM analysis, following both the "10-times rule" (Chin, 1998) and G*Power calculations (effect size = 0.15, α = 0.05, power = 0.95), which indicated a minimum requirement of 166 cases. The final sample is therefore adequate for testing the proposed UTAUT–VBN integrated model.

Table 1 Demographic Profile of Respondents

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	142	54.6
	Female	118	45.4
Age	21–30	85	32.7
	31–40	100	38.5
	Above 40	75	28.8
Education Level	College diploma	39	15
	Bachelor's degree	120	46.2
	Master's degree	84	32.3
	Doctoral degree	17	6.5
Entrepreneurial Experience	1–3 years	108	41.5
	4–6 years	96	36.9
	Above 6 years	56	21.5
AI Usage Experience	1–3 years	103	39.6
	4–6 years	88	33.8
	Above 6 years	69	26.5
Industry Sector	Renewable energy solutions	73	28.1
	Sustainable agriculture	64	24.6
	Green manufacturing	56	21.5
	Eco-friendly services	39	15
	Waste recycling	28	10.8

4.2 Measurements

The measurement instrument comprised 30 items adapted from validated scales in prior literature, covering five independent variables—Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Pro-environmental Personal Norm (PPN)—and the dependent variable, Green Entrepreneurial Intention (GEI).

All items were phrased as statements and assessed on a five-point Likert scale ranging from 1 (“Strongly Disagree”) to 5 (“Strongly Agree”). The original English version of the questionnaire was professionally translated into Chinese and then back-translated to ensure conceptual equivalence (Brislin, 1970). A pilot test with 20 respondents confirmed the clarity of the items and the reliability of the instrument.

Sample items include:

PE: “Using AI technologies will enhance the performance of my green entrepreneurship projects.”

EE: “It is easy for me to learn and operate AI systems in my entrepreneurial activities.”

SI: “People who influence my decisions think I should adopt AI for green entrepreneurship.”

FC: “I have access to the necessary resources and support to implement AI in my green business.”

PPN:“I feel a moral obligation to act in an environmentally friendly way in my business operations.”

GEI: “I intend to start or expand a green business using AI technologies within the next two years.”

Respondents were assured of confidentiality and informed that the data would be used solely for academic purposes. Descriptive statistics and reliability coefficients for each construct are presented in Table 2, with Cronbach’s alpha values exceeding the recommended threshold of 0.70 (Hair et al., 2012), indicating strong internal consistency.

Table 2 Constructs Descriptive Statistics

Construct	Mean	Std. Deviation	Cronbach’s Alpha
Performance Expectancy (PE)	3.86	0.73	0.891
Effort Expectancy (EE)	3.71	0.77	0.872
Social Influence (SI)	3.55	0.81	0.86
Facilitating Conditions (FC)	3.69	0.75	0.847
Pro-environmental Personal Norm (PPN)	4.12	0.59	0.918
Green Entrepreneurial Intention (GEI)	3.92	0.74	0.905

4.3Data Analysis

Data analysis was performed using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4. This variance-based approach was selected because the study is exploratory, the proposed relationships in the AI-enabled green entrepreneurship context have not been extensively tested, and the model involves multiple latent constructs and indicators. PLS-SEM is also suitable for predictive modeling and can accommodate moderate sample sizes effectively (Hair et al., 2012).

The analysis followed a two-stage procedure. In the first stage, the measurement model was evaluated in terms of indicator reliability, internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (average variance extracted, AVE), and discriminant validity using both the Fornell–Larcker criterion and heterotrait–monotrait (HTMT) ratios. In the second stage, the structural model was tested to assess the significance and magnitude of the hypothesized paths from the five independent variables—Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Pro-environmental Personal Norm (PPN)—to the dependent variable, Green Entrepreneurial Intention (GEI), through bootstrapping with 5,000 resamples.

Additional diagnostics were conducted to check for collinearity using variance inflation factors (VIF), and model quality was further examined through the coefficient of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2).

