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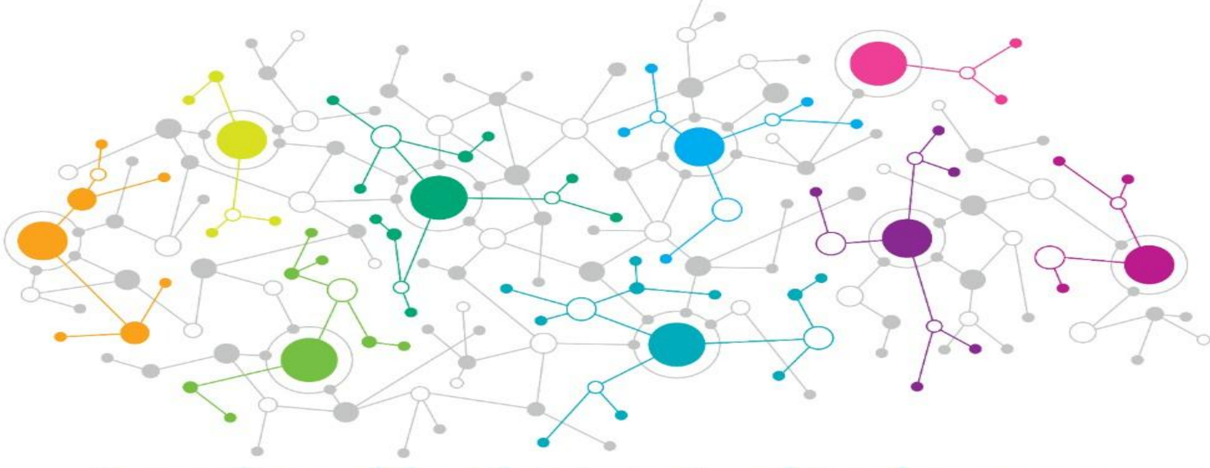

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Moroccan Doctoral Students and Artificial Intelligence:

The Correlation between Literacy and Trust

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Abstract

Nowadays, doctoral students and researchers rely on Artificial Intelligence (AI) technology to assist them with their studies, as the perceived helpfulness of those AI-powered tools cannot be denied. While many consider AI of great importance when reviewing the literature, others believe that analyzing data is the strongest suit of AI. This study investigates the relationship between AI literacy and AI trust among Moroccan doctoral students. It adopts a descriptive-correlational design and aims to assess the strength of the relationship between AI literacy and AI trust. Data was collected from doctoral students, using two scales: the Artificial Intelligence Literacy Scale (Ma & Chen, 2024) and the Human-Computer Trust Scale (Gulati et al., 2019). Pearson's correlation analysis, conducted using SPSS 25, revealed a weak positive correlation between AI literacy and AI trust. AI use was the most correlated with AI trust, while AI competence trust was the most correlated with AI literacy. These findings stress the role of AI literacy in influencing the trust doctoral students put in AI for research purposes.

Keywords: artificial intelligence, AI literacy, AI trust, doctoral students.

1. Introduction

Statistics have shown that 77% of devices that are in current use have Artificial Intelligence (AI) in some form (Webster, 2024). Thus, with the fast spread of AI technologies across numerous disciplines, it becomes difficult to overlook its different dimensions. In education, particularly, research has shown that 53% of doctoral students with postgraduate qualifications are in continuous engagement with AI tools (Kennedy et al., 2023). This number is certainly higher today, as the proliferation of AI in the past couple of years has been unprecedented. To this end, it is necessary to investigate the various aspects of AI use for a wider understanding of this issue. In this sense, two notable variables emerge: AI literacy and AI trust.

AI literacy is the ability to appropriately identify and use AI-powered technology while maintaining ethical standards (Wang et al., 2022). This feature is important for AI users as it represents the first step toward a better use of AI. Understanding and engaging with these technologies is the basis of the discussion on AI in the first place. AI trust (or distrust) is a later dimension associated with the degree of confidence users have toward AI-powered technologies. For instance, only 39% of users think that AI is safe and secure (Prestianni, 2025). Since AI is now integrated into many aspects, including academic research, it is crucial to investigate the relationship between literacy and trust.

