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Perceived AI Benefits and Entrepreneurial Opportunity Recognition Among University Students: The Moderating Role of AI Trust

Muhammad Junaid Anwer¹ Dr. Fahad Javed² Rao Abdul Hanna Jaffar³

¹ Phd Scholar, Institute of Business Management and Administrative Science (IBMAS), The Islamia University of Bahawalpur, Punjab, Pakistan.

² Assistant Professor, The Islamia University of Bahawalpur, Ryk Campus, Punjab, Pakistan.

Email: fahad.javed@iub.edu.pk

³ PhD Scholar, Monash University, Australia.

Email: raohannanjaffar@gmail.com

Corresponding Author: m.junaid_anwer@yahoo.com

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ABSTRACT

Generative artificial intelligence (AI) offers new opportunities for entrepreneurial learning, yet how students' perceptions of AI relate to opportunity recognition, and trust's role, remain unclear. Drawing on the Technology Acceptance Model and opportunity recognition theory, seven hypotheses tested how perceived usefulness, perceived ease of use, and AI creativity support affect opportunity recognition capability, with AI trust as a direct predictor and moderator. Data from 475 final-semester students at public universities in South Punjab, Pakistan, were analyzed using PLS-SEM in SmartPLS 4. Perceived usefulness ($\beta = 0.371$), perceived ease of use ($\beta = 0.291$), and AI creativity support ($\beta = 0.494$) were significantly and positively related to opportunity recognition capability (all $p < .001$). AI trust moderated the effects of perceived usefulness ($\beta = 0.154$, $p = .005$) and perceived ease of use ($\beta = 0.275$, $p < .001$), but had no significant direct effect or moderating effect on AI creativity support. Five of seven hypotheses were supported; the model explained 45.5% of the variance in opportunity recognition capability. The study suggested that universities should integrate artificial intelligence (AI) into entrepreneurship education to enhance students' entrepreneurial learning and capabilities.



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1. Introduction

Artificial intelligence (AI) and more specifically generative AI is creating new ways for individuals to access information, generate ideas and solve complex problems. Relevant to entrepreneurial tasks, generative AI tools can assist in information processing, idea development, and exploring alternative solutions, while digital technologies are transforming how entrepreneurial opportunities are pursued (Nambisan, 2017). The starting point for entrepreneurship is the identification of opportunities by entrepreneurs, which can be in the form of unmet market needs, changes in the business environment, or ideas that create economic or social value (Shane & Venkataraman, 2000).

Entrepreneurship is a process where opportunity recognition plays a vital role as it forms the foundation of new products, services and businesses. It involves more than gathering information: it requires connecting information, noticing patterns, recognizing unmet needs, and assessing potential business opportunities. Baron (2006) described opportunity recognition from a pattern-recognition perspective, in which entrepreneurs identify links between apparently unrelated pieces of information. Generative AI can help students brainstorm customer problems, analyze market trends, and generate alternative business ideas, and Renz et al. (2025) provided experimental evidence that large language models (LLMs) can significantly improve participants' opportunity recognition capability. However, access to AI does not guarantee that students identify opportunities effectively, and little is known about how students' perceptions of the usefulness, ease of use, and creativity support of AI relate to their opportunity recognition capability.

Davis (1989) identified perceived usefulness and perceived ease of use as the key beliefs underlying acceptance. In AI-supported entrepreneurial activity, perceived usefulness is students' belief that AI can help them identify and evaluate business opportunities, and perceived ease of use is how easy they find AI tools to use. However, their relationships with opportunity recognition capability should be empirically tested instead of assumed from their previously established relationship with technology acceptance.

The level of support of generative AI in entrepreneurial thinking is not fully captured by functional attributes like usefulness and ease of use. AI creativity support reflects users' perceptions of how much AI assists them in thinking, creating, evolving, or rethinking their ideas. Creativity is important to opportunity recognition because recognizing opportunities sometimes involves bringing together what is already known in new ways or in a new light (Amabile, 1996). While creative assistance does not guarantee the recognition of feasible opportunities, AI-generated suggestions can inspire students to think of ideas that they might not have thought of otherwise. The three perceptions are considered together as separate predictors since perceived creativity support is likely to be correlated with ease of use and usefulness.

Belief in AI is also a key consideration. While AI-generated content can provide valuable insights, it may also contain false information or unsupported claims. A student who has trust in AI might be more inclined to take the AI's suggestions, while a student who does not trust AI may be less inclined to believe AI outputs when considering a potential opportunity. But trust is not a measure of accuracy of AI, and higher trust does not necessarily result in improved entrepreneurial decisions (Lee & See, 2004; Parasuraman & Riley, 1997). Trust may therefore act both as a predictor and as a boundary condition that shapes how perceived AI benefits translate into opportunity recognition.

Although research interest in AI-enabled entrepreneurship is growing, the relationship between students' perceptions of AI and their opportunity recognition capability differs from the performance effect of AI use in a controlled task such as that studied by Renz et al. (2025). The present study therefore examines students at public sector universities in South Punjab, Pakistan. It tests perceived usefulness, perceived ease of use, and AI creativity support as three distinct predictors of opportunity recognition capability, examines the direct effect of AI trust, and explores whether AI trust moderates each of the three relationships. PLS-SEM is used to assess the proposed relationships.

The study has three aims. First, it distinguishes the

functional and creative benefits that students experience with AI rather than treating them as a single construct. Second, it treats entrepreneurial opportunity recognition as the outcome, moving beyond technology acceptance to a capability relevant to entrepreneurship. Third, it investigates whether AI trust is a boundary condition that accounts for the variation in these relationships among students. The results have practical guidance's for entrepreneurship educators and university leaders who want to incorporate AI tools into teaching and support students to critically examine AI-produced content.

