Online Journal of Communication and Media Technologies, 2025, **15**(4), e202529
e-ISSN: 1986-3497

OPEN ACCESS

Research Article

Artificial intelligence dependence in academic tasks: Design and validation of the SAID questionnaire

Raúl Alberto Garcia Castro [1*]
0000-0003-1875-6917

William Maximo Bartesaghi Aste [1]
0000-0003-4978-4494

Jose Luis Morales Quezada [2]
0000-0002-8546-8352

Lupita Esmeralda Arocutipa Huanacuni [1]
0000-0001-6219-9754

[1] Department of Natural Science Education, National University Jorge Basadre Grohmann, Tacna, PERU
[2] Private University of Tacna, Tacna, PERU
[*] Corresponding author: rgarciac@unjbg.edu.pe

Citation: Garcia Castro, R. A., Bartesaghi Aste, W. M., Morales Quezada, J. L., & Arocutipa Huanacuni, L. E. (2025). Artificial intelligence dependence in academic tasks: Design and validation of the SAID questionnaire. *Online Journal of Communication and Media Technologies, 15*(4), e202529. https://doi.org/10.30935/ojcmt/17303

ARTICLE INFO

Received: 12 Apr 2025
Accepted: 14 Jul 2025

ABSTRACT

Artificial intelligence (AI) is transforming the educational system by providing new learning opportunities; however, it also presents challenges such as teacher adaptation, the digital divide, data ethics, depersonalization, and technological dependence. This study addresses the need to assess AI dependence among secondary education students through the construction and validation of the SAID questionnaire. A mixed-methods approach with a sequential design was employed, applying the instrument to 370 students across eight educational institutions in Tacna, Peru. In the qualitative phase, the components of the construct were identified, while in the quantitative phase, the psychometric properties of the questionnaire were evaluated. Exploratory factor analysis and confirmatory factor analysis, along with reliability testing, demonstrated that the SAID questionnaire is a valid and reliable tool. It captured three key dimensions: “informative exclusivity with AI,” “trust in AI,” and “AI literacy.” The questionnaire provides robust empirical evidence of an emerging construct that, based on students’ perceptions, enables the assessment of AI dependence in academic settings. It serves as a valuable resource for exploring long-term implications and developing educational strategies to mitigate the negative effects of AI. The conscious and critical integration of AI in education is essential to ensure that these technologies function as supportive tools rather than substitutes for independent learning.

Keywords: dependence, artificial intelligence, SAID questionnaire, secondary education, psychometric validation, academic tasks

INTRODUCTION

Artificial intelligence (AI) systems such as virtual assistants are becoming increasingly integrated into various aspects of daily life, ranging from entertainment applications to decision making tools. Technologies like ChatGPT by OpenAI, Claude by Anthropic, and many others are designed to analyze large volumes of data and offer personalized suggestions, creating highly adaptive user experiences (Xu, 2023). In the field of

This article is the result of the research conducted as part of the project: *“Creation and design of specialized didactic multimethods to foster interest and learning in basic sciences among secondary education students”*, carried out at National University Jorge Basadre Grohmann.

education, AI is transforming learning by facilitating access to information and optimizing educational processes. These technologies allow students to interact with extensive datasets and receive customized recommendations, thereby enhancing the efficiency of knowledge acquisition (Liu, 2022). Furthermore, AI has been successfully applied in other fields, such as neuroscience, where its capacity to analyze complex data has provided new insights into both artificial and human intelligence.

In school environments, students are increasingly turning to AI to access educational resources, solve complex problems, and improve their learning outcomes (Deng & Yu, 2023). The use of these tools clearly enhances academic processes. For example, students in basic education can quickly and conveniently access a wide range of content using tools like ChatGPT to complete their schoolwork (Garcia et al., 2024). AI tools support numerous academic tasks. Applications such as Grammarly help students improve their writing skills by offering suggestions on structure, grammar, and style. Other tools can summarize long texts, which facilitates the understanding and retention of key information. Similarly, Wolfram Alpha assists in solving mathematical problems by providing step by step solutions, allowing students not only to arrive at correct answers but also to understand the logic and process behind problem solving (Okello, 2023).

