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ORIGINAL

Influence of Self-Efficacy in the Use of Artificial Intelligence (AI) and Anxiety Toward AI Use on AI Dependence Among Peruvian University Students

Influencia de la autoeficacia en el uso de la inteligencia artificial (IA) y la ansiedad hacia el uso de la IA en la dependencia de la IA entre estudiantes universitarios peruanos

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ABSTRACT

Introduction: the advancement of artificial intelligence (AI) in education has transformed the way students interact with technological tools, creating new challenges related to self-efficacy, anxiety, and AI dependence. Self-efficacy refers to one's confidence in their ability to use AI, while AI-related anxiety pertains to the fear or concern when interacting with these systems. These variables can influence technological dependence, affecting academic performance and emotional well-being.
Objective: this study aims to examine the influence of self-efficacy in AI use and anxiety toward AI on AI dependence among Peruvian university students.
Method: a descriptive cross-sectional study was conducted with 528 Peruvian university students aged 18 to 37 years (M = 19,00, SD = 3,84). Scales were used to measure AI self-efficacy, anxiety toward AI, and AI dependence. Correlation and multiple regression analyses were applied to identify predictors of technological dependence.
Results: the results showed that AI self-efficacy was positively correlated with AI anxiety (r = 0,43, p < ,01) and AI dependence (r = 0,61, p < ,01). Anxiety also significantly correlated with AI dependence (r = 0,71, p < ,01). Multiple regression analysis revealed that both AI anxiety (β = 1,131, p < ,001) and AI self-efficacy (β = 0,610, p < ,001) predicted AI dependence. Additionally, business administration students exhibited greater dependence compared to students from other fields (β = 1,025, p < ,05).
Conclusions: students with higher self-efficacy in AI use tend to utilize AI more frequently but also experience greater anxiety and dependence on AI. Educational interventions should focus on reducing AI-related anxiety to prevent excessive dependence, especially among students.

Keywords: Self-Efficacy; Technological Anxiety; Artificial Intelligence; Dependence; Higher Education.

RESUMEN

Introducción: el avance de la inteligencia artificial (IA) en la educación ha transformado la forma en que los estudiantes interactúan con las herramientas tecnológicas, creando nuevos desafíos relacionados con la autoeficacia, la ansiedad y la dependencia de la IA. La autoeficacia se refiere a la confianza en la propia capacidad para utilizar la IA, mientras que la ansiedad relacionada con la IA se refiere al miedo o la

preocupación al interactuar con estos sistemas. Estas variables pueden influir en la dependencia tecnológica, afectando el rendimiento académico y el bienestar emocional.
Objetivo: este estudio tiene como objetivo examinar la influencia de la autoeficacia en el uso de la IA y la ansiedad hacia la IA en la dependencia de la IA entre los estudiantes universitarios peruanos.
Método: se realizó un estudio descriptivo transversal con 528 estudiantes universitarios peruanos de 18 a 37 años (M = 19,00, DE = 3,84). Se utilizaron escalas para medir la autoeficacia en la IA, la ansiedad hacia la IA y la dependencia de la IA. Se aplicaron análisis de correlación y regresión múltiple para identificar predictores de la dependencia tecnológica.
Resultados: los resultados mostraron que la autoeficacia en IA se correlacionó positivamente con la ansiedad (r = 0,43, p < ,01) y la dependencia (r = 0,61, p < ,01). La ansiedad también se correlacionó significativamente con la dependencia (r = 0,71, p < ,01). El análisis de regresión múltiple reveló que tanto la ansiedad (β = 1,131, p < ,001) como la autoeficacia (β = 0,610, p < ,001) predijeron la dependencia. Además, los estudiantes de administración de empresas mostraron una mayor dependencia en comparación con los estudiantes de otras carreras (β = 1,025, p < ,05).
Conclusiones: los estudiantes con mayor autoeficacia en el uso de IA tienden a utilizar IA con mayor frecuencia, pero también experimentan mayor ansiedad y dependencia de la IA. Las intervenciones educativas deben centrarse en reducir la ansiedad relacionada con la IA para prevenir la dependencia excesiva, especialmente entre los estudiantes.

Palabras clave: Autoeficacia; Ansiedad Tecnológica; Inteligencia Artificial; Dependencia; Educación Superior.