2. Theoretical Foundations and Hypotheses Formation

2.1. Theoretical Foundations

This research builds on the Technology Acceptance Model (TAM) and the entrepreneurial opportunity recognition literature. TAM proposes that perceived usefulness and perceived ease of use shape individuals' attitudes toward, and use of, technology (Davis, 1989; Venkatesh & Davis, 2000), and later work confirmed performance- and effort-related beliefs as core predictors of technology use (Venkatesh et al., 2003). Here, these constructs are applied to AI-supported entrepreneurial activities to investigate whether students who find AI useful and easy to use in such activities report higher opportunity recognition capability (ORC).

Recognizing opportunities is a primary part of the entrepreneurial process. Shane and Venkataraman (2000) placed the discovery, evaluation, and exploitation of opportunities at the heart of entrepreneurship research, and Ardichvili et al. (2003) argued that opportunity identification and development are interrelated and shaped by prior knowledge, social networks, and entrepreneurial alertness (see also Kirzner, 1973). AI can help with this by providing information, brainstorming new ideas, and investigating solutions to problems, and experimental results indicate that LLMs can boost performance in an opportunity recognition task (Renz et al., 2025).

However, the impact of AI could vary based on students' perceptions of its usefulness, usability and creative support, as well as their trust in AI-generated content. Therefore, the study explores the role of perceived usefulness (PU), perceived

ease of use (PEOU), and AI creativity support (AICS) as factors predicting ORC. It also takes into account the AI trust (AIT) as a direct predictor and as a potential moderator of the three relationships. This framework (Figure 1) enables the study to explore direct relationships between perceptions of AI and ORC, and the extent to which trust enhances or detracts from the relationships.

2.2. Perceived Usefulness of AI and Opportunity Recognition Capability

Perceived usefulness is the extent to which a user feels that the use of a specific technology will improve his or her work (Davis, 1989). In entrepreneurial activities, it is their belief that AI will assist them in researching business opportunities, interpreting market data, understanding the needs of the consumer, and finding new solutions to problems. Students who appreciate the value of AI are more inclined to use its results when exploring opportunities. AI can be used to help structure information, explore alternatives, and identify business possibilities, which may be especially helpful for students with limited entrepreneurial experience or market knowledge.

Perceived usefulness and ORC are nevertheless conceptually distinct: the former concerns beliefs about the benefits of AI, and the latter concerns the capacity to recognize entrepreneurial opportunities. Whether perceived usefulness translates into ORC may depend on how well students evaluate and use the information AI produces. Based on TAM and the emerging evidence on AI and opportunity recognition (Renz et al., 2025), the following hypothesis is proposed:

H1: Perceived usefulness of AI has a positive effect on opportunity recognition capability among university students.

2.3. Perceived Ease of Use of AI and Opportunity Recognition Capability

Perceived ease of use is the degree to which an individual expects that using a technology will be free of effort (Davis, 1989). In AI-supported entrepreneurship, it concerns students' perceptions of how easily they can interact with AI tools, formulate requests, understand answers, and apply the resulting information in entrepreneurial tasks. Because exploring multiple

opportunities, finding information, and evaluating options takes time, ease of use may be relevant to opportunity recognition. When AI is easy to use, students can devote more attention to interpreting information and evaluating entrepreneurial possibilities, whereas perceived complexity may hinder the effective application of AI.

AI tools allow students to ask questions, explore other angles of an opportunity, and pose follow-up questions, which can support the exploration of information, especially for students without much technical experience. Using AI does not automatically mean that an opportunity is recognized, because students must critically judge the relevance and accuracy of AI-generated answers. Nonetheless, perceived ease of use is a central technology interaction belief in TAM (Davis, 1989), and it is expected to have a positive impact on ORC in AI-assisted entrepreneurial activities.

H2: Perceived ease of use of AI has a positive effect on opportunity recognition capability among university students.

2.4. AI Creativity Support and Opportunity Recognition Capability

AI creativity support is the degree to which people view AI as assisting them in creating, developing, improving, and exploring ideas. Whereas perceived ease of use and usefulness relate to expected benefits and required effort, AI creativity support concerns the perceived contribution to creative thinking and idea development, a dimension that has been used to evaluate digital tools with the help of Creativity Support Index (Cherry & Latulipe, 2014).

Creativity is relevant to opportunity recognition because opportunities may occur when an individual sees an unmet need, when the individual brings together information in a new way or when the individual develops a new way of solving a problem. Opportunities are not always so apparent as they seem; sometimes they require a different way of thinking and a connection between seemingly disconnected information. The opportunity recognition literature highlights the importance of individuals' knowledge and cognitive processes in developing opportunities (Ardichvili et al., 2003; Shane & Venkataraman, 2000).

AI can assist in brainstorming and provide alternative ideas, reimagining a product or service, and solutions that users may not have thought of at first. Students may, for example, use AI to brainstorm solutions to local market problems, consider alternative customer groups, or think about how existing resources might be used for new business activities. Although the findings of Renz et al. (2025) do not show that perceived creativity support leads to higher ORC in all contexts, they provide a useful empirical basis for examining AI-supported opportunity exploration. Students' ORC is therefore expected to be higher when they perceive AI to support their creativity.

H3: AI creativity support has a positive effect on opportunity recognition capability among university students.

2.5. AI Trust and Opportunity Recognition Capability

Trust is important when people use technology to obtain information or make decisions under uncertainty. Trust has been defined as a readiness to be vulnerable to second party on the basis of good expectations (Mayer et al., 1995), and McKnight et al. (2002) proposed that trust in technology-mediated transactions comprises trust-related beliefs and intentions that reduce uncertainty and promote reliance on technology-based systems. Trust and TAM beliefs have also been shown to jointly shape technology use (Gefen et al., 2003). Here, AI trust is the student's confidence in AI as a source of information and help in completing entrepreneurial tasks.

