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Article

AI Literacy, Human-AI Interaction, and Generative-AI Decision Support for Entrepreneurial Opportunity Seeking: A Convergent Mixed-Methods Study

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Abstract: Generative artificial intelligence (AI) systems are increasingly used as interactive information and decision-support tools, but their value is associated with users' capacity to formulate requests, interpret outputs, verify information, and exercise ethical judgment. This study examines AI literacy as a multidimensional user capability associated with AI-assisted entrepreneurial opportunity seeking. A convergent mixed-methods design combined survey data from 57 Bachelor of Science in Entrepreneurship students with qualitative interviews and focus-group responses from 14 participants. AI literacy was measured through awareness, application skills, evaluation of AI outputs, and ethical use, while AI-assisted opportunity seeking covered opportunity discovery, evaluation, and development. The four literacy dimensions jointly significantly predicted AI-assisted opportunity seeking in the regression model: $R^2 = .506$; adjusted $R^2 = .468$; $F(4,52) = 13.315$, $p < .001$. AI awareness ($B = .302$, $p = .016$), application skills ($B = .313$, $p = .047$), and ethical use ($B = .244$, $p = .016$) were significant positive predictors; evaluation of AI outputs was not significant ($B = -.041$, $p = .751$). Qualitative data confirmed themes of prompting difficulty, unreliable outputs, verification problems, internet-access constraints, weak contextual fit, and overdependence. These challenges were associated with lower-quality human-AI interaction. The study contributes to computer information systems research by identifying a gap between operational AI use and information-quality evaluation. It proposes design and governance implications for prompt scaffolding, source provenance, verification workflows, contextual data integration, and human oversight in AI-enabled entrepreneurial decision support.

Keywords: AI literacy; generative AI; human-AI interaction; decision support; information quality; responsible AI; entrepreneurial opportunity seeking

1. Introduction

Generative AI has moved from a specialized computational technology to a widely accessible class of interactive computer information systems. Conversational interfaces allow users to request explanations, generate alternatives, analyze text, summarize market signals, and develop preliminary recommendations through natural-language interaction. In higher education, these systems are used not only for writing and information retrieval but also for problem solving, feedback, creative exploration, and decision support (Dwivedi et al., 2023; Kasneci et al., 2023; Virmani et al., 2026). Their increasing accessibility makes human capability, rather than access alone, a central determinant of system value.

Entrepreneurial opportunity seeking is a suitable applied domain for examining this relationship. Opportunity seeking requires users to gather and interpret information, identify patterns in customer needs and market change, compare possible ventures, assess uncertainty, and transform an initial idea into a more coherent business concept. Generative AI can support these activities by producing alternatives, organizing information, simulating questions, and offering preliminary analysis. It therefore functions as an AI-enabled decision-support resource within a broader human judgment process (Park et al., 2025; Somià & Vecchiarini, 2024; Yu et al., 2025).

System use, however, does not automatically produce reliable decisions. Effective interaction is associated with whether users understand what AI can and cannot do, can formulate appropriate prompts, can select and apply tools, can evaluate information quality, and can use outputs responsibly. These capabilities are captured by AI literacy, commonly understood as the knowledge and skills required to understand, use, critically evaluate, and ethically engage with AI systems (Long & Magerko, 2020; Ng et al., 2021). From an information-systems perspective, AI literacy is a user-side capability associated with the quality of interaction between a person, an AI interface, the information produced, and the task being performed.

Prior studies have linked AI-assisted learning with productivity, creativity, self-efficacy, entrepreneurial intention, and digital entrepreneurial competence (Dunan et al., 2025; Duong, 2025; Gong et al., 2025; Xie & Wang, 2025). Yet three issues remain insufficiently examined. First, much of the literature focuses on adoption or intention rather than the actual stages of an information-intensive entrepreneurial task. Second, operational use is often treated as evidence of competence even when users cannot verify sources, detect limitations, or judge contextual fit. Third, quantitative models rarely explain the human-computer interaction problems that underlie observed statistical relationships, such as poor prompt formulation, information overload, low trust, unreliable connectivity, and overdependence.

These gaps are particularly relevant in emerging and rural higher-education settings, where students may have strong interest in AI but uneven access to digital infrastructure, formal training, and institutional guidance. Philippine studies show growing use of AI among students and educators alongside concerns about readiness, policy, academic integrity, and infrastructure (Giray et al., 2024; Villarino, 2025). Examining entrepreneurship students in this context provides evidence on how AI systems are used for applied management tasks and how user capability is associated with the perceived value of AI-assisted decision support.