INTRODUCTION

In recent decades, artificial intelligence (AI) has evolved from an emerging technology into a fundamental pillar across various sectors, especially in higher education. AI has transformed the way university students access information, interact with learning platforms, and solve academic problems (Guan et al., 2020). However, this advancement has also brought new psychological and behavioral challenges, particularly in developing self-efficacy in using these technologies, anxiety associated with AI interaction, and increasing dependence on these tools (Grassini, 2023).

Self-efficacy, defined as the belief in one's ability to organize and execute actions necessary to achieve specific goals (Bandura, 1997), is a key concept in adapting to new technologies, including artificial intelligence. In the context of AI, self-efficacy refers to the confidence university students have in their ability to effectively interact with AI-powered systems, such as automated learning platforms and virtual assistants (Morales-García et al., 2024a). This perception of self-efficacy is essential not only for adopting and efficiently using these technologies but also for integrating them into academic and professional settings (Rodríguez-Ruiz et al., 2024). The role of self-efficacy is particularly relevant in educational environments, where AI interaction can facilitate access to advanced resources and personalize the learning experience (X. H. Jia & Tu, 2024). However, not all students experience this process equally. Those with higher self-efficacy tend to make better use of technological tools, while those lacking confidence in their abilities face barriers that limit their academic performance. In fact, recent research suggests that high self-efficacy in AI use can reduce excessive dependence on technology, promoting more autonomous and efficient use (Morales-García et al., 2024a).

Despite the potential benefits of AI in education, many students experience high levels of anxiety when interacting with these technologies. AI-related anxiety is defined as a persistent sense of fear or worry associated with interacting with AI-driven systems (Kim et al., 2023). This phenomenon has been linked to several factors, such as unfamiliarity with algorithms and fear that AI may replace key human skills, leading to cognitive overload among students (Anderson & Smith, 2014; Li & Huang, 2020). Technological anxiety negatively affects self-efficacy, limiting students' ability to make effective decisions in educational settings and impacting their academic performance. Anxiety toward AI can also hinder autonomous learning, as students may avoid using advanced technologies for fear of making mistakes or not fully understanding how the systems work (Morales-Rodríguez & Pérez-Mármol, 2019). Furthermore, this anxiety creates a vicious cycle where students with low self-efficacy tend to rely more on AI to complete tasks, which, in turn, increases their stress and further diminishes their confidence in their own abilities (X. H. Jia & Tu, 2024).

Dependence on artificial intelligence is another emerging phenomenon that has raised concerns in the educational field (Huang et al., 2024). It refers to the compulsive use of AI-based systems to complete academic tasks, which can lead to a decrease in autonomy, confidence in cognitive abilities, and critical thinking (Morales-García et al., 2024c). This technological dependence not only affects academic performance but also has implications for students' emotional well-being, causing issues such as social isolation, lack of motivation, and deterioration of interpersonal relationships (Zhang et al., 2024). Students with low self-efficacy are more prone to developing dependence, as they overly rely on AI technologies for basic tasks, which can erode their

cognitive skills and increase their vulnerability to technostress (Chang et al., 2024). Conversely, those with high self-efficacy tend to use AI more strategically, reducing their risk of dependence and promoting a more balanced use of these technologies (Morales-García et al., 2024a).

Recent studies suggest that high self-efficacy can act as a protective factor, reducing both anxiety and dependence on AI (Rodríguez-Ruiz et al., 2024). In contrast, low self-efficacy not only increases anxiety but also promotes compulsive use of AI, fostering harmful dependence (X. H. Jia & Tu, 2024). Moreover, overexposure to automated technological tools has been linked to a reduction in problem-solving skills and a decrease in students' ability to perform tasks independently (Chang et al., 2024). This phenomenon is particularly concerning in the university environment, where critical thinking and autonomy are essential skills for academic and professional success (Liang et al., 2023). As a result, dependence on AI may not only limit academic performance but could also have long-term consequences on the development of future professionals, compromising their ability to adapt to work environments that require a high degree of autonomy and decision-making (Mercader-Rubio et al., 2023).