Opportunity recognition involves finding and assessing potential opportunities using information that is incomplete, ambiguous, or dynamic. Students who trust AI may be more willing to accept AI-generated ideas, explore alternative interpretations, and use AI-provided information in opportunity identification exercises. Reliance does not, however, mean that AI-generated information is accurate. AI systems can give incorrect or misleading responses, and overreliance can cause users to overlook important contextual information (Lee & See, 2004; Parasuraman & Riley, 1997). Responsible use therefore involves carefully considering AI outputs and checking them against other sources. Even so, students with greater trust may be more open to AI-aided entrepreneurial exploration, and

a positive direct relationship between AI trust and ORC is therefore proposed, subject to empirical testing.

H4: AI trust has a positive effect on opportunity recognition capability among university students.

2.6. The Moderating Role of AI Trust

It is assumed that the perceived ease of use and usefulness, and AI creativity support are related to students' ORC, but the relationships may vary based on students' trust in AI. A moderator is a variable that changes the nature of the association among a predictor and an outcome (Aiken & West, 1991; Dawson, 2014). Each of the three relationships is proposed as being moderated by AI trust, as students' knowledge of the benefits of AI may not be the same for all students and may not be the same for the same student across the three. Even when AI is helpful, easy to use, and can assist with creative thinking, students might not be willing to use the output of AI if they do not trust it.

On the other hand, students who are more confident about the trustworthiness of the AI-generated content may be more inclined to use it as a tool to explore entrepreneurial opportunities (McKnight et al., 2002). The moderation effects are thus analyzed separately for each predictor.

2.6.1. AI Trust as a Moderator of the Relationship Between Perceived Usefulness and Opportunity Recognition Capability

Perceived usefulness is the students' confidence in the ability of AI to improve their performance, while AI trust is their trust in the AI tool. Students may not be able to use AI outputs to their full extent for opportunity recognition if they are not confident in the reliability of the outputs. The relationship between PU and ORC should be stronger for students with high trust as they are more likely to interact with AI-generated information to explore market challenges, understand customer needs, and think about business ideas. Students with less trust might understand the benefits of AI, but be reluctant to accept its suggestions, which would weaken the relationship. This is consistent with general findings on the importance of trust for reliance on technology (McKnight et al., 2002).

H5: AI trust positively moderates the relationship between perceived usefulness of AI and opportunity recognition capability, such that the relationship is stronger when AI trust is higher.

2.6.2. AI Trust as a Moderator of the Relationship Between Perceived Ease of Use and Opportunity Recognition Capability

Perceived ease of use reflects students' belief that using AI is relatively effortless. Ease of interaction alone, however, may not motivate students to use AI-generated information to identify entrepreneurial opportunities, because an easily used tool is not necessarily a reliable one. Students who trust AI may be more inclined to use an accessible AI tool to brainstorm ideas, ask questions, and research possible solutions, so user-friendliness can support opportunity recognition. Students with lower trust may remain hesitant to use AI suggestions even when the tool is user-friendly. The positive relationship between PEOU and ORC is therefore expected to be stronger when AI trust is higher. This proposition extends TAM by treating trust as a boundary condition for the relationship between PEOU and an entrepreneurial cognitive outcome, and it requires empirical testing.

H6: AI trust positively moderates the relationship between perceived ease of use of AI and opportunity recognition capability, such that the relationship is stronger when AI trust is higher.

2.6.3. AI Trust as a Moderator of the Relationship Between AI Creativity Support and Opportunity Recognition Capability

AI creativity support concerns how far students feel that AI helps them generate and develop ideas. This help can support opportunity recognition by prompting students to consider alternative solutions and viewpoints, but students will not necessarily be ready to use creative suggestions. A stronger connection between AICS–ORC would be achieved if the students are more confident in the source, thus they are more willing to discuss AI-generated alternatives, use them as a starting point for further exploration, and connect them with their own understanding of

market needs. If students are not confident, they may doubt the value or reliability of the ideas created by AI and may not engage with them as much, thereby weakening the relationship. This does not mean that students should accept AI-generated ideas uncritically; rather, trust can shape their attitude toward using AI for creative support.

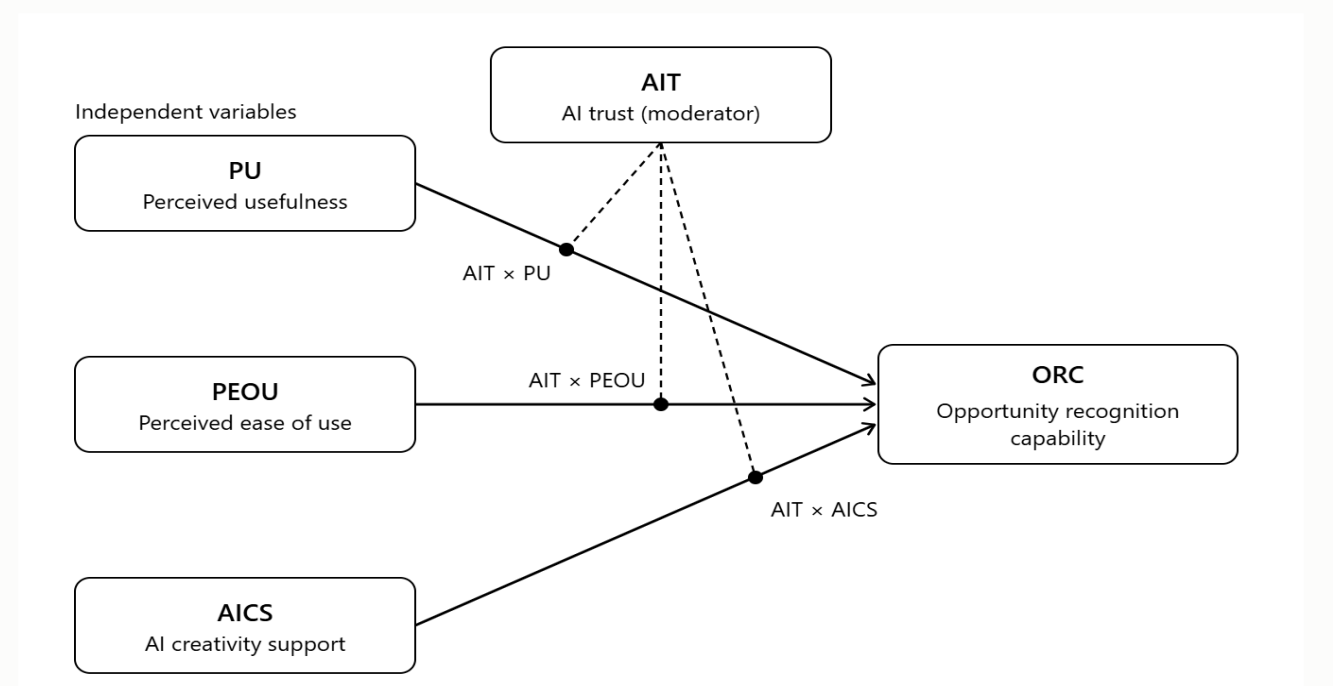
H7: AI trust positively moderates the relationship between AI creativity support and opportunity recognition capability, such that