This study therefore investigates the association between AI literacy and AI-assisted entrepreneurial opportunity seeking and interprets that association through students' reported experiences and challenges. The study makes three contributions. First, it models AI literacy as a multidimensional user capability for a domain-specific AI decision-support task. Second, it connects statistical predictors with concrete human-AI interaction problems, particularly prompting, information verification, contextualization, and ethical dependence. Third, it derives system-design, information-governance, and instructional implications that are relevant to computer information systems used in entrepreneurial and managerial settings.

1.1 Research Questions and Hypothesis

The study addressed the following research questions:

1. What are the levels of AI awareness, AI application skills, evaluation of AI outputs, and ethical AI use among entrepreneurship students?
2. To what extent do students use AI for opportunity discovery, opportunity evaluation, and opportunity development?
3. Do the four AI literacy dimensions significantly predict AI-assisted opportunity seeking?
4. How do students experience human-AI interaction during entrepreneurial opportunity seeking?
5. What technical, informational, contextual, and ethical challenges limit effective AI-assisted opportunity seeking?

The quantitative analysis tested the hypothesis that the AI literacy dimensions, taken together, significantly predict AI-assisted opportunity seeking. The individual regression coefficients were examined to determine which dimensions contributed to the model.

2. Related Work and Conceptual Model

2.1 Generative AI as an Interactive Information and Decision-Support System

Generative AI systems differ from conventional educational software because users interact with them through open-ended natural language and receive probabilistic, context-sensitive outputs. The user does not merely retrieve stored content; the user frames a problem, supplies context, evaluates a generated response, and often iterates through several turns. This interaction resembles a collaborative information-processing loop in which both system capability and user behavior affect the quality of the result. Generative AI can accelerate routine cognitive work and increase productivity, but its outputs may also include fabricated facts, hidden assumptions, bias, or recommendations that are poorly matched to local circumstances (Dwivedi et al., 2023; Kasneci et al., 2023; Noy & Zhang, 2023).

In entrepreneurial learning, the system can function as a lightweight decision-support interface. Students may ask it to scan trends, identify customer pain points, compare venture ideas, formulate value propositions, generate risk lists, or improve a business model. These uses are meaningful only when outputs are treated as provisional information rather than authoritative decisions. The human user must specify the task, assess relevance, introduce local knowledge, and decide whether further evidence is required.

2.2 AI Literacy as a User Capability

AI literacy is multidimensional. Awareness concerns recognition of AI-enabled systems and an understanding of their general functions. Application skills refer to the ability to select tools, formulate prompts, refine queries, and incorporate outputs into work. Evaluation involves judging accuracy, reliability, limitations, and task suitability. Ethical use concerns accountability, transparency, academic integrity, privacy, fairness, and the preservation of human agency (Long & Magerko, 2020; Ng et al., 2021; UNESCO, 2021).

This multidimensional view is important because frequent use may coexist with limited critical competence. Reviews of AI literacy research show that operational familiarity is often stronger than systematic evaluation, while educational studies repeatedly identify weak source checking and uncertainty about responsible use (Lintner, 2024; Sari et al., 2025). In computer information systems, this distinction separates interface fluency from informed and accountable system use.

2.3 AI-Supported Entrepreneurial Opportunity Seeking

Entrepreneurial opportunity seeking is commonly described as a process of identifying, evaluating, and developing opportunities (Ardichvili et al., 2003; Shane & Venkataraman, 2000). Discovery involves recognizing unmet needs, emerging trends, and possible solutions. Evaluation involves examining feasibility, demand, risk, value, and resource requirements. Development involves refining the concept, business model, strategy, and implementation logic. AI can support all three stages by increasing the range of information and alternatives available to the user.

Existing research suggests that AI-assisted entrepreneurship education can strengthen idea generation, entrepreneurial self-efficacy, market analysis, and business planning (Gong et al., 2025; Park et al., 2025; Xie & Wang, 2025). However, the same system features that expand exploration can increase cognitive burden. A user may receive many plausible ideas without a reliable basis for ranking them, or may confuse linguistic fluency with factual accuracy. Consequently, opportunity seeking provides a useful test of whether AI literacy supports not just system use but disciplined decision support.