In Morocco, a noticeable challenge for doctoral students is the fact that AI use in academia is a gray area. There are no specific guidelines on how to effectively implement these technologies in research. To this end, this issue needs a deeper understanding through investigating variables that may alter doctoral students' perception and engagement with AI. I believe that one way to do that is by researching AI literacy and AI trust. Insights from this study can guide doctoral students toward a self-reflection process on the way they associate AI understanding and trust. Consequently, this study aims to investigate the relationship between AI literacy and AI trust for doctoral students in a Moroccan context, where research in this area remains limited.

2. Literature Review and Theoretical Framework

2.1. AI and Academic Research

One of the consistent definitions of AI is the use of computer algorithms and statistical models to process, analyze, or interpret data in any field, including academia and research (Wilson, 2022). In academic writing, for instance, researchers face several difficulties with grammar, structure, citations, and other standards. Thus, the influence of AI on writing, methodology, and data analysis has become inevitable. The cutting-edge learning algorithms and Natural Language Processing Technologies (NLPT) are used by academics in all areas of research, from reviewing the literature to data interpretation. In the era in which we are living, AI tools can help improve the quality of research, which enables researchers to focus on more creative aspects (Golan et al., 2023).

The systematic review of Khalifa and Albadawy (2024) identified six domains in which AI can enhance and assist with research. The first domain is idea development and research design. Here, AI tools function as thought generators through brainstorming, identifying gaps in the literature, and generating questions and hypotheses. Also, they can plan the research and act as designing assistants. Nevertheless, the two scholars have found this domain to be the least AI-assisted by researchers. The next domain is developing and structuring content. Writing tools, such as text prediction and autocompletion, help refine texts. In addition, they help with the structure of the content and can further generate and integrate visual aids and multimedia such as images or graphs. The third domain, which has to do with the theoretical foundation, is reviewing and synthesizing elements from the literature. This includes the extraction and organization of information based on reviewed materials such as articles and book chapters.

Another salient domain, the fourth, is managing and analyzing data. In this domain, AI both describes and interprets data for the researcher. This is done through the AI capability to transform complex data into insights and themes. The fifth domain, supporting edition and reviewing, is when AI tools are used to refine writing and peer review the work as a whole (Tang et al., 2023). It is the second most common domain with AI assistance. The sixth, and final, domain is labeled communication, outreach, and ethical compliance. It is the domain in which AI is used by researchers the most. It highlights the role of AI in disseminating and presenting research conclusions according to ethical considerations.

In two studies (Khalifa & Albadawy, 2024; Wang & Wang, 2024), several AI tools that can assist research were identified. Platforms such as Elicit and Jenni employ NLPT to transform articles into summaries. Powerdrill and Litmaps are specifically designed to identify gaps. Other smart technologies currently used in managing the literature and organizing citations include Zotero, Mendeley, and EndNote. For writing assistance and text generation, the most renowned tools are Grammarly and ChatGPT. Similarly, Turnitin and Copyscape are the most used to detect plagiarism and ensure the originality of the work. Furthermore, in the area of data analysis, Tableau and Julius stand as pivotal tools for researchers, as they are used to transform data into visual formats. For those who seek to apply qualitative methods, NVivo and MAXQDA are prominent. They offer data coding and pattern identification services. Table 1 summarizes the main domains of research as well as some AI tools that can assist them.

Table 1

Research Domains and the Employed AI Tools

Research Domain	**Employed AI Tools**
Theoretical Background	Elicit, Jenni, Powerdrill, Litmaps
Writing and Structuring	Zotero, Mendeley, EndNote, Grammarly, ChatGPT
Data Analysis	Tableau, Julius, NVivo, MAXQDA
Editing and Reviewing	Turnitin, Copyscape

Although a plethora of AI tools are beneficial to research, researchers are still expected to bring originality and innovation to their work. One major concern in the area of AI and academic research, as identified by Wang and Wang (2024), is hallucination. The latter is when AI systems produce inconsistent or inaccurate information that may appear plausible but is, in fact, fabricated or unsupported by reliable sources. This phenomenon can lead to the unintentional inclusion of false data, erroneous citations, or misleading interpretations in academic work. Hallucination typically arises when the AI model attempts to fill in gaps in knowledge or generate responses beyond its training data, prioritizing fluency over factual accuracy. In addition, AI tools can be biased, as they remain human-trained on datasets that may be incomplete or flawed. If researchers do not evaluate and edit content, AI may be a burden to research by providing misguidance and false conclusions. On the ethical side, researchers must keep their work authentic and reliable, as Wang and Wang explicitly expressed: "[…] when AI tools are used to generate or process data, researchers must explicitly disclose this and explain the methodology and involvement of the tools in the research process" (para. 31). Hence, reliance on AI must go hand in hand with critical evaluation of the data provided. Researchers require competence to properly use AI applications and platforms. In the literature, this competence is referred to as AI literacy.