The potential of AI to transform educational activities lies in its ability to tailor learning experiences to individual needs (Adiguzel et al., 2023; Chen et al., 2020; Hamal et al., 2022). However, the use of this technology can also influence human behavior in both positive and negative ways. One growing concern relates to the psychological consequences associated with the use of AI technologies (Salvi & Singh, 2023). As dependence on these tools' increases, so do concerns about their potential impact on human behavior and overall well-being. From a psychological perspective, addiction or dependency is not limited to the use of substances such as drugs or alcohol. Certain behavioral patterns can also generate dependency, characterized by impulsiveness in seeking immediate rewards and a disconnection from reality, even in the absence of substance use (Poulton & Hester, 2019; Sinitaru, 2022). One example of behavioral dependency is the dysfunctional use of new information and communication technologies (Lage et al., 2023).

Although dependence on AI shares certain traits with other forms of technological addiction, such as compulsive use, the pursuit of immediate gratification, and the avoidance of cognitive effort (Yankouskaya et al., 2025), it also presents distinct characteristics that justify a specific theoretical approach. Unlike smartphone or internet addiction, where content is predominantly passive or socially driven, AI tools actively interact with users, generate content autonomously, and provide personalized responses based on machine learning. This adaptive capability fosters an illusion of reciprocity or collaborative interaction, in which the user perceives that the AI "understands" their needs and solves problems intelligently (Ma et al., 2025).

In educational contexts, this can reinforce patterns of cognitive delegation, where students stop applying their own strategies of analysis, synthesis, or argumentation, relying blindly on the response generated by the AI, which correlates with a decline in skills such as critical thinking and intellectual autonomy (Gerlich, 2025). These dynamics not only increase usage frequency but also modify cognitive style, which distinguishes AI dependence from other forms of excessive technology use (Deckker & Sumanasekara, 2025). Therefore, this type of dependence may be conceptualized as a particular form of behavioral addiction, associated with algorithmic processes that replace complex cognitive functions and affect the development of intellectual autonomy (Gerlich, 2025).

In basic education, intensive use of AI tools may lead to dependency like behaviors in the completion of academic tasks. AI dependency can manifest as a growing tendency among students to rely on these technologies to perform routine tasks, make decisions, and solve problems, to the extent that their cognitive capacity is reduced to mere automation, neglecting other sources of knowledge such as books or academic texts (Salvi & Singh, 2023). The ease with which students can complete assignments using AI fosters habits like copy and paste, and without proper supervision, such behaviors may result in dependency. This could negatively affect the development of skills such as inquiry, argumentation, and critical thinking, and may even lead to academic dishonesty (Garcia et al., 2024).

While digitalization and AI provide a more convenient environment for learning and living, they also pose risks of technological dependence (Vinichenko et al., 2021). Recent studies have highlighted how AI can alter human attention and emotional responses, with implications for communication and empathy (Keshishi & Hack, 2023; Trabelsi et al., 2023). Zhuo et al. (2023) warn that growing obedience to algorithms may foster social conformity and reduce independent judgment. In Korea, Kim et al. (2024) found that 87.60% of students are at risk of problematic smartphone use, which heightens concerns about technology related dependency. Zhang et al. (2024) explored AI dependency in educational settings and found that academic self-efficacy and stress, mediated by performance expectations, are linked to increased reliance on AI, leading to reduced creativity and critical thinking. Other researchers have suggested that factors such as participation in extracurricular activities, family support, and strong academic performance can protect students from overuse of mobile devices and the internet (Sayyad et al., 2020; Vicente-Escudero et al., 2019). However, around the age of 15, a turning point often occurs, characterized by increased screen time and the potential development of addiction, which may be accompanied by psychological issues such as depression and anxiety (Kapus et al., 2021).

The existing literature includes several efforts to measure AI related dependency. Suh and Ahn (2022) emphasized the importance of developing validated instruments to assess students' attitudes toward AI in educational contexts. They created a tool to quantify such attitudes, highlighting that positive attitudes are crucial for successful learning with AI. Grassini (2023) developed the artificial intelligence attitude scale to assess public perceptions of AI technologies. This four-item, single-factor scale offers a useful framework for understanding general attitudes toward AI. Similarly, Schepman and Rodway (2020) introduced the general attitudes toward artificial intelligence scale, which includes both positive and negative subscales that reflect users' perceptions of AI's benefits and concerns.