2.4 Information Quality, Trust, and Responsible Human Oversight

Information quality is central to AI-assisted decision making. Users must determine whether outputs are accurate, current, complete, relevant, and supported by credible evidence. When systems do not expose provenance or confidence, users may rely on surface plausibility. This creates risks of automation bias, uncritical acceptance, and the transfer of incorrect assumptions into business decisions. Research on educational AI similarly identifies misinformation, bias, overreliance, and reduced critical engagement as persistent concerns (Garzón et al., 2025; Matos et al., 2025).

Responsible AI use therefore requires human oversight and governance. At the user level, this includes disclosure, verification, reflective judgment, and awareness of the limits of generated content. At the system and institutional levels, it includes clear use policies, data-protection practices, source and uncertainty cues, equitable access, and tasks designed so that AI augments rather than replaces human reasoning.

2.5 Conceptual Model

The conceptual model treats AI literacy as a set of user capabilities that may be associated with AI-assisted opportunity seeking. Awareness, application skills, output evaluation, and ethical use form the quantitative predictor set. Opportunity discovery, evaluation, and development form the task outcome. Qualitative findings provide an explanatory interaction layer by identifying how prompting difficulty, unreliable outputs, verification problems, internet access, weak contextual fit, and overdependence relate to the observed statistical association.

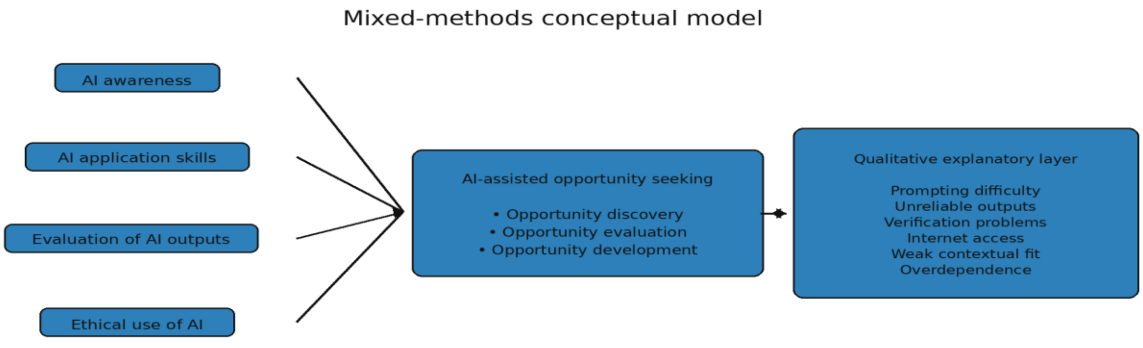

Figure 1. Conceptual model linking AI literacy, AI-assisted opportunity seeking, and the qualitative human-AI interaction layer.

3. Methodology

3.1 Research Design and Setting

A convergent mixed-methods design was used. Quantitative and qualitative data were gathered within the same study period, analyzed separately, and integrated during interpretation. This design was selected because the regression model could establish whether AI literacy dimensions significantly predicted reported AI-assisted opportunity seeking, while interviews and focus-group responses could clarify how users interacted with AI systems and why particular capabilities showed stronger or weaker statistical associations.

The study was conducted at Kalinga State University in Tabuk City, Philippines, within the Bachelor of Science in Entrepreneurship program. Participants were first-year students enrolled in an Opportunity Seeking course during the second semester of Academic Year 2025-2026. The course requires students to identify, evaluate, and develop business opportunities and therefore provides an appropriate task environment for examining AI-assisted information processing and decision support.

3.2 Participants

The sampling frame comprised 59 students enrolled in the course, and 57 complete survey responses were available for quantitative analysis. Total enumeration was used for the class cohort. For the qualitative component, 14 participants were purposively selected across different AI literacy levels to capture variation in user experience. Participant excerpts were anonymized using identifiers P1–P14.

3.3 Measures and Data-Collection Instruments

The survey contained 32 items rated on a five-point agreement scale. Twenty items measured four dimensions of AI literacy: AI awareness, AI application skills, evaluation of AI outputs, and ethical AI use. Twelve items measured AI-assisted opportunity seeking across opportunity discovery, opportunity evaluation, and opportunity development. The instrument was adapted from established AI literacy and entrepreneurial-opportunity concepts and modified for the study context.

Table 1. Measurement framework.