2.2. AI Literacy

AI is being increasingly incorporated within technology. Nevertheless, many people have limitations when it comes to understanding these technologies (Long & Magerko, 2020). As a result, AI has emerged as a sub-field different from Digital Literacy (DL). It includes aspects from different fields, such as computer science, psychology, and sociology. The concept of literacy itself has changed over time. Years ago, literacy referred to basic reading and writing skills. But now, it includes television literacy, information literacy, and DL, among others. Because of this shift and the fast spread of AI, the world needs AI literacy not only to use AI technologies, but also to critically evaluate their abilities and ethical implications (Ma & Chen, 2024).

To this moment, there is no universal agreement on one exact definition of AI literacy. Some scholars define it as a set of competencies that make people able to critically evaluate and use AI technologies and communicate with them (Long & Magerko, 2020). Others have considered AI literacy a dimension of DL, which is about AI-related skills (Carolus et al., 2023). This study adopts AI literacy as the ability to appropriately identify and use AI-powered technology while maintaining ethical standards (Wang et al., 2022).

A scale that is widely used (Artificial Intelligence Literacy Scale; AILS) divides AI literacy into four dimensions: awareness, usage, evaluation, and ethics (Wang et al, 2022). Awareness refers to the mere understanding of AI concepts and principles. Then, usage involves applying the knowledge about AI tools in daily life. Next, evaluation means the critical assessment of AI-generated content. Finally, ethics emphasizes the ethical and responsible use of AI technologies (Ma & Chen, 2024). In a similar way, Ng et al. (2021) proposed an almost identical framework that categorizes AI literacy into four key competencies: knowing and understanding AI, using and applying AI, evaluating and creating AI, and considering AI ethics. These competencies mirror Bloom's taxonomy of educational objectives, which structures learning skills from basic knowledge recall to higher-order skills such as evaluation and creation.

In conclusion, as AI literacy frameworks keep evolving to include new aspects, they must consider the dynamic nature of AI technologies. Unlike traditional DL, which primarily focuses on static skills, AI literacy demands continuous learning and adaptation to keep up with the evolutionary nature of AI (Carolus et al., 2023). For researchers and students to stay AI-literate, they must possess the ability to stay updated with AI advancements. Also, they need to understand the ethical dilemmas of using AI in research. Lastly, they must critically evaluate the content and services provided by AI-generated tools and applications (Long & Magerko, 2020). Having gone through these steps, it is only then that researchers can decide on whether to trust AI or not.

2. 3. AI Trust

Whether researchers trust AI or not makes an impact on the way they interact with it. Lee and See (2004) suggest a definition of trust as "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (p. 6). This definition matches the idea that AI trust is influenced by our perceptions of AI's abilities to function under conditions of uncertainty (Vereschak et al., 2021).

Within the AI literature, numerous frameworks have been proposed to measure trust in AI. Many of these are based on the original scales designed to measure traditional interpersonal trust (Hoffman et al., 2022). The founding trust frameworks and models typically try to answer two questions: Do you trust the machine's outputs? And would you follow the machine's advice? These questions stress both trust and reliance on AI-generated recommendations.

The human-computer trust models stress the key influences that impact trust. One consistent factor across numerous models is the perceived risk. This refers to users' subjective assessment of the likelihood of negative outputs of computer systems (McKnight et al., 2011). This aspect of perceived risk is particularly important in AI trust research because AI systems function as black boxes; it is difficult to interpret how their decisions are made (Gulati et al., 2018). Another factor of AI trust is benevolence: automation's abilities to provide assistance and help users achieve their goals (Mayer et al., 1995). An additional factor of the human-computer trust model is competence. It is defined as the system's capability to perform its intended tasks effectively (McKnight et al., 2011). Reciprocity is another factor, defined as the tendency of users to apply social norms to AI interactions; in other words, AI is to be perceived as a social entity (Gulati et al., 2019).