Where applicable, a multi-group analysis (PLS-MGA) was employed to explore potential differences in path coefficients between subgroups (e.g., demographic categories or entrepreneurial experience levels). Prior to conducting PLS-MGA, the measurement invariance of composite models (MICOM) procedure was applied to ensure comparability across groups (Hair Jr et al., 2017).

5.Results

5.1. Common Method Bias

Given that the study employed a self-reported survey method with all variables collected from the same respondents, the potential for common method bias (CMB) was examined. First, Harman's single-factor test was conducted using exploratory factor analysis (EFA) in SPSS 28. The unrotated factor solution revealed that the first factor accounted for 34.7% of the total variance, well below the critical threshold of 50% (Podsakoff et al., 2003), indicating that CMB is unlikely to be a serious concern.

Second, the full collinearity test was performed in SmartPLS 4 following Kock (2015). The variance inflation factors (VIFs) for all latent constructs ranged from 1.28 to 2.41, below the threshold of 3.3, further suggesting the absence of substantial common method variance. Collectively, these results provide evidence that CMB does not significantly affect the data in this study.

5.2. Measurement Model Assessment

All constructs demonstrated satisfactory internal consistency, with Cronbach's alpha values ranging from 0.846 to 0.918 and composite reliability (CR) values between 0.889 and 0.954, exceeding the recommended threshold of 0.70 (Hair et al., 2012; Hair Jr et al., 2017). Convergent validity was supported as all average variance extracted (AVE) values ranged from 0.652 to 0.781, above the 0.50 criterion, and all standardized factor loadings were greater than 0.70. These results indicate that the measurement model possesses adequate reliability and convergent validity.

Table 3 Measurement Model Assessment Results

Construct	Item	Outer Loading	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Performance Expectancy (PE)	PE1	0.761	0.892	0.927	0.762
	PE2	0.909			
	PE3	0.906			
	PE4	0.833			
Effort Expectancy (EE)	EE1	0.812	0.874	0.915	0.689
	EE2	0.849			
	EE3	0.727			
	EE4	0.898			
Social Influence (SI)	SI1	0.741	0.861	0.902	0.703
	SI2	0.901			
	SI3	0.758			
	SI4	0.822			
Facilitating Conditions (FC)	FC1	0.833	0.846	0.903	0.652
	FC2	0.79			
	FC3	0.813			
	FC4	0.868			
Pro-environmental Personal Norm (PPN)	PPN1	0.917	0.918	0.954	0.781
	PPN2	0.878			
	PPN3	0.852			
	PPN4	0.77			
	PPN5	0.833			
	PPN6	0.847			
Green Entrepreneurial Intention (GEI)	GEI1	0.727	0.905	0.932	0.711
	GEI2	0.833			
	GEI3	0.736			
	GEI4	0.894			

5.3. Structural Model Assessment

The structural model was evaluated to examine the hypothesized relationships among the constructs. Bootstrapping with 5,000 resamples was employed to assess the significance of path coefficients. As shown in Table 4 and illustrated in Figure 3, all five hypothesized paths were statistically significant.

Performance Expectancy ($\beta = 0.168$, $t = 3.210$, $p = 0.001$), Effort Expectancy ($\beta = 0.124$, $t = 2.280$, $p = 0.023$), Social Influence ($\beta = 0.097$, $t = 2.010$, $p = 0.045$), and Facilitating Conditions ($\beta = 0.131$, $t = 2.430$, $p = 0.015$) demonstrated positive and significant effects on Green Entrepreneurial Intention (GEI). Importantly, Pro-environmental Personal Norm ($\beta = 0.215$, $t = 4.020$, $p < 0.001$) exerted the strongest influence, underscoring the central role of normative commitments in driving AI-enabled green entrepreneurship.