Construct / dimension	Operational meaning	Items	Conceptual basis

AI awareness	Recognition and understanding of AI technologies and their functions in learning and business tasks.	5	Long & Magerko (2020); Sari et al. (2025)
AI application skills	Ability to select and operate AI tools, formulate prompts, generate alternatives, and integrate outputs into work.	5	Ng et al. (2021); Sari et al. (2025)
Evaluation of AI outputs	Ability to judge accuracy, reliability, limitations, suitability, and the need for external verification.	5	Long & Magerko (2020); Ng et al. (2021)
Ethical AI use	Awareness and practice of responsible, accountable, and integrity-preserving AI use.	5	Ng et al. (2021); UNESCO (2021)
Opportunity discovery	Use of AI to identify customer needs, market signals, problems, and possible products or services.	4	Shane & Venkataraman (2000); Baron (2006)
Opportunity evaluation	Use of AI-generated information to examine feasibility, demand, risk, and comparative viability.	4	Ardichvili et al. (2003); Shepherd & DeTienne (2005)
Opportunity development	Use of AI to refine an idea, formulate strategy, improve a business model, and form a complete concept.	4	Ardichvili et al. (2003)

A semi-structured interview and focus-group guide explored how students used AI for idea generation, market and feasibility analysis, opportunity refinement, and business concept development. It also examined prompting difficulty, unreliable outputs, verification problems, internet access, weak contextual fit, ethical concerns, and overdependence.

3.4 Data Collection and Ethical Procedures

Participants were informed of the purpose of the study and were invited to participate voluntarily. Responses were treated confidentially and used for academic research. Interviews and group discussions were recorded only with participant permission and were transcribed for analysis. No personally identifying information is reported.

3.5 Data Analysis and Mixed-Methods Integration

Means were computed to describe the seven measured dimensions. Multiple linear regression was used to predict overall AI-assisted opportunity seeking from AI awareness, application skills, evaluation of AI outputs, and ethical use. The reported regression coefficients are unstandardized coefficients and are labeled B. Linearity, residual normality, homoscedasticity, and extreme outliers were examined through scatterplots and residual diagnostics before the model was interpreted.

Qualitative data from 14 participants were analyzed thematically through familiarization, initial coding, theme development, review, and interpretation. Quantitative and qualitative findings were integrated through a joint-display logic: each statistical result was compared with participant descriptions of system use, interaction barriers, and responsible-use concerns. This integration assessed convergence, complementarity, and apparent divergence between measured competence and reported practice.

4. Results

4.1 Descriptive Results

Students reported generally high AI literacy and high use of AI across the entrepreneurial opportunity-seeking workflow. Ethical AI use had the highest AI literacy mean ($M = 4.08$), followed by application skills ($M = 4.02$). Awareness and evaluation of AI outputs both had means of 3.96. Within opportunity seeking, development was highest ($M = 4.19$), while discovery and evaluation were both 4.11.

Table 2. Dimension-level descriptive results (N = 57).

Construct	Dimension	Mean	Interpretation	Diagnostic pattern
AI literacy	AI awareness	3.96	Agree	Students recognized AI's task-support value, but were less confident identifying AI embedded in everyday applications.
AI literacy	AI application skills	4.02	Agree	Tool use was strong; prompt formulation was the lowest-rated application item (M = 3.89).
AI literacy	Evaluation of AI outputs	3.96	Agree	Tool selection was stronger than cross-checking AI information with external sources (M = 3.89).
AI literacy	Ethical AI use	4.08	Agree	Responsible-use awareness was high, although avoiding academic misuse was comparatively weaker (M = 3.91).
Opportunity seeking	Opportunity discovery	4.11	Agree	Trend scanning was stronger than direct identification of customer needs.
Opportunity seeking	Opportunity evaluation	4.11	Agree	Market-demand analysis was stronger than holistic feasibility assessment.
Opportunity seeking	Opportunity development	4.19	Agree	Students strongly used AI to convert ideas into more complete business concepts.

The item-level pattern is important. Students were comfortable using named AI platforms and perceived AI as useful for trend analysis and concept development. The lower ratings were concentrated in prompting, source comparison, customer-focused interpretation, and integrated feasibility assessment. These results suggest that system use was broad, but the interaction practices required to validate and contextualize generated information were less mature.

4.2 Regression Model

Table 3. Multiple linear regression predicting AI-assisted opportunity seeking with unstandardized coefficients (B) (N = 57).