Research has shown that trust is a key determinant of AI adoption, especially in educational settings (Wang et al., 2023). Doctoral students, as early adopters of AI-powered systems, play a major role in shaping the future integration of AI at the level of universities. This works as a process: AI trust impacts attitudes toward adoption, which shapes the willingness to integrate AI for research purposes, which shapes trust, and so forth. In sum, AI trust is a multifaceted concept with many different elements. I believe understanding those dimensions is necessary to create AI user confidence and successful AI integration in academic settings.

Despite a big reliance on AI in education and research, and the richness of the literature, one research gap must be addressed for a better understanding: the correlation between AI literacy and AI trust among doctoral students, particularly in the Moroccan context. Current literature indeed stresses the significance of AI literacy for research practices, but studies have not investigated the influence of AI literacy on trust in these systems for doctoral students. While several factors have been linked to trust (such as perceived usefulness, competence, transparency, etc.), AI literacy is not among them. Given that doctoral students represent a population that shapes AI use, investigating the suggested relationship for them is important.

3. Method

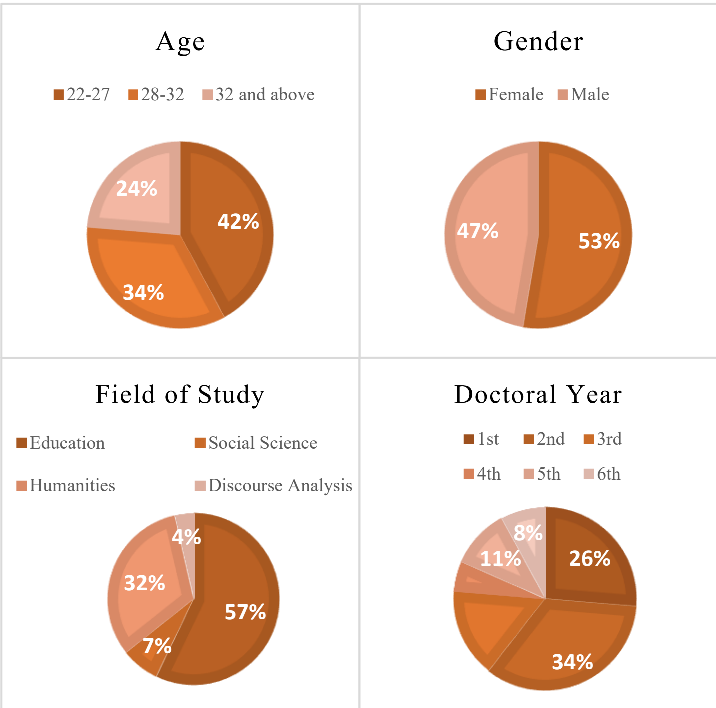
3.1. Sample & Participants

This study employed a convenience sampling method to gather data from participants. A questionnaire was created using Google Forms and shared with doctoral students. This sample was chosen due to its accessibility and relevance to the study's focus on AI literacy and AI trust for doctoral students. The questionnaire was distributed via WhatsApp to ensure quick access. A total of 38 responses were collected (N = 38), forming the basis of the sample.

The demographic section of the survey gave insights into the diversity of participants (see Figure 1). Concerning age, there was a close even distribution in the three age groups: 22-27 (42.1%), 28-32 (34.2%), and 32 and above (23.7%). As for gender, female doctoral students constituted 52.6% of the sample, while 47.4% were males. 1st and 2nd year doctoral students were the majority (60.5%), while the rest (39.5%) were in more advanced years. All participants specialized in non-STEM fields, including education, social sciences, humanities, and discourse analysis. Finally, it should be noted that no participant reported 'never' to the question: How often do you interact with AI technologies in your academic work? This means that all participants engaged, to different degrees, with AI in their studies.

Figure 1

Participants' Demographics



3.2. Instruments

The Artificial Intelligence Literacy Scale for Chinese College Students (AILS-CCS) was developed by Ma and Chen in 2024 to address the issue of the lack of scales to measure AI literacy in educational settings in developing countries, specifically for Chinese college students. The study by which the scale was validated distinguishes AI literacy from DL and identifies its four elements discussed in the previous chapter: awareness, usage, evaluation, and ethics (Ma & Chen, 2024). The two researchers recruited 546 Chinese students in a survey and later ran a confirmatory factor analysis, which resulted in a validated and reliable tool of 15 items using a 5-point Likert style (1 = strongly disagree; 5 = strongly agree).