The Peruvian educational context has undergone rapid digitalization, accelerated by the COVID-19 pandemic, increasing the use of emerging technologies, including AI, in learning platforms. In this context, understanding how students interact with these technologies is essential for optimizing educational outcomes. However, research indicates that anxiety toward AI use may hinder this adaptation and foster harmful dependence on technology (Alania-Contreras et al., 2024). Additionally, concerns have been raised about the risks of AI, such as misuse for academic dishonesty and the loss of personal interaction, highlighting the need for ethical and effective technological training (Rodrigues et al., 2024). For Peruvian students, the digital divide and lack of adequate training in technological skills contribute to a greater propensity for AI-related anxiety (Flores-Cueto et al., 2023). In a country where technological infrastructure still presents significant limitations, especially in rural areas, this type of anxiety is a key factor that can influence AI dependence for efficiently completing academic tasks (Morales-García et al., 2024b). This technological dependence could become a major issue in the Peruvian university context. The lack of adequate technological skills and the fear of making mistakes when using AI can lead students to rely excessively on these tools for completing basic tasks, potentially compromising their academic development and ability to solve problems independently (Cisneros et al., 2023).

In this regard, the aim of this study is to evaluate anxiety and self-efficacy toward AI as predictors of AI dependence among Peruvian university students.

METHOD

Study Design

This study employed a descriptive cross-sectional. The study participants were Peruvian university students. The inclusion criteria were as follows: (a) students enrolled in programs such as Business Administration, Accounting, Education, Nursing, Engineering, Medicine, Nutrition, Psychology, and Theology; (b) students with access to artificial intelligence (AI) tools and a minimum of 3 to 6 months of experience using them for academic purposes; (c) students who voluntarily agreed to participate in the study through informed consent.

The sample size was calculated using G*Power 3.1.9.7 software (Erdfelder et al., 2009). For multiple linear regression analysis with five explanatory variables, an effect size of 0.05, statistical power of 0.90 (1 − ß), and a significance level (α) of 0.05 were assumed. Based on these parameters, the minimum required sample size was 355 participants. To account for potential dropouts, surveys were distributed via a Google Forms questionnaire, shared through social media platforms like WhatsApp, following an internet-based methodology (Hoerger & Currell, 2011). A total of 528 valid responses were analyzed, with 3 surveys excluded due to incomplete answers.

Procedure

We contacted the coordinators of the various university faculties to explain the purpose of the study and obtain the necessary permissions. The questionnaires were sent to university students via a Google Forms link, which was distributed through WhatsApp groups, following an internet-based methodology (Hoerger & Currell, 2011). Data were collected between April and May 2024. Participants were informed about the purpose of the study, explaining that the data collected would be used exclusively for research purposes. They were assured that the questionnaires would be anonymous and confidential, and that they could withdraw from the study at any time without any repercussions. The study protocol was reviewed and approved by the ethics committee of a Peruvian university, under code CE-000058, following the principles established in the Declaration of Helsinki.

Instruments

Demographic Questionnaire. The demographic characteristics collected included gender, age, student status, academic major, and place of origin.

Self-Efficacy in the Use of Artificial Intelligence: The Self-Efficacy in the Use of Artificial Intelligence Scale (GSE-6AI) was validated among university students in Peru (Morales-García et al., 2024a). This scale is an adapted version of the General Self-Efficacy Scale (GSE-6) and consists of 6 items. The GSE-6AI has a unidimensional

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structure. The reliability, measured using Cronbach's Alpha (α) and McDonald's Omega (ω), was 0,91 for the entire scale. The scale uses a 4-point Likert-type response format.

Dependence on Artificial Intelligence: The Artificial Intelligence Dependence Scale (DAI) was validated among university students in Peru (Morales-García et al., 2024c). The scale consists of 5 items and is unidimensional. Reliability was assessed through Cronbach's Alpha (α = 0,87) and McDonald's Omega (ω = 0,87), indicating high internal consistency. The scale uses a 5-point Likert-type response format, where participants rate their level of agreement with statements related to dependence on artificial intelligence.

Anxiety Toward the Use of Artificial Intelligence: The Anxiety Toward the Use of Artificial Intelligence Scale was developed and used, consisting of 2 items: 1) Feeling nervous, anxious, or tense when faced with tasks or challenges related to artificial intelligence, and 2) Inability to stop worrying or control restlessness about not staying up-to-date or not adequately handling artificial intelligence. The reliability of the scale was assessed through Cronbach's Alpha (α = 0,85), indicating adequate internal consistency. The scale uses a 4-point Likert-type response format, where 0 represents "Never," 1 corresponds to "Less than half of the days," 2 indicates "More than half of the days," and 3 signifies "Nearly every day."