the relationship is stronger when AI trust is higher.

2.7. Conceptual Framework and Summary of Hypotheses

The framework in Figure 1 is based on TAM and the opportunity recognition literature, and proposes that PU, PEOU and AICS predict ORC (H1–H3). AIT is directly linked with ORC (H4) and is a moderator of the three relationships (H5–H7).

Figure 1: *Conceptual Framework of the Study*



3. Research Methodology

3.1. Research Design

The study used a quantitative, cross-sectional survey design to examine the relationships among PU, PEOU, AICS, AIT, and opportunity recognition capability (ORC) among university students. A quantitative approach was suitable because the study tests theoretically derived hypotheses about direct and moderating effects. Data were gathered from respondents at a single point in time, so the study estimates relationships among the constructs rather than changes in perceptions over time. The model included four direct predictors (PU, PEOU, AICS, and AIT) and three interaction effects in which AIT was hypothesized to moderate the relationships between the three AI-related perceptions and ORC.

3.2. Study Population and Research Context

The respondents were final-semester students at public sector universities in South Punjab, Pakistan. This population was chosen because students at this stage are about to enter the workforce, become self-employed, or pursue other career paths, which makes their ability to identify entrepreneurial opportunities relevant to the potential of generative AI for entrepreneurial development. Data were collected from three public sector universities: The Bahauddin Zakariya University (BZU), Khwaja Fareed University of Engineering and Information Technology (KFUEIT) and Islamia University of Bahawalpur (IUB). The findings should therefore be interpreted in the context of this population and setting, and they cannot be assumed to represent students at private universities, universities in

other parts of Pakistan, or practicing entrepreneurs.

3.3. Sampling Technique and Sample Size

Stratified convenience sampling was employed, and the three universities (IUB, BZU and KFUEIT) were considered as strata. Convenient sampling of final semester students was done within each stratum based upon their availability and willingness to participate. The sample was not a probability sample as the recruitment was not random and therefore cannot be considered as representative of all final semester students in South Punjab. A total of 475 effective responses were retained for analysis which was considered sufficient for the analytical needs of the proposed PLS-SEM model, including the direct and moderating effects.

3.4. Data Collection Procedure

The primary data were gathered by the structured online questionnaire, which was provided in Google Forms. Eligible final-semester students from the three universities were invited to participate, and participation was voluntary. The online approach enabled data collection at all participating institutions without the need for paper questionnaires, and could facilitate the collection of data from geographically dispersed respondents, but also may result in a self-selection of those who wish to participate (Evans & Mathur, 2005). In combination with convenience

sampling, this means that students who returned the questionnaire may be different in relevant ways from students who did not return the questionnaire.

3.5. Measurement of Constructs

The questionnaire consisted of 29 items that assessed five constructs: PU, PEOU, AICS, ORC, and AIT (Table 1). The items were chosen from existing sources and modified for this study. PU and PEOU were each measured with six items adapted from Davis (1989), who developed the original measures of PU and PEOU in technology acceptance research. AICS was measured with five items adapted from the Creativity Support Index developed by Cherry and Latulipe (2014) to evaluate the support that digital tools provide for creativity; in this study, the construct reflects students' perception of generative AI as an aid to creative thinking and idea development. ORC was measured with five items from Kuckertz et al. (2017), who differentiated opportunity recognition from opportunity exploitation; the construct reflects students' perceived ability to identify entrepreneurial opportunities. AIT was measured with seven items adapted from the human-computer trust instrument of Madsen and Gregor (2000), which was originally designed to measure trust in computer systems across several dimensions. All constructs were measured on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree).

Table 1: *Constructs measurement and Sources*

Construct	Original source	Items	Response scale
Perceived Usefulness of Generative AI (PU)	Davis (1989)	6	Seven-point Likert
Perceived Ease of Use of Generative AI (PEOU)	Davis (1989)	6	Seven-point Likert
AI Creativity Support (AICS)	Cherry & Latulipe (2014)	5	Seven-point Likert
Opportunity Recognition Capability (ORC)	Kuckertz et al. (2017)	5	Seven-point Likert
AI Trust (AIT)	Madsen & Gregor (2000)	7	Seven-point Likert
Total		29	

3.6. Data Analysis Technique

The data were examined using PLS-SEM in SmartPLS 4, a variance-based approach suited to testing complex models that include interaction terms (Hair et al., 2019, 2022). The analysis proceeded in two steps: the measurement model was assessed first, and the structural model second, following the procedure described by Hair et al. (2022) for reflective measurement models, structural relationships, and moderation effects.