The coefficient of determination for GEI was $R^2 = 0.583$, indicating that the five predictors jointly explain 58.3% of the variance in GEI. The Stone–Geisser Q^2 value for GEI was 0.371, exceeding zero and confirming the model's predictive relevance. Effect size analysis showed that PPN ($f^2 = 0.092$) and PE ($f^2 = 0.058$) exerted relatively stronger influences, while SI had the weakest but still significant effect ($f^2 = 0.020$).

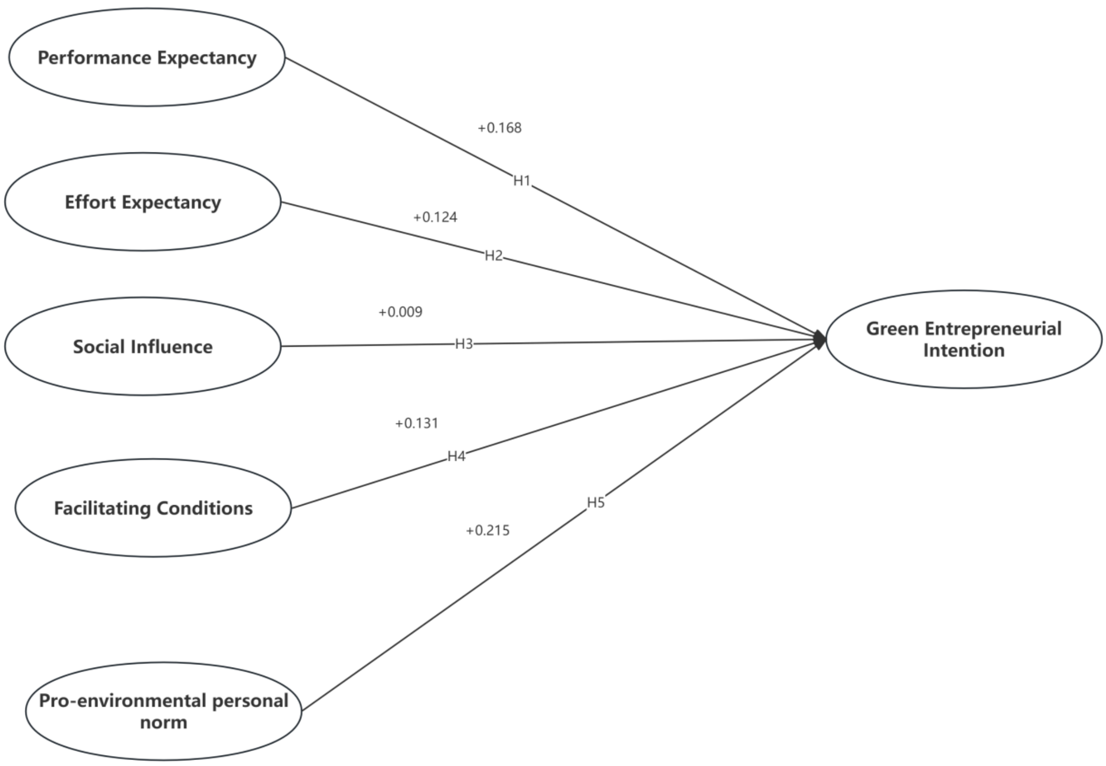
These results support the robustness of the revised model and highlight the complementary roles of technological acceptance (UTAUT) and value-based personal norms (VBN) in shaping AI-enabled green entrepreneurial intentions.

Table 4 Structural Model Assessment Results

Hypothesis	Path	β	t-value	p-value	f^2	Results
H1	PE → GEI	0.168	3.21	0.001	0.058	Supported
H2	EE → GEI	0.124	2.28	0.023	0.03	Supported
H3	SI → GEI	0.097	2.01	0.045	0.02	Supported
H4	FC → GEI	0.131	2.43	0.015	0.034	Supported
H5	PPN → GEI	0.215	4.02	<0.001	0.092	Supported

Notes: Bootstrapping with 5,000 resamples. $R^2(GEI) = 0.583$; $Q^2(GEI) = 0.371$.
f^2 benchmarks: 0.02 = small, 0.15 = medium, 0.35 = large.