A relevant related development is the Bergen Facebook addiction scale (BFAS), created by Andreassen et al. (2012), which evaluates dimensions such as salience, mood modification, tolerance, withdrawal, conflict, and relapse. This scale has been validated in various studies, including those by Lee-Won et al. (2015) and Hu et al. (2023), who linked problematic Facebook use to factors such as social anxiety, the need for social reassurance, loneliness, and rumination. Zhang et al. (2024) applied a six-item questionnaire derived from the BFAS to assess AI dependency in educational settings, using ChatGPT as a reference. Their results showed that academic self-efficacy, performance expectations, and stress are significantly associated with dependency on AI tools. Nonetheless, most of the existing studies do not focus on identifying specific components for measuring AI dependency, suggesting a research gap that remains to be addressed.

As AI becomes more integrated into our daily lives, the extent to which it can improve life or introduce new problems continues to be a subject of significant debate and investigation (Ilyas, 2022). Its accessibility encourages frequent use, which makes it essential to understand how this relationship affects human behavior. In this context, it becomes increasingly important to monitor the risk of AI dependency among secondary school students. Ensuring that AI is used as a tool for support rather than a substitute for independent learning is essential.

There is a clear need for easy to use instruments not only for specialized professionals but also for classroom teachers who interact directly with students. Such tools would allow for the early and accurate identification of dependency issues, enabling school administrators to implement control strategies that promote a healthy balance. This would support both the effective use of AI and the development of students' autonomous learning skills.

Given these considerations, it is essential to measure and better understand behaviors associated with AI dependency among secondary school students. Although existing scales evaluate technology addiction related to social media or general digital use, there is still a lack of instruments specifically designed to measure AI dependency in educational settings. The rapid expansion of AI has introduced new challenges, including issues of informational exclusivity and AI literacy, that need to be addressed. Therefore, the objective of this research is to design and validate a questionnaire to measure AI dependency among secondary school students. This tool will provide an innovative way to assess AI dependency in educational environments and offer new insights into how students are using these technologies in their academic work.

METHODOLOGY

This research is a psychometric study with a qualitative component. In the initial qualitative phase, the components of the construct of AI dependency were explored through an extensive literature review and expert consultation. Once the initial questionnaire was developed, the second quantitative phase focused on validating the psychometric properties of the instrument using statistical tools to identify emerging dimensions and confirm construct validity. This stage was aimed at evaluating the psychometric performance of the questionnaire initially designed in the first phase. The combination of qualitative and quantitative data made it possible to build a valid conceptual structure of AI dependency through cross-checking and triangulation of findings, resulting in a more comprehensive theoretical measurement model (Creswell & Creswell, 2018).

Participants

A total of 370 students were randomly selected and divided into two groups of 185 each. They belonged to eight basic education schools in Tacna, Peru, and were in the last two years (4^{th} and 5^{th} grade) of secondary education. Among the participants, 53.5% were female and 46.5% male, allowing for a balanced analysis of potential gender differences. The students' age ranged from 15 to 17 years, with an average age of 16.6 years (standard deviation [SD] = 0.92). This average age suggests that the participants were in middle adolescence, a stage characterized by the development of more advanced cognitive skills and greater interaction with technology, making them a relevant population for this study. The selection of educational institutions was based on the socioeconomic and cultural diversity of the Tacna Region, with the aim of obtaining a representative sample of the area's varied realities and avoiding selection bias in the results.

Procedure

The study was divided into two phases. In the first, qualitative phase, the factors forming the conceptual structure of AI dependency were identified. This phase included an extensive literature review (Robson & McCartan, 2016), which resulted in a factor model used as the basis for designing the initial questionnaire. To validate its content (Bryman, 2016), feedback was obtained from two experts from Spain and eight local experts, whose observations helped improve the instrument. A pilot test was then conducted with 50 4^{th} and 5^{th} year secondary school students to assess the clarity and appropriateness of the items. Based on the students' feedback, comprehension difficulties were identified in some of the item statements, as well as confusion in the interpretation of certain expressions. As a result, six items were rewarded to improve their semantic clarity. For example, in item 2, the original phrase **"**IA es confiable**"** was corrected to **"**La IA es confiable**"** by adding the definite article to improve grammatical accuracy and clarity. Additionally, the wording of certain items containing technical language, such as item 15, was adjusted to better contextualize the term "algorithms" and make it more accessible to students. All of these modifications focused on improving the clarity of the item statements, without altering the structure or response scale of the questionnaire.