Statistical Analysis

Statistical analysis was performed using R 4.1.1 software. Descriptive statistics were used to summarize participant characteristics, with means and standard deviations presented for the variables of self-efficacy, AI-related anxiety, and AI dependence. The Kruskal-Wallis test (W-KW) was used to compare differences in these variables based on gender, major, and place of origin, with no significant differences found. Pearson correlation showed positive relationships between self-efficacy in AI use, AI-related anxiety, and AI dependence. Finally, multiple linear regression analysis was conducted to identify predictors of AI dependence, considering self-efficacy and anxiety toward AI use. Categorical variables, such as academic major, were entered as dummy variables.

RESULTS

Preliminary analysis

The university students' ages ranged from 18 to 37 years (M = 19,00, SD = 3,84). The results in Table 1 indicate that no statistically significant differences were found in the variables of self-efficacy with the use of AI (W-KW = 3408, p > 0,05), anxiety toward the use of AI (W-KW = 355, p > 0,05), and dependence on artificial intelligence (W-KW = 353, p > 0,05) between males and females. When analyzing the academic fields, significant differences were observed in dependence on artificial intelligence (p < 0,05), where students in administration and nursing presented higher levels of dependence compared to other fields. However, no significant differences were found in the variables of self-efficacy and anxiety based on academic field. Furthermore, no statistically significant differences were observed in any of the analyzed variables (p > 0,05) regarding the geographical origin of the students (coast, jungle, highlands).

Table 1. Self-efficacy, Anxiety, and Dependence on AI According to Sociodemographic Characteristics

Characteristics		n	%	Self-efficacy with AI	W-KW	p	Anxiety toward AI	W-KW	p	Dependence on AI	W-KW	p
Sex	Female	280	53	3,11 ± 0,96	3408	0,71	1,85 ± 1,73	355	0,63	13,02 ± 4,76	353	0,74
	Male	248	47	3,01 ± 1,10			1,79 ± 1,75			12,95 ± 5,08		
Academic Field	Administration	74	14	3,09 ± 1,02	7,97	0,44	2,15 ± 1,82	13,8	0,09	14,34 ± 5,24	19,3	0,01
	Accounting	33	6,3	2,76 ± 1,03			1,70 ± 1,98			12,91 ± 4,87		
	Education	35	6,6	2,69 ± 0,90			1,69 ± 1,86			12,17 ± 5,07		
	Nursing	44	8,3	3,02 ± 1,15			2,34 ± 1,73			14,05 ± 4,62		
	Engineering	94	17,8	3,26 ± 0,99			1,62 ± 1,67			13,18 ± 4,60		
	Medicine	127	24,1	3,09 ± 1,05			1,57 ± 1,60			11,54 ± 4,77		
	Nutrition	9	1,7	2,56 ± 1,33			1,89 ± 2,26			12,89 ± 3,92		
	Psychology	86	16,3	3,17 ± 0,95			2,05 ± 1,70			13,63 ± 4,90		
	Theology	26	4,9	2,96 ± 1,04			1,58 ± 1,60			12,81 ± 5,00		
Geographical Origin	Coast	269	50,9	3,11 ± 1,01	0,03	0,98	1,71 ± 1,64	1,71	0,42	12,74 ± 4,64	1,32	0,51
	Jungle	139	26,3	3,04 ± 1,01			1,92 ± 1,91			13,00 ± 5,19		
	Highlands	120	22,7	2,99 ± 1,10			1,97 ± 1,73			13,52 ± 5,15		

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Mean Scores of Self-Efficacy, Anxiety, and Dependence on Artificial Intelligence and the Correlation between Variables

In table 2, the correlation analysis shows that self-efficacy with the use of AI has a significant positive correlation with anxiety toward AI use (r = 0,43, p < ,01) and with dependence on AI (r = 0,61, p < ,01). Additionally, anxiety toward AI use is positively correlated with dependence on AI (r = 0,71, p < ,01). These results suggest that students who report higher self-efficacy with the use of AI also tend to experience higher levels of anxiety and dependence on this technology. Furthermore, students with higher anxiety tend to rely more on AI.