3.6.1. Measurement Model Assessment

The outer loadings of the items were used to examine indicator reliability. Cronbach's alpha, rho_A, and composite reliability (rho_C) were used to determine internal consistency reliability and the average variance extracted (AVE) was used to determine convergent validity. The heterotrait–monotrait ratio of correlations (HTMT) developed by Henseler et al. (2015) for variance-based SEM was used to test the discriminant validity. These assessments determined whether the measurement model was adequate for interpreting the structural relationships.

3.6.2. Structural Model Assessment

After the measurement model assessment, the structural model was evaluated. Collinearity among predictors was checked using variance inflation factors (VIFs) and the variance in ORC explained by its predictors was calculated using the coefficient of determination (R^2). The path coefficients, t-statistics and p-values were generated by the bootstrapping method for statistical significance test, and the path coefficients were interpreted in terms of their magnitude and direction in SmartPLS 4. H1–H4 were tested through the direct effects of PU, PEOU, AICS and AIT on ORC, while H5–H7 were tested for the interaction effects with AIT.

3.6.3. Moderation Analysis

Three interaction terms were added to the structural model to test for moderation: $AIT \times PU$, $AIT \times PEOU$, and $AIT \times AICS$. The $AIT \times PU$ interaction was tested with H5, the $AIT \times PEOU$ interaction was tested with H6 and the $AIT \times AICS$ interaction was tested with H7. The interaction coefficients were evaluated by their direction and statistical significance: a statistically significant positive coefficient supports the corresponding hypothesis. The significance of each interaction was evaluated independently of the direct effect of AIT, so a non-significant direct relationship between AIT and ORC would not in itself indicate an absence of moderation.

3.7. Ethical Considerations

The participation was voluntary and The participants were final-semester students from the three public sector universities.

4. Results and Analysis

4.1. Demographic Details of Respondents

The demographic details of the 475 students are summarized in Table 2. Respondents came from three public sector universities in South Punjab: IUB (49.68%), BZU (32.63%), and KFUEIT (17.68%). By academic discipline, 47.58% studied Business and Management Sciences, 44.00% studied Computer Science and IT, and 8.42% studied Engineering. The male respondents constituted 54.53% of the sample while the female respondents made up 45.47% of the sample. Most respondents were aged 20–22 years (66.95%), followed by those aged 23–25 years (24.84%), below 20 years (6.11%), 26–28 years (1.47%), and above 28 years (0.63%). In general, the sample consisted of students from all three universities, from various disciplines, from both genders and from different age groups.

Table 2: *Demographic Profile of Respondents (N = 475)*

Characteristic	Category	Frequency (n)	Percentage (%)
University	IUB	236	49.68
	BZU	155	32.63
	KFUEIT	84	17.68
	Total	475	100.00
Academic discipline	Business and Management Sciences	226	47.58
	Computer Science and IT	209	44.00
	Engineering	40	8.42
	Total	475	100.00
Gender	Male	259	54.53
	Female	216	45.47
	Total	475	100.00
Age	Below 20 years	29	6.11
	20–22 years	318	66.95
	23–25 years	118	24.84
	26–28 years	7	1.47
	Above 28 years	3	0.63
	Total	475	100.00

4.2. Measurement Model

4.2.1. Internal Consistency Reliability and Convergent Validity

Internal consistency reliability and convergent validity were evaluated by Cronbach's alpha, rho_A, composite reliability (rho_C) and AVE. As shown in Table 3, Cronbach's alpha values ranged from 0.894 to 0.931, rho_A values from 0.895 to 0.935, and rho_C values from 0.920 to 0.946. The internal consistency of the five constructs (AICS, AIT, ORC, PEOU, and PU) was satisfactory, with all coefficients being higher

than 0.70, which is the minimum recommended value.

AVE values ranged from 0.622 to 0.744, exceeding the recommended threshold of 0.50 (AICS = 0.703, AIT = 0.622, ORC = 0.715, PEOU = 0.713, and PU = 0.744). This means that the average of the variance in the indicators explained by each construct is more than 50%. Overall, these findings indicate that the constructs are reliable internally and have convergent validity. Discriminant validity is assessed in the next subsection.

Table 3: Reliability and Convergent Validity

Items	Cronbach's alpha	Composite reliability (rho_A)	Composite reliability (rho_C)	AVE
AICS	0.894	0.895	0.922	0.703
AIT	0.899	0.911	0.920	0.622
ORC	0.901	0.908	0.926	0.715
PEOU	0.919	0.923	0.937	0.713
PU	0.931	0.935	0.946	0.744

Note. AICS = AI creativity support; AIT = AI trust; ORC = opportunity recognition capability; PEOU = perceived ease of use; PU = perceived usefulness; AVE = average variance extracted.

4.2.2. Discriminant Validity

Discriminant validity was assessed using HTMT, together with the 95% bootstrap confidence intervals. As shown in Table 4, the HTMT estimates for the ten pairs among the five main constructs ranged from 0.282 to 0.806, all below the conservative threshold of 0.85.

The bootstrap confidence intervals further

supported discriminant validity. The lower bounds ranged from 0.178 to 0.732, and the upper bounds ranged from 0.379 to 0.868. None of the intervals included 1.00; for example, the interval for AICS and ORC was 0.610–0.759, and the interval for PEOU and PU was 0.732–0.868 (the only upper bound above 0.85, but still well below 1.00). These results provide evidence that the five main constructs are empirically distinct under the HTMT inference criterion.