Predictor	B	SE	t	p	Result
Constant	0.850	0.521	1.632	.109	-
AI awareness	0.302	0.121	2.491	.016	Significant
AI application skills	0.313	0.154	2.035	.047	Significant
Evaluation of AI outputs	-0.041	0.128	-0.319	.751	Not significant
Ethical AI use	0.244	0.098	2.486	.016	Significant

Model summary: $R^2 = .506$; adjusted $R^2 = .468$; $F(4,52) = 13.315$, $p < .001$.

The regression model was statistically significant and accounted for 50.6% of the variance in AI-assisted opportunity seeking, with an adjusted estimate of 46.8%. AI awareness, application skills, and ethical use significantly predicted AI-assisted opportunity seeking in the regression model. Application skills had the largest unstandardized coefficient, although its significance was comparatively modest ($p = .047$). Evaluation of AI outputs was not a significant predictor and had a near-zero negative unstandardized coefficient.

The results show that higher AI awareness, stronger application skills, and stronger responsible-use orientations were associated with higher reported opportunity-seeking scores. Evaluation of AI outputs was not significantly associated with additional opportunity-seeking scores after the other literacy dimensions were controlled in the regression model. This non-significant coefficient does not demonstrate that verification is unimportant; the qualitative findings clarify the gap between reported evaluative awareness and routine verification practice.

4.3 Students' Experiences of Human-AI Interaction

Fourteen qualitative participants described five ways in which they used AI during opportunity seeking: as an idea generator, an analytical aid, a learning accelerator, a creativity partner, and a business-concept development tool. Their accounts indicate that AI was incorporated across an information-processing workflow rather than used for a single isolated task.

Table 4. Experiences of using AI for entrepreneurial opportunity seeking.

Theme	System role	Representative evidence	Interpretation
Idea generation and opportunity discovery	Expands alternatives and surfaces trends or unmet needs.	"Helps me discover business opportunities by analyzing market trends" (P1); "gives different suggestions that I did not think of before" (P7).	Participants described AI as broadening the opportunity search space and supporting pattern recognition.
Data-informed opportunity evaluation	Provides preliminary feasibility, demand, financial, and risk analysis.	"Analyze market feasibility, predict financial performance, and assess potential risks" (P1); "test if my idea is feasible in our community" (P2).	AI is treated as a provisional analytical and decision-support resource.
Learning acceleration	Reduces time needed for preliminary research and explanation.	"Real-time analysis ... unlike traditional methods" (P1); "makes learning faster and easier" (P5).	Rapid interaction was perceived as improving accessibility and task efficiency.
Creativity and idea enhancement	Generates variants, features, and alternative concepts.	"It gives me many ideas that I can improve" (P3); "helps me think of new and creative concepts" (P7).	AI functions as a generative partner, while selection remains a human task.
Business-concept development	Supports refinement of features, marketing, strategy, and business-model logic.	"Helped me improve my business idea by suggesting better features and marketing" (P5).	Participants used AI to move from an initial idea toward a more structured venture concept.

Participants' accounts were consistent with the significant regression coefficients for awareness and application skills. Students who understood possible AI uses and could interact with the systems reported using them across several task stages. However, the descriptions also show that outputs were mainly used to expand and organize possibilities. Final interpretation, local validation, and commitment decisions remained the responsibility of the user.

4.4 Challenges Associated with System Use and Information Quality

Qualitative data from participants P1–P14 confirmed eight related challenge themes. Six were especially central to the integrated findings: prompting difficulty, unreliable outputs, verification problems, internet access, weak contextual fit, and overdependence. The most direct human-computer interaction problem concerned prompt formulation. Students understood that output quality was associated with input specificity but were uncertain how to express constraints, refine instructions, or ask follow-up questions. One participant explained, “Kailangan ayusin mo ... kapag hindi maayos, mali yung ibibigay” [the prompt must be constructed properly; otherwise, the system gives an incorrect response] (P1).

Table 5. Challenges in AI-assisted opportunity seeking.