Table 2. Correlation Coefficient, Mean Scores, and Standard Deviation

Variable	M	SD	1	2	3
Self-efficacy with AI	1,82	1,73	-		
Anxiety toward AI use	14,77	4,22	0,43**	-	
Dependence on AI	12,99	4,91	0,61**	0,71**	-

Analysis of Factors Influencing Dependence on AI

The multiple linear regression analysis showed that anxiety toward AI use (β = 1,131, p < ,001) and self-efficacy with AI use (β = 0,610, p < ,001) had a significant positive influence on dependence on AI. Additionally, the Administration field of study (β = 1,025, p < ,05) had a positive impact, while the Medicine field (β = -1,050, p < ,01) showed a negative influence. Age also demonstrated a significant negative relationship with dependence on AI (β = -0,104, p < ,01). This model explained 61,2 % of the variability in dependence on AI among participating university students (table 3).

Table 3. Multiple Linear Regression Analysis on Dependence on AI

	Estimate	Std. Error	t	p	
(Intercept)	4,00236	0,99103	4,039	< ,001	***
Age	-0,10496	0,03876	-2,708	< ,01	**
Field (Administration)[a]	1,02594	0,43512	2,358	< ,05	*
Field (Medicine)[a]	-1,05013	0,3734	-2,812	< ,01	**
Anxiety toward AI	1,13168	0,09556	11,843	< ,001	***
Self-efficacy with AI	0,61011	0,03944	15,468	< ,001	***
F (p)	131,2 (<,001)				
R2	0,612				
Adjusted R2	0,608				

Note: t = Test statistic, p = Probability. [a] Dummy coded. 80 '***' ,001 '**' ,01 '*' Dependent variable: dependence on AI

DISCUSSION

AI has transformed the university educational environment by facilitating access to information and personalizing learning. However, it has also brought psychological challenges such as anxiety toward its use, self-efficacy in managing it, and technological dependence. Self-efficacy is crucial for the adoption of new technologies, as those with higher confidence in their abilities tend to use AI autonomously, while low self-efficacy fosters excessive dependence. Anxiety toward AI, characterized by fear or concern when interacting with these technologies, negatively affects self-efficacy and promotes compulsive use of AI to complete tasks. This creates a vicious cycle where low self-efficacy increases technological dependence, which, in turn, affects academic performance and cognitive skills. Dependence on AI involves excessive use of automated technologies, which can reduce critical thinking and academic autonomy. In the Peruvian context, where digitalization has rapidly increased, it is important to study how self-efficacy and anxiety interact to influence university students' dependence on AI, especially given the risk of deterioration in their cognitive abilities and problem-solving skills.

The results of this study confirmed that age has a significant negative relationship with AI dependence. These findings align with previous research that has reported a lower inclination toward the adoption and use of new technologies, including AI, among older individuals (Czaja, 2005; Venkatesh et al., 2012). Specifically, studies on technological adoption have highlighted that as individuals age, their willingness and dependence

on emerging technologies, such as AI, decrease due to factors like technological familiarity and fear of change (Mitzner et al., 2010). As people age, their ability to adapt to emerging technologies, like AI, may be affected not only by technological barriers but also by a set of cognitive, social, and psychological factors (Sanchez-Franco, 2009). This leads to lower dependence on AI compared to younger generations who have grown up in a more digitalized environment. Moreover, fear of technological obsolescence is another factor to consider. Research in aging psychology has documented that older generations exhibit higher levels of anxiety and distrust toward emerging technologies (Chu et al., 2022), which could reduce their dependence on AI. Younger generations, such as Millennials and Generation Z, have been exposed to AI-based technologies from an early age, resulting in greater familiarity and confidence in these tools (Chan & Lee, 2023). In contrast, older generations, who have experienced a more gradual technological evolution, may not view AI as an indispensable tool in their daily lives.