In the second, quantitative phase, the questionnaire was initially administered to a group of 185 students. This first dataset allowed the identification of the latent dimensions of the instrument. After a 20-day interval, the revised questionnaire was administered to another 185 students in the second group, with the aim of evaluating the hypothesized factorial structure and confirming whether the empirical data matched the predefined structure from the exploratory factor analysis (EFA). Reliability analysis was then performed using ordinal alpha and McDonald's omega coefficient. Throughout the process, data privacy was ensured through anonymization procedures and secure storage, guaranteeing that students did not feel pressured to give socially desirable responses. Additionally, before administering the questionnaire, participants received a clear explanation of the study's purpose, emphasizing that there were no right or wrong answers, which helped reduce social desirability bias.

The study was approved by the Ethics Committee at National University Jorge Basadre Grohmann under code 2023-010-CEIUNJBG, in compliance with national and international ethical guidelines for research involving minors. Informed consent was obtained from all participants, ensuring that they understood the purpose of the study and their rights. To protect the students, written informed consent was requested from their parents or legal guardians prior to data collection. Likewise, informed assent was obtained from the students themselves, using clear and age-appropriate language, emphasizing that their participation was voluntary and that they could withdraw at any time without consequences.

Table 1. Summary of the most relevant instruments for measuring AI dependency

Title	Reference	Dimensions
Validation of a new scale for measuring problematic internet use: Implications for pre-employment screening	Davis et al. (2004)	Decreased impulse control, loneliness/depression, social comfort, and distraction.
A components model of addiction within a biopsychosocial framework	Griffiths (2025)	Salience, mood modification, tolerance, withdrawal symptoms, conflict, and relapse.
The compulsive Internet use scale (CIUS): Some psychometric properties	Meerkerk et al. (2006b)	Loss of control, preoccupation, conflict, withdrawal symptoms, and coping.
Development of a Facebook addiction scale	Andreassen et al. (2012)	Salience, mood modification, tolerance, withdrawal, conflict, and relapse.
Adicción a Facebook y adultos emergentes: La influencia de variables sociodemográficas, comunicación familiar y diferenciación del self [Facebook addiction and emerging adults: The influence of sociodemographic variables, family communication, and self-differentiation]	Sotero et al. (2020)	Salience, mood modification, tolerance, withdrawal symptoms, conflict, and relapse.
Development and validation of a scale for dependence on artificial intelligence in university students	Morales-García et al. (2024)	Sense of vulnerability, concern about relevance and performance, need for an updated image, external validation, fear of personal obsolescence.

Data Analysis

First, the discriminative power of the items was assessed through univariate analysis (means, SDs, skewness, kurtosis, and item-test correlations) and bivariate analysis (Pearson correlations). Then, EFA was conducted using the factor software (version 12.04.05), including Bartlett's (1951) test of sphericity to assess the data matrix properties (Yanai & Ichikawa, 2006) and the Kaiser-Meyer-Olkin (KMO) coefficient to evaluate sample adequacy for EFA (Kaiser, 1970). Minimum rank factor analysis with Promax oblique rotation was used for factor extraction, retaining items with factor loadings greater than 0.3 (Velicer & Fava, 1998). Model fit was evaluated using the RMSR value.

After 20 days, the questionnaire was administered again for confirmatory factor analysis (CFA) using Mplus software (version 8.11). Model fitting was performed with the DWLS estimator, which is effective for handling categorical data and provides more accurate estimates in non-normal data distributions (Li, 2016). The Chi-square index, comparative fit index (CFI), Tucker-Lewis index (TLI), and root mean square error of approximation (RMSEA) were calculated. Finally, the internal consistency of the questionnaire was reported using McDonald's omega coefficient and composite reliability, calculated with the RStudio statistical software (version 2023.06.1+524) and the corresponding packages. It is important to note that the questionnaires were completed in person under direct supervision, and the responses were checked at the time of submission. Therefore, no missing data were recorded in either the EFA or CFA sample.