Challenge	Observed problem	Representative evidence	Information-systems implication
Prompting difficulty	Users struggled to construct clear, specific, and iterative instructions.	“I do not know how to ask the right questions” (P7).	Interfaces and instruction should provide task-specific prompt scaffolds and examples.
Unreliable outputs	Generated content could be incorrect, outdated, misleading, or unsupported.	“Sometimes AI gives wrong information” (P10); “AI outputs are not always reliable” (P5).	Outputs require uncertainty cues, evidence links, and human review.
Verification problems	Students had trouble confirming sources, credibility, and factual accuracy.	“Hard to confirm if insights are based on credible data” (P2).	Verification workflows and provenance visibility should be built into use practices.
Information overload	The system generated too many alternatives for easy comparison.	“AI generates dozens of outputs ... challenging to prioritize” (P2).	Systems should support filtering, ranking, comparison, and decision criteria.
Limited technical skills	Users lacked advanced navigation, tool-selection, and refinement skills.	“Lack technical skills to navigate the tool” (P3).	Training should progress from basic operation to strategic interaction and error recovery.
Weak contextual fit	Outputs did not adequately reflect community, cultural, geographic, or operational realities.	“AI cannot fully understand real-life situations” (P5); “AI might miss cultural specifics” (P6).	Local data, contextual prompts, and domain-expert validation are necessary.
Internet-access constraints	Unstable or slow internet reduced consistent access and interaction.	“Unstable internet access” (P2); “slow internet affects my use of AI” (P7).	Deployment should consider bandwidth, cost, device access, and resilient alternatives.

Overdependence and ethical concerns	Students worried about excessive reliance, misuse, and reduced independent thinking.	"Students rely on AI ... not use their mind" (P10).	Governance should preserve human accountability, disclosure, and reflective judgment.

The themes of unreliable outputs and verification problems help interpret the non-significant coefficient for evaluation of AI outputs. Students reported using AI frequently, but systematic validation was not embedded in their normal workflow. The descriptive item on comparing AI-generated information with other sources was also among the lowest-rated evaluation items. Thus, operational interaction was associated with task completion, whereas information-quality control remained inconsistent.

4.5 Integrated Findings

Table 6. Mixed-methods joint display and system implications.

Quantitative finding	Qualitative explanation	Integrated interpretation	Design / governance implication
AI awareness was significant (B = .302, p = .016).	Students recognized uses for trend scanning, customer problems, and idea generation.	Awareness was associated with identifying where AI could be inserted into the task workflow.	Provide use-case discovery, onboarding, and transparent descriptions of system capability and limits.
AI application skills were significant (B = .313, p = .047).	Students used AI across discovery, evaluation, and development but struggled with advanced prompting.	Practical interaction was associated with more extensive use, while quality depended on iterative query and refinement skills.	Offer stage-specific prompt templates, examples, conversational repair, and comparison tools.
Ethical use was significant (B = .244, p = .016).	Students valued responsible use and expressed concern about overdependence and academic misuse.	Ethical orientation was associated with intentional, accountable, and bounded system use.	Use disclosure rules, human-approval checkpoints, privacy guidance, and reflective-use prompts.
Evaluation was not significant (B = -.041, p = .751).	Students reported unreliable outputs, weak source verification, and difficulty judging contextual fit.	Evaluation was recognized conceptually but was not significantly associated with additional opportunity-seeking scores in the regression model.	Expose provenance, require external evidence, display uncertainty, and integrate verification tasks.

5. Discussion

5.1 AI Literacy as a Human Capability in AI-Enabled Decision Support

The findings support the view that AI literacy is not merely knowledge about artificial intelligence; it is a practical user capability associated with the extent to which an AI system is used as decision support. Awareness was associated with recognition of possible system-task matches. Application skills were associated with interaction, iteration, and incorporation of outputs. Ethical use was associated with more bounded and accountable application of outputs. Together, these dimensions accounted for a substantial share of variation in students' reported use of AI for entrepreneurial opportunity seeking.

This result extends prior entrepreneurship-education research by shifting the analytical focus from entrepreneurial intention to an actual information-intensive workflow. Studies have shown that AI can strengthen self-efficacy, creativity, planning, and digital entrepreneurial skills (Duong, 2025; Gong et al., 2025; Xie & Wang, 2025). The present findings indicate that reported benefits were associated with user capabilities that connected a conversational AI interface with a sequence of managerial tasks.

5.2 The Operational-Use versus Information-Evaluation Gap

The most important finding is the divergence between high self-reported evaluation scores and the non-significant regression coefficient for evaluation. Qualitative data from participants P1–P14 confirmed prompting difficulty, unreliable outputs, verification problems, internet-access constraints, weak contextual fit, and overdependence. Students understood, in general, that AI could be wrong, yet they did not consistently verify outputs or use independent data to judge credibility. Knowing that verification is desirable is different from performing verification as part of a decision workflow.