Table 4: HTMT Ratios and 95% Bootstrap Confidence Intervals

Construct pair	Original sample (O)	Sample mean (M)	2.5%	97.5%
AIT ↔ AICS	0.324	0.324	0.229	0.414
ORC ↔ AICS	0.688	0.688	0.610	0.759
ORC ↔ AIT	0.282	0.283	0.178	0.379
PEOU ↔ AICS	0.769	0.769	0.687	0.839
PEOU ↔ AIT	0.405	0.405	0.314	0.490
PEOU ↔ ORC	0.609	0.609	0.511	0.697
PU ↔ AICS	0.745	0.744	0.659	0.821
PU ↔ AIT	0.419	0.419	0.330	0.503
PU ↔ ORC	0.498	0.496	0.393	0.595
PU ↔ PEOU	0.806	0.806	0.732	0.868

Note. HTMT = heterotrait–monotrait ratio of correlations.

4.3. Structural Model

4.3.1. Assessment of Collinearity

Collinearity was assessed before interpreting the

structural relationships, to determine whether strong associations among the predictors could distort the estimation of the path coefficients. Inner VIF values were examined for all predictors

of ORC, including the three interaction terms, using a VIF value below 3.3 as a conservative guideline. As per Table 5, VIF values ranged from 1.204 (AIT → ORC) to 2.831 (PEOU → ORC). The VIF values for the interaction terms were also below 3.3: AIT × AICS = 1.661, AIT × PEOU =

2.739, and AIT × PU = 2.689. None of the seven VIF values exceeded the threshold and there was no problematic collinearity, and the model was deemed to be suitable to evaluate the explanatory power and the hypothesized relationships.

Table 5: Inner VIF Values for the Structural Model

Predictor relationship	VIF
AICS → ORC	2.332
AIT → ORC	1.204
AIT × AICS → ORC	1.661
AIT × PEOU → ORC	2.739
AIT × PU → ORC	2.689
PEOU → ORC	2.831
PU → ORC	2.665

Note. VIF = variance inflation factor. AICS = AI creativity support; AIT = AI trust; PEOU = perceived ease of use; PU = perceived usefulness; ORC = opportunity recognition capability.

4.3.2. Assessment of the Coefficient of Determination (R^2)

The coefficient of determination (R^2) is the percentage of variance in an endogenous construct accounted for by the predictors and the adjusted R^2 also takes into consideration the number of predictors. As shown in Table 6, ORC was able to achieve an R^2 of 0.455 and an adjusted R^2 of

0.447. The predictors thus account for 45.5% of the variance in ORC (44.7% after adjustment), with the difference between these two values (0.008) being relatively small, indicating that the ORC estimate is not very sensitive to the number of predictors. The model thus accounts for a meaningful proportion of the variance in ORC in this sample, although the strength of R^2 should be interpreted in light of the research context.

Table 6: Coefficient of Determination for Opportunity Recognition Capability

Endogenous construct	R^2	Adjusted R^2
Opportunity Recognition Capability (ORC)	0.455	0.447

Note. R^2 = coefficient of determination.

4.3.3. Assessment of Path Coefficients and Hypothesis Testing

The structural relationships were evaluated using path coefficients (β), t -statistics, and p -values from the bootstrapping procedure in SmartPLS 4. Significance was assessed at the 5% level using two-tailed tests, and a hypothesized positive relationship was considered supported when its path coefficient was positive and statistically significant. P -values displayed as 0.000 by SmartPLS are reported as $p < .001$.

As shown in Table 7, AICS had a positive and statistically significant relationship with ORC ($\beta = 0.494$, $t = 7.606$, $p < .001$), supporting H3. PU was also positively and significantly associated with ORC ($\beta = 0.371$, $t = 4.561$, $p < .001$), supporting H1, and PEOU was positively linked with ORC ($\beta = 0.291$, $t = 4.681$, $p < .001$), supporting H2. The direct effect of AIT was positive but not significant ($\beta = 0.056$, $t = 1.323$, $p = .186$), so H4 was not supported. The moderation hypotheses (H5–H7) are examined in Section

4.3.4. Overall, five of the seven hypotheses were supported and two were not statistically

supported.

Table 7: Path Coefficients and Hypothesis Testing Results

Hypothesis	Path	β	t	p	Decision
H1	PU $\rightarrow$ ORC	0.371	4.561	< .001	Supported
H2	PEOU $\rightarrow$ ORC	0.291	4.681	< .001	Supported
H3	AICS $\rightarrow$ ORC	0.494	7.606	< .001	Supported
H4	AIT $\rightarrow$ ORC	0.056	1.323	.186	Not supported
H5	AIT $\times$ PU $\rightarrow$ ORC	0.154	2.788	.005	Supported
H6	AIT $\times$ PEOU $\rightarrow$ ORC	0.275	3.681	< .001	Supported
H7	AIT $\times$ AICS $\rightarrow$ ORC	0.043	1.383	.167	Not supported

Note. β = standardized path coefficient. H1–H4 are direct effects; H5–H7 are moderating effects of AI trust.