RESULTS

Identification of Dimensions Through Literature Review

A thorough review of the literature on technological dependency and interaction with AI in educational settings revealed several recurring dimensions. Among the most prominent was *salience*, which refers to the dominance of technology use in the individual's life (Andreassen et al., 2012; Griffiths, 2005; Widyanto & McMurran, 2004; Sotero et al., 2020), and *mood modification*, which describes how internet use can temporarily alter emotional well-being (Andreassen et al., 2012; Griffiths, 2005; Sotero et al., 2020). Other identified dimensions included *tolerance*, or the need to increase usage time to achieve the same level of satisfaction (Andreassen et al., 2012; Griffiths, 2005; Sotero et al., 2020), and *withdrawal symptoms*, which manifest as physical or emotional discomfort when usage is reduced (Andreassen et al., 2012; Griffiths, 2005; Meerkerk et al., 2006a; Sotero et al., 2020). Additional key dimensions were *conflict*, or interference with other important life activities (Andreassen et al., 2012; Griffiths, 2005; Meerkerk et al., 2006a; Sotero et al., 2020), and *relapse*, or the return to problematic use after a period of abstinence (Andreassen et al., 2012; Griffiths, 2005; Sotero et al., 2020) (**Table 1**).

Table 2. Descriptive statistics and item-test correlations

Items	Mean	Standard deviation	Skewness	Kurtosis	Item-test correlation
p1	3.36	.94	–.38	.19	.47
p2	3.18	.85	–.46	.69	.54
p3	3.47	.91	–.31	.20	.64
p4	3.66	.95	–.54	.36	.57
p5	3.18	1.02	–.16	–.45	.48
p6	3.20	1.02	–.32	–.22	.70
p7	3.46	.96	–.55	.27	.63
p8	2.94	1.06	.21	–.52	.70
p9	2.89	.97	.01	–.34	.70
p10	3.06	.97	–.08	–.19	.53
p11	3.00	1.01	.10	–.39	.66
p12	2.98	1.13	–.00	–.75	.62
p13	3.33	1.03	–.39	–.31	.69
p14	3.08	1.02	–.17	–.52	.70
p15	3.15	.99	–.33	–.14	.59
p16	3.14	.97	–.18	.012	.57
p17	3.35	.99	–.54	.35	.55
p18	3.35	.98	–.46	.10	.50
p19	2.89	.94	.02	–.24	.56
p20	2.85	.87	–.05	.10	.53
p21	3.14	1.13	–.09	–.53	.49

Based on the previous analysis, the categories were formulated and the questionnaire items were designed using a numerical Likert-type scale ranging from 1 to 5, where 1 represents the lowest rating (strongly disagree) and 5 the highest rating (strongly agree). The questionnaire, composed of 21 scalar items, analyzes AI dependence by considering patterns such as frequency of use (Riedl, 2019), tasks delegated to AI (Hemmer et al., 2023), trust in AI (Madhavan & Wiegmann, 2007), impact on productivity (Brynjolfsson & McAfee, 2014), changes in personal skills, decision-making based on AI (Steyvers & Kumar, 2023), and anxiety when lacking access to AI (Hemmer et al., 2023). These dimensions provided a solid framework for understanding AI dependence and its impact on users. The final categories are summarized below:

1. **Trust in AI:** Refers to the extent to which individuals trust the accuracy, fairness, and reliability of AI systems to provide information and make decisions (Madhavan & Wiegmann, 2007).
2. **Informational exclusivity with AI:** This behavior describes users' tendency to rely exclusively on AI to carry out tasks and obtain information, disregarding alternative sources. This could lead to a limited or biased view of reality based solely on what AI provides (Riedl, 2019).
3. **AI literacy:** The ability of individuals to interpret and evaluate information generated by AI systems. It includes understanding how AI algorithms work, assessing the quality and relevance of the information provided, and discerning between objective and biased content (Wang et al., 2022).
4. **AI resistance (abstinence):** Refers to individuals' willingness to question, verify, and resist information generated by AI systems when necessary (Davenport & Ronanki, 2018).

Descriptive and Discriminative Analysis of the Items

Table 2 shows that the item means range from 2.85 to 3.6, with standard deviations clearly above zero, indicating good variability and suggesting that the items are likely to discriminate well among participants. The skewness values for the items fall within the acceptable range of –1 to +1. Likewise, the kurtosis values range between –2 and +2, which is considered excellent. The analysis of the items' discriminative power reports corrected item-total correlation values between 0.466 and 0.699, which fall within the acceptable range and exceed the minimum threshold of 0.20 proposed by Kline (2016). The overall analysis does not reveal any problematic items that would require revision or removal.