The result is consistent with research showing that AI users may demonstrate high operational fluency while remaining vulnerable to inaccurate, biased, or context-poor outputs (Dwivedi et al., 2023; Sari et al., 2025). For computer information systems, it indicates that user competence cannot be inferred from frequency of use or ease of interaction. Evaluation behavior should be treated as a separate outcome and supported through interface design, information architecture, and task controls.

5.3 Human-Computer Interaction Implications

Prompt formulation emerged as the clearest interaction bottleneck. The quality of conversational AI output depends heavily on problem framing, context, constraints, and iterative follow-up. Novice users may issue broad requests, accept the first response, or fail to diagnose why an answer is weak. A system intended for entrepreneurial decision support should therefore provide task-oriented prompt scaffolding rather than relying entirely on an empty chat box.

At minimum, an entrepreneurship-oriented interface could ask users to specify the target customer, geographic context, available resources, evidence base, decision criteria, and stage of opportunity development. It could support side-by-side comparison of alternatives, flag unsupported claims, ask users to confirm assumptions, and prompt them to attach local market data. These features would reduce information overload and encourage deliberate interaction.

The findings also show that AI creativity should be paired with selection and refinement mechanisms. Generating many ideas was perceived as useful, but participants found it difficult to prioritize them. Ranking functions, feasibility rubrics, traceable criteria, and editable decision matrices would help convert generative breadth into manageable decision support.

5.4 Information Governance and Responsible AI

Ethical AI use significantly predicted opportunity seeking in the regression model and appeared in qualitative accounts as concern about academic misuse and reduced independent thinking. Responsible-use orientation was associated with more intentional AI engagement and continued human accountability for decisions. Institutional governance should therefore define acceptable assistance, disclosure expectations, privacy safeguards, and activities that must remain under human control.

Information provenance is a priority. Students should be able to distinguish generated synthesis from verified evidence. Where possible, systems should display sources, dates, and uncertainty, while instructional workflows should require users to compare AI outputs with official statistics, market observations, customer interviews, or other credible evidence. Human approval should be required before generated claims are used in feasibility studies, business plans, or external communications.

5.5 Implications for Industrial Management and Entrepreneurial Information Systems

Although the study was conducted in an educational setting, the task structure resembles early-stage managerial decision making. Entrepreneurs and small firms frequently operate with limited analytical staff and may use general-purpose AI systems for market intelligence, customer analysis, risk scanning, strategy formulation, and business-model design. The student findings identify user-side risks relevant to small-enterprise adoption: prompting difficulty, unreliable or unverified information, weak contextual fit, internet-access constraints, and overdependence on fluent outputs.

For industrial-management applications, effective deployment should combine AI capability with user training, domain data, governance, and interface support. A general-purpose model becomes more useful when embedded in a structured information system that captures task context, documents evidence, supports comparison, and records human decisions. The goal is not to automate opportunity judgment but to improve the quality, speed, and transparency of the information available to the decision maker.

6. Conclusion, Limitations, and Future Research

6.1 Conclusion

This study reframed AI-assisted entrepreneurial learning as a computer information systems problem involving user capability, human-AI interaction, information quality, and responsible decision support. AI literacy significantly predicted AI-assisted opportunity seeking, with awareness, application skills, and ethical use contributing positively. Students used AI throughout opportunity discovery, evaluation, and development, particularly for trend scanning, idea generation, preliminary analysis, and business-concept refinement.

The central weakness was not lack of use but lack of embedded evaluation. Students reported difficulty verifying information, judging contextual relevance, and managing large numbers of generated alternatives. The non-significant evaluation coefficient, together with these qualitative findings, points to an operational-use versus information-evaluation gap. Students perceived generative AI as supporting efficiency and creativity, but the credibility of those benefits remained associated with provenance, verification, local context, and human oversight.

The results support a sociotechnical approach to AI-enabled decision support. User training should be accompanied by prompt scaffolding, source visibility, comparison tools, contextual data integration, ethical guidance, and explicit human approval. Such features can help transform conversational AI from a convenient answer generator into a more accountable and effective component of entrepreneurial information systems.