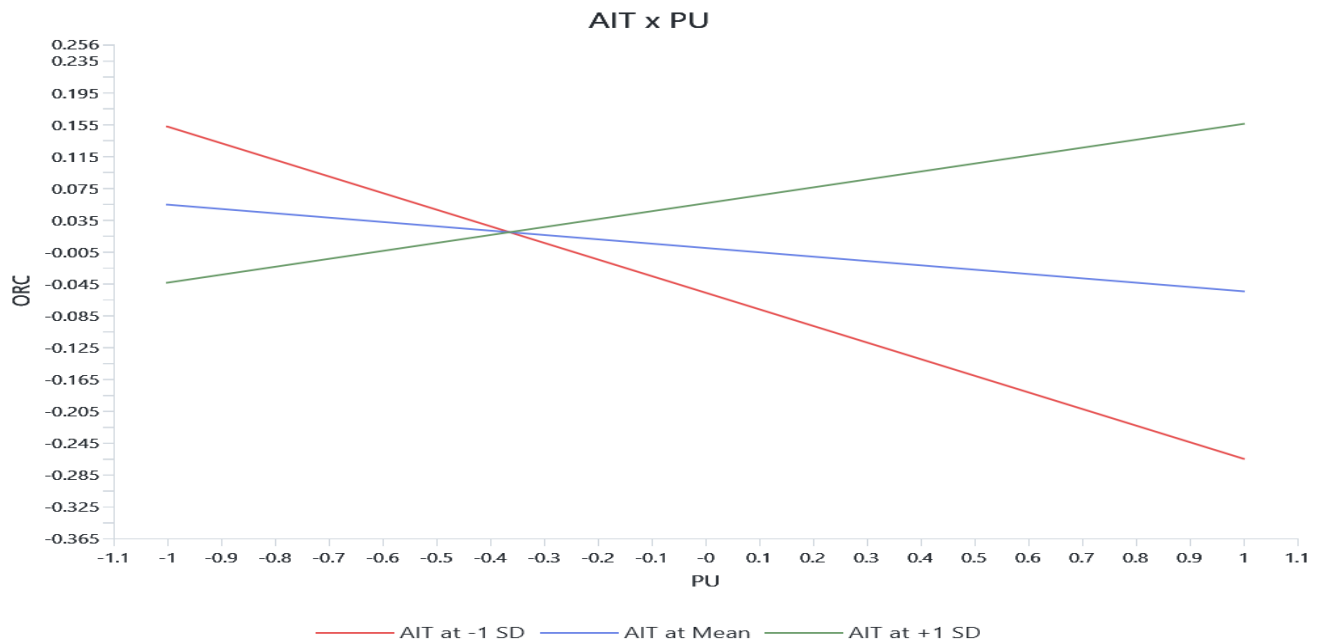
4.3.4. Moderation Analysis

The moderating role of AIT was examined to determine whether it changed the relationships of PU, PEOU, and AICS with ORC. Moderation was analyzed based on the estimated interaction terms and their bootstrapped significance, following the PLS-SEM guidelines (Hair et al., 2022). If there is a significant interaction, it means that the relationship between the predictor and the outcome is different at different levels of the moderator, so the interaction coefficient must be interpreted separately from the direct effect of the predictor on the outcome (Dawson, 2014).

H5 was supported by the positive and statistically significant AIT $\times$ PU interaction ($\beta = 0.154$, $t = 2.788$, $p = .005$), as reported in Table 7. This means that the PU–ORC relationship becomes more positive as AI trust increases. H6 was also supported: the AIT $\times$ PEOU interaction was positive and statistically significant ($\beta = 0.275$, $t = 3.681$, $p < .001$), indicating that the positive relationship between PEOU and ORC is stronger when AI trust is higher. Both significant

interactions occurred alongside significant direct effects of PU ($\beta = 0.371$) and PEOU ($\beta = 0.291$) on ORC, so AI trust strengthens these direct relationships rather than replacing them. The AIT $\times$ AICS interaction was positive but not statistically significant ($\beta = 0.043$, $t = 1.383$, $p = .167$), so H7 was not supported. This non-significant finding does not imply that moderation is absent in all situations, only that the hypothesized interaction was not supported by the present data.

The interaction plot for AIT $\times$ PU (Figure 2) is consistent with the significant positive interaction. The line for high AI trust (+1 SD) slopes upwards, the line for low AI trust (–1 SD) slopes downwards, and the line at the mean level of AI trust has a comparatively shallow negative slope. The plot is, however, descriptive, and separate simple-slope tests were not conducted, so it is not possible to conclude that any one of the three conditional slopes is individually significant. The moderation conclusion is based on the bootstrapped interaction term, not on the lines' appearance (Dawson, 2014).

Figure 2: Interaction Plot for AI Trust and Perceived Usefulness

Note. The lines represent AI trust at -1 standard deviation, the mean, and $+1$ standard deviation. The figure is interpreted descriptively; inferences about moderation are based on the bootstrapped interaction coefficient.

Overall, the moderation analysis supports H5 and H6 but not H7. Thus, the effect of AI trust on students' opportunity recognition may depend on the type of perceived benefit of generative AI: the evidence for moderation was specific to perceived usefulness and perceived ease of use, and was not found for AI creativity support.

5. Discussion of Findings

This study examined how PU, PEOU, and AICS relate to university students' ORC, and whether AIT influences these relationships. PU, PEOU, and AICS all had significant positive relationships with ORC, and AIT positively moderated both the PU–ORC and PEOU–ORC relationships. These results suggest that students' perceptions of generative AI as useful, easy to use, and supportive of creative exploration may all be relevant to recognizing entrepreneurial opportunities, and that trust conditions how PU and ease of use translate into opportunity recognition.

AICS had the strongest direct association with ORC ($\beta = 0.494$, $p < .001$), followed by PU ($\beta = 0.371$, $p < .001$) and PEOU ($\beta = 0.291$, $p < .001$). Students who perceive generative AI as supporting idea generation and alternative perspectives also tend to report stronger

opportunity recognition capability, and those who find AI useful and easy to use may explore questions, investigate customer needs, and compare possible solutions with less effort. These findings are compatible with the emphasis of TAM on perceived usefulness and perceived ease of use as key technology-related beliefs (Davis, 1989), while suggesting that perceived creative support is also relevant when students consider entrepreneurial opportunities. The results, however, are based on reported associations and do not imply that the use of AI leads to better opportunity recognition or commercially viable ideas.