Figure 3 Structural model results



6.Discussion

6.1 Summary of Key Findings and Theoretical Implications

This study investigated the determinants of AI-enabled green entrepreneurial intention (GEI) by integrating the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Value-Belief-Norm (VBN) theory. Using survey data from 260 green entrepreneurs in Beijing, the findings showed that performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and pro-environmental personal norm (PPN) all exerted significant and positive effects on GEI. Among them, PPN had the strongest influence, highlighting that moral obligation and ecological values play a pivotal role in shaping entrepreneurial decisions.

From the UTAUT perspective, the results validate the roles of perceived usefulness, ease of use, social encouragement, and available support in technology-driven entrepreneurship (Venkatesh et al., 2003; Williams et al., 2015). From the VBN perspective, the strong effect of PPN confirms that intrinsic values and personal norms are powerful predictors of sustainability-oriented behavior (Stern, 2000). Together, these findings extend prior research by showing that technology adoption and value-based motivation jointly drive AI adoption in green ventures.

6.2 Practical Implications

The findings provide several actionable insights. First, entrepreneurs should strengthen AI literacy and integrate intelligent tools into green business models to enhance efficiency and foster eco-innovation. Second, policymakers can improve facilitating conditions by investing in AI infrastructure, offering targeted training, and providing fiscal incentives for sustainable technology adoption. Third, investors and incubators are encouraged to support AI-enabled green startups, given their combined environmental and economic potential. Fourth, AI providers can promote adoption by enhancing usability and demonstrating the ecological benefits of their systems. Finally, environmental organizations can leverage normative influence to reinforce entrepreneurs' pro-environmental personal norms and encourage AI integration in sustainability practices.

6.3 Unexpected Insights, Limitations, and Future Research

Although all hypothesized relationships were significant, social influence (SI) showed a relatively weaker effect compared to other predictors. This suggests that in emerging ecosystems, entrepreneurs may rely more on personal values (PPN) and perceived utility (PE, EE) than on external peer pressure. Such findings highlight that normative and intrinsic motivations may outweigh social dynamics in the early stages of AI adoption for sustainability.

This study also has limitations. The reliance on a Beijing-based sample restricts the generalizability of the findings; future research should explore diverse cultural and geographic contexts. The cross-sectional design precludes causal inference, pointing to the need for longitudinal studies. Moreover, future studies could investigate mediating mechanisms such as environmental commitment or satisfaction with AI usage, and moderating factors such as environmental regulation or industry type. Comparative research across regions or between AI-enabled and traditional green entrepreneurs would further enrich understanding of how technology and values interact in driving sustainable entrepreneurship.

7.Conclusion

This study examined the determinants of AI-enabled green entrepreneurial intention (GEI) by integrating the Unified Theory of Acceptance and Use of Technology (UTAUT) with the Value-Belief-Norm (VBN) theory. Survey data from 260 green entrepreneurs in Beijing confirmed that performance expectancy, effort expectancy, social influence, facilitating conditions, and pro-environmental personal norms significantly influence GEI, with normative values (PPN) emerging as the strongest predictor.

The findings contribute to the literature by extending UTAUT and VBN into the domain of AI-enabled sustainable entrepreneurship, demonstrating that both technological acceptance and value-based motivations jointly drive entrepreneurial intentions. Practically, the results provide insights for entrepreneurs, policymakers, and AI providers on enhancing adoption through usability, supportive conditions, and normative reinforcement.

While the study is limited by its Beijing-based sample and cross-sectional design, it offers a foundation for future research to test the model across contexts and over time. Overall, the integration of technology acceptance and ecological values highlights a dual pathway through which AI can promote environmentally responsible entrepreneurship and support sustainable development goals.

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