6.2 Limitations

The study has several limitations. It involved 57 students from one higher-education institution and used self-reported measures, limiting generalizability and creating the possibility of common-method and social-desirability bias. The cross-sectional design does not establish causality. The study did not analyze system logs, prompt histories, response accuracy, actual source-verification behavior, or venture performance. It also treated AI tools as a general category rather than comparing specific models, interfaces, or subscription levels. Finally, institutional readiness, prior digital competence, internet quality, and instructor guidance were not included in the regression model.

6.3 Future Research

Future work should test the model across institutions, disciplines, and enterprise settings using larger samples. Behavioral studies should combine surveys with interaction logs, prompt quality measures, fact-checking tasks, and independent assessments of generated output. Experiments could compare unstructured chat interfaces with systems that provide prompt templates, provenance, uncertainty cues, ranking tools, and local-data integration. Longitudinal research should examine whether AI literacy predicts the quality of validated opportunities, business models, and actual venture outcomes. Further research is also needed on trust calibration, explainability, cultural and geographic context, low-bandwidth deployment, and governance for AI use in micro, small, and medium enterprises.

Appendix A. Item-Level Descriptive Results

The following table preserves the item-level descriptive statistics used to interpret the dimension means. These results may be transferred to supplementary material when required by the journal.

Table A1. Item-level means and interpretations (N = 57).

Dimension	Item	Mean	Interpretation
AI awareness	I can distinguish between devices or applications that use artificial intelligence and those that do not.	3.88	Agree
AI awareness	I am aware that many digital tools and applications today use artificial intelligence.	3.98	Agree

AI awareness	I understand that artificial intelligence can assist in performing various tasks.	4.09	Agree
AI awareness	I can identify examples of AI technologies used in everyday applications.	3.86	Agree
AI awareness	I am familiar with different types of AI tools that can support learning or business activities.	3.98	Agree
AI application skills	I can use AI tools (e.g., ChatGPT, Gemini, Copilot) effectively.	4.18	Agree
AI application skills	I can formulate clear prompts to get useful responses from AI tools.	3.89	Agree
AI application skills	I can use AI to assist me in completing academic tasks.	4.07	Agree
AI application skills	I can use AI to generate ideas or solutions to problems.	4.07	Agree
AI application skills	I can integrate AI outputs into my work appropriately.	3.96	Agree
Evaluation of AI outputs	I can evaluate whether information generated by AI tools is accurate.	3.93	Agree
Evaluation of AI outputs	I can identify limitations of AI-generated responses or suggestions.	4.00	Agree
Evaluation of AI outputs	I can compare AI-generated information with other sources to verify reliability.	3.89	Agree
Evaluation of AI outputs	I can determine whether AI-generated suggestions are suitable for my tasks.	3.95	Agree
Evaluation of AI outputs	I can choose the most appropriate AI tool for a specific task or problem.	4.02	Agree
Ethical AI use	I understand that AI should be used responsibly in academic or professional work.	4.23	Strongly Agree
Ethical AI use	I am aware of ethical issues involved in using AI technologies.	4.05	Agree
Ethical AI use	I avoid using AI tools in ways that may lead to academic dishonesty.	3.91	Agree
Ethical AI use	I consider potential risks and consequences of using AI technologies.	4.02	Agree
Ethical AI use	I believe AI should be used in a way that respects ethical standards and social responsibility.	4.19	Agree
Opportunity discovery	I use AI tools to identify customer needs that could lead to a business idea.	3.95	Agree
Opportunity discovery	AI tools help me discover possible business opportunities based on market trends.	4.26	Agree

Opportunity discovery	I use AI tools to generate possible solutions for consumer problems.	4.02	Agree
Opportunity discovery	AI helps me explore different possibilities for new products or services.	4.19	Agree
Opportunity evaluation	I use AI tools to evaluate whether a business idea is feasible.	3.98	Agree
Opportunity evaluation	AI tools help me analyze potential customers and market demand for a business idea.	4.25	Strongly Agree
Opportunity evaluation	I use AI tools to compare different business ideas to determine which is more viable.	4.05	Agree
Opportunity evaluation	AI helps me identify possible risks or challenges associated with a business idea.	4.16	Agree
Opportunity development	I use AI tools to refine and improve a selected business idea.	4.11	Agree
Opportunity development	AI helps me develop strategies for implementing a business opportunity.	4.21	Strongly Agree
Opportunity development	AI tools help me design or improve the business model of my idea.	4.21	Strongly Agree
Opportunity development	AI tools help me develop my business idea into a more complete business concept.	4.25	Strongly Agree

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