In the present study, AILS-CCS was used to collect data concerning AI literacy. This is justified by the scale's four dimensions, which comprehensively capture the multifaceted nature of AI literacy. Given its detailed validation process, the scale demonstrates strong reliability and construct validity, which enhances the credibility of findings upon its application. Moreover, its focus on college students makes it particularly relevant for this study, which examines AI literacy in the context of Moroccan doctoral students. While originally designed for Chinese students, the scale's universal structure and theoretical grounding make it adaptable to different educational settings, including Morocco. Nevertheless, being relatively lengthy, the scale was reduced to eight items (each two targeting a construct).

As for the second variable, the Human-Computer Trust Scale (HCTS) was developed by Gulati and colleagues in 2019. They recognized that previous trust scales lacked foundation and then built on existing models and validated a multi-dimensional trust scale through two independent studies (N = 118; N = 183). The research used future scenarios and design fiction as innovative methods to assess trust in AI systems. The authors identified the four key factors influencing trust, which were discussed in the previous chapter: perceived risk, benevolence, competence, and reciprocity. Through Partial Least Squares Structural Equation Modeling (PLS-SEM), the scale demonstrated strong reliability and was validated.

The HCTS is an instrument that aligns with the objectives of the present study. The scale's four key dimensions capture the multifaceted nature of trust in AI systems, which ensures a comprehensive assessment. Furthermore, its adaptability to different contexts makes it suitable for this study, as it allows for meaningful insights into AI trust dynamics for Moroccan doctorate students. Being relatively lengthy, the scale was also reduced to eight items (each two measuring a construct).

3.3. Data collection procedures

This study used a survey-based approach with a descriptive-correlational design to explore the relationship between AI literacy and AI trust for Moroccan doctoral students. Data was collected using an online questionnaire created with Google Forms, which comprised three sections: demographic information, the AILS-CCS, and the HCTS.

The Google Forms questionnaire was shared in several WhatsApp groups comprising Moroccan doctoral students who belong to different universities across the country. Participants were informed about the purpose of the study and instructed to respond honestly. Participation was voluntary, and confidentiality was assured. The data collection period lasted for 3 weeks.

Daily reminders were sent via the WhatsApp groups to encourage participation. By the end of the data collection period, 38 responses were received. Convenience sampling was used to ease access to the participants through the selected WhatsApp groups.

3.4. Data analysis

The data collected from 38 participants was analyzed using SPSS 25 to examine the relationships between the two variables. Before the analysis, the normality of the data was assessed using the Shapiro-Wilk test. This test ensured that the normality of the data was met before proceeding with correlation tests. To assess the internal consistency of the two scales used in this study, Cronbach's alpha was calculated for each scale. A threshold of .70 was set as the acceptable level of reliability for each one. Descriptive statistics were calculated for each item. Subsequently, Pearson's correlation was used to explore the relationships between AI literacy and AI trust, as well as the correlations between the specific constructs within the two variables. This analysis aimed to identify the strength and direction of the relationships. Correlation coefficients were interpreted with values ranging from .10 to .29 considered small, .30 to .49 medium, and .50 or above large. Finally, the significance of all correlation coefficients was tested using a p-value < .05.

4. Results

Ahead of correlation tests between the two variables and their respective sub-constructs, there was a need to test their reliability. Therefore, the reliability of the AILS-CCS and the HTCS was measured through SPSS 25. Results (see Table 2) indicate Cronbach's alpha of .889 for the AILS-CCS and .737 for the HCTS. This indicates strong internal consistency of the items.

Following the reliability test, the Shapiro-Wilk test was conducted prior to the correlation tests of the main study. This test aims to assess the normality of the data obtained to see if it is worthy of Pearson's correlation. For the AILS-CCS, the significance was p = .356 > .05, which indicates the rejection of the null hypothesis and assumes that the data follows a normal distribution. Similarly, for the HTCS, p = .253 > .05, also indicating a normal data distribution.

Table 2

Reliability and Normality Results of the AILS-CCS and the HCTS

	Cronbach's Alpha	p-value
AILS-CCS	.889	.356
HCTS	.737	.253

Afterward, the descriptive statistics for the two scales were computed through SPSS 25. For the AILS-CCS (8 items), the sample size was 38 participants. The mean score was 29.36, meaning that participants leaned toward agreement with the AI literacy scale. In addition, the standard error of .949 indicates that the mean estimate is fairly stable. The standard deviation was 5.851; this moderate value means that responses are spread out but not totally scattered. Lastly, the variance was calculated to be 34.239. This suggests a reasonable spread of responses.