The results obtained in this study suggest that the field of Administration had a positive impact on AI dependence, while the field of Medicine had a negative influence. These findings are consistent with previous research indicating that differences in exposure to, use of, and perceptions of technological tools vary significantly across academic and professional disciplines. Previous studies have noted that Administration students tend to adopt emerging technologies like AI more rapidly due to their direct connection with process automation and strategic decision-making optimization (Brown & Adler, 2008). On the other hand, Medicine students show greater resistance to AI use, partly due to ethical concerns and the perception that AI could replace critical human skills, such as clinical judgment (Obermeyer et al., 2019). The positive impact of the Administration field on AI dependence can be explained by several key factors. First, the nature of the administrative field requires a high level of interaction with information management technologies and data analysis, which reinforces the adoption of tools like AI to automate and improve decision-making processes (McAfee & Brynjolfsson, 2017). The literature suggests that Administration students are not only exposed to highly technical environments but are also encouraged to use AI to enhance organizational efficiency and competitiveness in the global market (Marsh et al., 2022). This positive relationship between AI and Administration is explained by the increasing integration of AI in areas such as human resources management, financial decision-making, and digital marketing (Davenport & Ronanki, 2023), which drives greater dependence on these technologies among students to gain a competitive advantage in their future careers. Recent research has also demonstrated that Administration students develop higher self-efficacy in the use of AI as they become familiar with predictive models, big data analysis, and automated management systems that enhance their analytical skills (Jarrahi, 2018). This early and frequent exposure creates a greater level of comfort and dependence on AI, which could also explain the results obtained in our study. In contrast, the negative relationship observed between the field of Medicine and AI dependence may be influenced by several cultural and educational factors. Medicine, as a field, heavily relies on the doctor-patient relationship and human clinical judgment, elements that healthcare professionals find difficult to replicate through AI (Thomas, 2021). Ethical and legal concerns, such as liability in cases of medical error caused by AI systems, may also contribute to greater resistance toward the use of these technologies (Z. Jia et al., 2023). Furthermore, the literature has highlighted that Medicine students tend to have a more critical and conservative perception of AI, viewing it more as a complementary tool rather than a substitute for human skills (Kimmerle et al., 2023). The slower adoption of AI in the medical field also reflects regulatory barriers and the incomplete integration of these technologies into healthcare systems (Petersson et al., 2022), contributing to lower dependence among Medicine students.

The confirmation that anxiety toward AI use positively and significantly influences dependence on this technology reflects a psychological and behavioral dynamic explored in various studies. Previous research has demonstrated that, in technological adoption contexts, negative emotions such as anxiety can paradoxically promote greater dependence on the very object causing that anxiety (Huang et al., 2024). This paradox can be explained through several psychological mechanisms. First, anxiety toward AI may induce a sense of uncertainty or lack of control, motivating users to interact more frequently with the technology in an attempt to reduce this uncertainty. This phenomenon is supported by studies showing that anxiety about using new technologies promotes a greater inclination to engage with them, either to improve perceived competence or to avoid failures in their use (Scott et al., 2021). In the context of AI, this constant interaction can become dependence as users grow accustomed to using automated solutions for complex or repetitive tasks. On the other hand, while anxiety can negatively impact readiness for change or the adoption of new technologies, when users are ultimately required to use these tools, anxiety may intensify the need to rely on them to reduce the tension associated with their use (Novita & Sulastri, 2023). This mechanism aligns with psychological models of stress adaptation, where individuals try to minimize uncertainty by increasing the frequency of use of tools they deem necessary for their performance. The link between anxiety and dependence can also be understood through the concept of the "perceived cost of not using" AI. As AI becomes more integrated into daily decision-making, not using it can generate a sense of competitive disadvantage or inefficiency. In this sense, anxiety amplifies this perception, causing users to depend more on AI to avoid feeling obsolete or incapable of performing tasks up

to current technological standards (Hasani et al., 2024).

Similarly, the significant positive influence of self-efficacy with AI use on dependence on AI was confirmed. This finding aligns with previous research highlighting the crucial role of self-efficacy in the adoption and continued use of advanced technologies, including AI applications (Venkatesh et al., 2003). Specifically, our results reinforce the idea that individuals who perceive themselves as highly capable of interacting with AI systems are more likely to develop dependence on these technologies, reflecting greater confidence in their continuous and extensive use (Parsakia, 2023). As university students develop more confidence in their ability to use AI, they are more likely to integrate these tools into their daily academic lives, increasing habitual use and, consequently, dependence (Bancoro, 2024). Additionally, recent studies have shown that technological dependence, especially on AI, is driven not only by perceived utility but also by users' perceived mastery (Morales-García et al., 2024c). When students feel they effectively control a complex technology like AI, they are more likely to rely on it for a wide range of tasks, reinforcing a cycle of recurrent use and dependence. In this sense, self-efficacy can act as a key facilitator that encourages students to adopt AI not just as an academic tool, but as an indispensable resource for managing their workload and solving complex problems.