The direct effect of AIT on ORC was not significant ($\beta = 0.056$, $p = .186$), so trust in AI alone was not an independent predictor of higher ORC in this model. This suggests that trust matters mainly through the way it conditions other perceptions rather than on its own, and that trust may not be sufficient if students are unable to analyze and assess the information generated by AI and relate it to real market needs; this explanation was not directly tested.

Importantly, AIT positively moderated the PU–ORC relationship ($\beta = 0.154$, $p = .005$), supporting H5, and the PEOU–ORC relationship ($\beta = 0.275$,

$p < .001$), supporting H6. This indicates that perceived usefulness and ease of use are more strongly related to opportunity recognition when trust in AI is high, in line with the view that trust governs reliance on technology (Lee & See, 2004; McKnight et al., 2002). Simple slopes were not tested separately, so the interaction patterns should be interpreted descriptively. The interaction of AIT with AICS ($\beta = 0.043$, $p = .167$) was not significant, so H7 was not supported, which suggests that creative support relates to ORC irrespective of the level of trust in this sample. Overall, five of the seven hypotheses were supported (PU $\rightarrow$ ORC, PEOU $\rightarrow$ ORC, AICS $\rightarrow$ ORC, AIT $\times$ PU $\rightarrow$ ORC, and AIT $\times$ PEOU $\rightarrow$ ORC), highlighting the importance of perceived usefulness, ease of AI interaction, and perceived creative support, and suggesting that the role of trust is specific to the functional perceptions (PU and PEOU) rather than universal across all AI benefits.

6. Theoretical and Practical Implications

6.1. Theoretical Implications

The positive effects of PU, PEOU, and AICS on ORC indicate that students might be better able to spot opportunities when AI tools are useful, easy to use, and help them create, revise, or rethink ideas. This broadens the application of TAM by demonstrating that perceived usefulness and ease of use are linked to a cognitive outcome related to entrepreneurship and not just to technology acceptance (Davis, 1989; Venkatesh & Davis, 2000). The result for AICS also aligns with the view that opportunity recognition involves developing and evaluating ideas through cognitive and information-processing activities (Ardichvili et al., 2003; Shane & Venkataraman, 2000).

The significant AIT $\times$ PU and AIT $\times$ PEOU interactions indicate that the relationships of PU and PEOU with opportunity recognition differ according to students' level of trust in AI. Because PU and PEOU also had significant direct effects, trust appears to amplify these relationships rather than replace them: students' confidence in AI can influence how they translate the perceived benefits into opportunity recognition activities. The non-significant AIT $\times$ AICS interaction shows that this boundary condition does not apply equally to all perceived benefits. This provides a context-based view of technology acceptance

research and supports examining trust as a boundary condition in students' interaction with AI-powered tools (Gefen et al., 2003; McKnight et al., 2002).

6.2. Practical Implications

Universities can support students in learning entrepreneurship with the help of generative AI as a structured support. In business and entrepreneurship courses, students might engage in tasks where they leverage AI to analyze customer issues, brainstorm solutions, research market options, and analyze and assess opportunities. Since PU and PEOU were found to have positive relationships with opportunity recognition, it is recommended that institutions demonstrate practical uses of AI in entrepreneurial tasks, give introductory guidance, provide hands-on practice, and give clear examples of effective prompting. AI creativity support was also positively correlated with opportunity recognition, so students should be encouraged to explore ideas using AI but should also be expected to check the facts, evaluate feasibility, and provide their own opinion.

The moderation result also highlights the importance of responsible and transparent AI use. Universities should inform students about the strengths and weaknesses of AI systems, discuss privacy concerns and potential inaccuracies, and remind them to validate the information provided by AI before incorporating it into business decisions. These practices can be used to help students build a trust that is appropriate, instead of blindly trusting AI (Lee & See, 2004). The recommendations should be taken in the context of the study as the results are specific to the final semester students of public universities of South Punjab, Pakistan, and cannot be generalized to all students and entrepreneurs.

7. Limitations and Future Research

Firstly, the data was collected from final-semester students from public universities of South Punjab, Pakistan, through non-probability sampling, thus limiting the generalizability to other regions, private universities and other educational and cultural contexts. Second, the cross-sectional design only provides insights at one point in time, and thus does not allow for causal relationships to be established. Third, the study is self-reported,

which could be influenced by individual perceptions or response biases (Podsakoff et al., 2003). Fourth, simple slopes for the significant interactions were not tested separately, and an interaction plot is presented only for AIT $\times$ PU. These limitations could be addressed in future studies by obtaining data from a variety of geographical and institutional contexts, longitudinal designs, and other data sources, if possible.

Other factors that could affect the relationship between generative AI and entrepreneurial opportunity recognition could be explored in future studies, including AI literacy, prior entrepreneurial experience, and the quality of the AI-generated information, as well as the potential differences between academic disciplines and the level of AI experience. In particular, the significant moderating role of AI trust in the relationships of PU and PEOU with opportunity recognition warrants further investigation in other student populations and entrepreneurial settings.

Conflict of Interest

The authors showed no conflict of interest.

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8. Conclusion

This study inspected the relationships between the perceived benefits of generative AI and opportunity recognition capability among university students, considering the moderating role of AI trust. PU, PEOU, and AI creativity support were positively related to opportunity recognition capability, and AI trust significantly moderated the relationships of PU and PEOU with opportunity recognition capability. The results provided the importance of trust in understanding how students translate the perceived benefits of AI into entrepreneurial opportunity recognition.

Overall, the study contributes to understanding the role of generative AI in entrepreneurship education and suggests that universities can support students' opportunity recognition by promoting accessible AI tools, encouraging AI-assisted creativity, and fostering informed and responsible trust in AI. These findings provide a basis for future research across broader educational and entrepreneurial contexts.

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