For the HTCS (8 items), a total of 38 participants were included in the analysis. The mean score was 27.52, which is relatively high given the total possible score of 40. This indicates that participants generally have a moderate to high level of AI trust. The standard error of .620 is low, which means that the sample mean is a precise estimation of the population mean. The standard deviation for this scale was 3.825, which suggests less spread out and more consistency across participants. The variance was found to be 14.63, which confirms that participants had less variability. These descriptive results of the 38 participants are summarized in Table 3.

Table 3

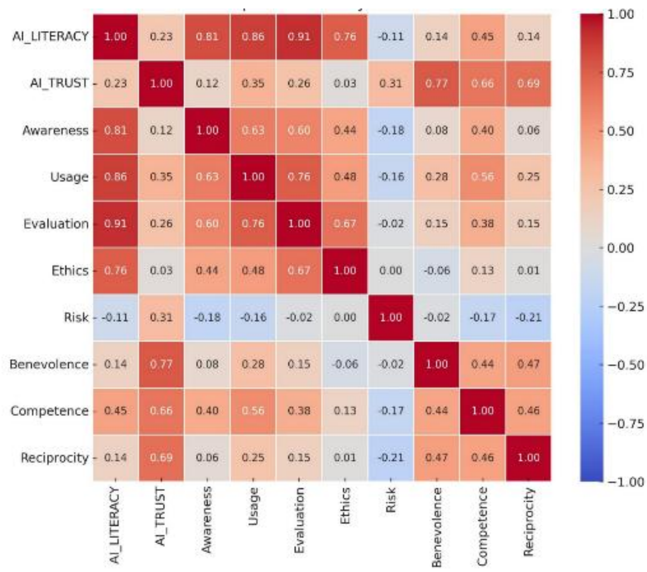
Descriptive Statistics of the data collected

	N	Mean	Std. Error	Std. Dev.	Variance
AILS-CCS	38	29.36	.949	5.851	34.239
HTCS	38	27.52	.620	3.825	14.634

Again, a Pearson's correlation analysis was conducted to examine the relationships between AI literacy and AI trust, as well as between their respective sub-constructs (see Figure 2). The analysis revealed a weak positive correlation between the total AI literacy score and the AI trust score ($r = .230$), which indicates some association between the two constructs. For AI trust constructs, the dimension of competence showed the strongest correlation with AI literacy ($r = .450$), while the perceived risk had a weak negative correlation ($r = -.110$). As for AI literacy, the dimension of usage was the most correlated with trust ($r = .350$). Yet, ethics was almost not correlated with trust ($r = .030$). Concerning correlations among constructs, awareness was most correlated with competence ($r = .400$) and least with reciprocity ($r = .06$). As for usage, the most correlation is also with competence ($r = .560$), and the least with the perceived risk ($r = -.160$). For evaluation, it was most correlated, similar to the other constructs, with competence ($r = .380$), and least correlated with the perceived risk ($r = -.02$). Ethics, conversely, showed very weak correlation with all other constructs of AI literacy ($-.06 \leqslant r \leqslant .130$). for the constructs of AI trust, trust in competence was positively and moderately correlated with all aspects of AI literacy ($-.13 \leqslant r \leqslant .560$). Nevertheless, the other constructs (perceived risk, benevolence, and reciprocity) showed minimum correlations with AI literacy ($-.18 \leqslant r \leqslant .250$).

Figure 2

Correlation Results



5. Discussion

A weak, but positive, correlation was found between AI literacy and AI trust (r = .230). This suggests that there is some sort of association between the two variables, but not a very strong one. This evidence matches the discussed literature that proposes connections between literacy and trust despite variances in their strength according to different contexts (Gulati et al., 2019). This weak correlation may indicate that there are impacts of AI literacy on AI trust, but other external factors and personal experiences influence the degree of AI trust.

Unique patterns have emerged during the examination of correlations among the constructs of AI literacy. Usage, particularly, was the most correlated with AI trust (r = .350). This suggests that as students engage more with AI-powered systems, their trust increases. This conclusion aligns with previous research, which found that hands-on usage can increase trust levels (Lee, 2004). One justification may be that using AI makes doctoral students more understanding of its potential; they consequently trust it more.