Implications

The findings of this study reveal important implications for professional practice, educational policy formulation, and theoretical development in the context of AI use in higher education. The discovery of a positive relationship between self-efficacy with AI use and dependence on this technology suggests that, although students are confident in their ability to interact with AI-based systems, this confidence may lead to excessive use and, ultimately, harmful dependence. This dependence, in turn, can erode academic autonomy and critical thinking, which are essential for success in higher education. Similarly, the significant relationship between anxiety toward AI use and dependence highlights the need to address emotional factors in the adoption of advanced technologies.

In the professional sphere, these results suggest that educators should adopt proactive strategies to encourage healthy and balanced use of AI among students. University curricula should include training in the ethical and critical use of AI-based technologies, accompanied by programs that increase technological self-efficacy without promoting excessive dependence. Furthermore, university psychological support services should be equipped to identify and address technological anxiety, offering psychological and educational interventions to help students develop a healthier relationship with digital tools. Mental health professionals can also use these findings to design therapies focused on reducing anxiety toward AI and improving technological resilience.

At the level of educational policy, the results highlight the need to establish regulatory frameworks and clear guidelines on the use of AI in educational environments. Since technological anxiety can increase dependence on AI, it is crucial for institutions to implement policies that promote comprehensive training in digital competencies. This training should go beyond technical skills, integrating ethical and psychological aspects of AI use to prevent the development of pathological dependence. Additionally, it is essential to promote digital literacy at all educational levels, especially in contexts with significant technological gaps, such as rural areas of Peru, where students may be more vulnerable to developing anxiety toward AI due to lack of access and training.

In theoretical terms, this study contributes to the understanding of the interaction between self-efficacy, anxiety, and technological dependence in the context of AI. The significant relationship between self-efficacy and dependence on AI challenges the traditional notion that higher self-efficacy always leads to better outcomes. Instead, the findings suggest that in highly technological contexts, higher self-efficacy may not be sufficient to avoid dependence if it is not accompanied by critical literacy and adequate anxiety management. This opens new avenues for future research exploring how the balance between self-efficacy and emotional regulation can influence healthy use of advanced technologies.

Limitations

The cross-sectional design of the study limits the ability to establish causal relationships between self-efficacy, anxiety toward AI, and dependence on AI. It is not possible to determine whether low self-efficacy and high anxiety cause greater dependence, or if this dependence affects self-efficacy and anxiety. Longitudinal studies could help clarify this dynamic. Additionally, although the sample size was adequate, it was limited to Peruvian university students from certain disciplines, which restricts the generalization of the results. Future research should include more diverse samples in terms of disciplines and geographic contexts. The use of self-reported measures may have introduced social desirability bias. More objective evaluation methods, such as observations of AI use or physiological measures of anxiety, could improve the accuracy of future studies. Lastly, the study did not delve into the technological context and inequalities in access to AI, which is particularly relevant in a country like Peru. Future studies should explore how these technological inequalities influence psychological and academic outcomes.

CONCLUSION

This study provides valuable evidence on the interaction between self-efficacy, anxiety, and dependence on AI among Peruvian university students, significantly contributing to the understanding of the psychological factors involved in the use of emerging technologies in education. The results demonstrate that both self-efficacy and anxiety toward AI significantly influence the development of dependence on these tools. Specifically, students with higher levels of anxiety and self-efficacy tend to show greater dependence on AI, highlighting the complexity of these relationships and presenting new challenges for developing technological competencies in the university context. This finding is especially relevant in the Peruvian educational context, where rapid digitalization, compounded by technological limitations and the digital divide, may increase students' vulnerability to excessive dependence on AI tools. The positive relationship between self-efficacy and dependence suggests that, although students are confident in their ability to use AI, this confidence does not necessarily reduce their compulsive use of these technologies. Instead, it may lead to overexposure that limits their autonomy and ability to solve problems without technological assistance. As confirmed in this study, anxiety toward AI also plays a crucial role, acting as an amplifier of this dependence, underscoring the need to address this emotion in the academic context.

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