On another note, the correlation between ethics and the overall AI trust was nearly non-existent (r = .03). This means that ethical considerations of AI usage may not be a major factor that influences participants' trust in AI. This finding contradicts the literature that highlighted the importance of ethics in shaping AI trust (Afroogh et al., 2024). This may be explained by the fact that ethical concerns surrounding AI have not yet reached an influential level in participants' academic environments, or it might reflect a gap in the perceptions of AI ethics among participants.

In addition, while awareness did not strongly correlate with AI trust (r = .120), it was moderately associated with the construct of competence (r =.400). This suggests that knowledge about AI functioning systems leads to trust in those systems' competencies. On the contrary, the weak correlation between awareness and reciprocity indicates that knowing AI does not necessarily translate into relational trust.

Another AI literacy construct that showed a strong correlation with competence was usage (r = .560). This supports the idea that engaging with AI tools leads to more trust in the power of those tools. This also aligns with the view that practical usage usually leads to a deeper understanding of what AI tools can do, and thus leads users to trust AI capabilities (Glikson & Woolley, 2020). To continue the discussion on usage, its correlation with perceived risk was negative and minimal (r = -.160). This surprisingly indicates that students who engage more with AI tend to perceive less AI risk. One reason may be that the more familiar students become with AI, the less they think it can cause threats. In other words, the increasing usage of AI can mitigate concerns about its risks.

As for the construct of evaluation, correlation results were also significant. Evaluation was moderately correlated with competence (r = .380). This reinforces the idea that doctoral students with a critical assessment of AI tend to understand its capabilities better. Similar to the other constructs, evaluation showed almost no correlation with perceived risk (r = -.02), which means evaluating AI-generated content is not associated with the awareness of its potential risks. This can be due to the absence of assessment and risk calculation of AI (hallucinations and biases).

In sum, using AI constantly, and critically evaluating the generated content may lead to higher degrees of trust doctoral students have concerning AI. On the contrary, being AI-literate does not necessarily lead to higher degrees of trust concerning the perceived risk and reciprocity.

Concerning AI trust constructs, the strongest correlations were the ones observed between competence and the overall AI literacy (r = .450), awareness (r = .400), usage (r = .560), and evaluation (r = .380). Participants who use AI on a frequent basis, who have higher literacy, and who critically evaluate AI-generated content lean toward trusting AI in general. The strongest predictor is usage, which again reinforces the idea that hands-on experiences foster trust between doctoral students and AI. This is consistent with previous studies that suggest that competence-based trust in AI is rooted in people's technical understanding (awareness) and usage of the AI-powered system, often available in the web (Gulati et al., 2018).

6. Implications, Recommendations and Conclusions

The analysis revealed a weak positive correlation between AI literacy and AI trust. This indicates that whereas literacy may influence trust, more external factors mediate this relationship. Within the AI literacy construct, *usage* was the most correlated with AI trust. This suggests that hands-on applications of AI tools are a major predictor of trust that doctoral students put in AI. Alternatively, the dimension of *competence* was the most correlated with AI literacy. This means that doctoral students with high AI literacy tend to trust the capabilities of AI-powered technologies.

The findings suggest that hands-on engagement with AI tools reinforces their trust in AI. If universities want to build AI trust, there should be an integration of practical AI into the curricula. This may ensure that students gain immediate experience with AI usage. Some effective strategies for such integration may be workshops and/or interactive training sessions conducted by experts in the field of AI. Furthermore, because of the weak correlation between AI ethics and trust, universities should raise awareness about the ethical considerations in AI. This is more susceptible to lead to a higher critical engagement and ethical reflections on AI for doctoral students.

7. Limitations & Directions for Future Research

One of the limitations of the current study is the dependence on self-reported scales, leading to response bias, which may affect the results. In addition, the employed correlational analysis does not, in any way, establish causality. This leaves room for external factors that were not taken into consideration in the present study.

Future research may explore the causal relationship between AI literacy and AI trust using longitudinal studies or experimental designs with regression analysis. Additionally, qualitative studies should be considered to provide more insights into educational personal experiences that shape the relationship between the variables. Most importantly, studies need to widen the sample size for more generalizing results. Lastly, there should be an investigation of other impacts (such as media, policies, attitudes, etc.) that influence the strength of the relationship between literacy and trust in the field of AI.

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