Exploratory Factor Analysis

First, the significance of the test was verified using the KMO index, which yielded a value of 0.92587, indicating an excellent level of sampling adequacy. This suggests that the data are appropriate for factor

Table 3. Rotated component matrix

Items	Factor 1	Factor 2	Factor 3	Factor 4
p2	0.53			
p3	0.58			
p4	0.92			
p6		0.83		
p7		0.36		
p8		0.74		
p9			0.49	
p10			0.97	
p11		0.33		
p12		0.59		
p14		0.76		
p15				0.70
p16				0.95
p17				0.70
p18				0.66

analysis (Field, 2018; Kaiser, 1974). Bartlett's test of sphericity (χ^2 [120] = 1,612.1; p = 0.00001 < 0.01) provides strong evidence that the data are suitable for EFA, due to the presence of significant interrelationships among the variables, although any p-value below 0.05 is considered acceptable. The RMSR result of 0.0275 indicates excellent model fit, being substantially lower than the expected value of 0.0739 for an acceptable model. The total variance explained was 73.29%, which represents a satisfactory threshold according to the criteria of Rietveld and van Hout (1993).

The results in **Table 3** show that items 1, 5, 13, 19, and 20 were removed, as they did not contribute significantly to the identified factors. A threshold of 0.3 was established as the minimum acceptable value for factor loadings, following the recommendation of Velicer and Fava (1998). Additionally, item 21 was excluded because it did not adequately explain the shared variance with the other items, obtaining a low score (< 0.5) in the communalities results, in accordance with the criteria of Hair et al. (2019). This adjustment improved the explained variance from 72.2% to 73.29%.

Under this threshold, factor 1, corresponding to the dimension "trust in AI", is composed of items 2, 3, and 4. Factor 2, from the dimension "informational exclusivity with AI", includes items 6, 7, 8, 12, and 14. Factor 3, which consisted of items 9 and 10, was removed based on the criterion of Costello and Osborne (2005), as two items are insufficient to ensure the robustness and stability of a factor. Factor 4 is composed of items 15, 16, 17, and 18, which are theoretically consistent, as they belong to the dimension "ability to interpret and evaluate AI-generated information". As a result, the final version of the questionnaire consists of 13 items and 3 factors (dimensions).

Confirmatory Factor Analysis

After identifying the main factors in the EFA, the structure was confirmed through CFA. This process allowed for verification of whether the empirical data supported the proposed theoretical structure, revealing an acceptable model fit, with a significant chi-square value (χ^2 = 162.465, p < 0.0001, df = 62), indicating some discrepancy between the model and the observed data. However, the RMSEA index of 0.063 suggests a good model fit, as it falls within the accepted standard (< 0.08), according to Levy and Varela (2006). Additionally, the CFI and TLI indices, with values of 0.91 and 0.901, respectively, indicate an adequate fit (> 0.90), based on the criterion proposed by Kline (2016). Most of the standardized factor loadings were satisfactory, with values above 0.50 for items p2, p3, p4, p6, p7, p8, p11, p12, p14, p15, p16, and p17, suggesting that these items are good indicators of their respective constructs (**Table 4**). Item p18 showed a moderate loading and a corrected item-total correlation of 0.42, which may suggest the need for revision. In summary, the model shows an adequate fit with the three factors (dimensions) that group the 13 items.

Internal Consistency Analysis of the Instrument

Table 5 presents the results regarding the reliability of the questionnaire, divided into three dimensions. Composite reliability and McDonald's omega coefficient were calculated for each dimension, showing that all three dimensions have acceptable reliability, ranging from 0.71 to 0.81, which exceeds the 0.70 threshold

Table 4. Results of the CFA

Items	Extracted factors		
	Factors	Factor loading	Corrected item-Total correlation
Factor 1. Trust in AI			
P2	I trust the impartiality of AI when providing information on controversial or sensitive topics.	0.56	0.58
P3	I consider AI to be reliable for completing school assignments.	0.66	0.66
P4	I trust in AI's ability to adapt and improve its results over time.	0.72	0.71
Factor 2. Informational exclusivity with AI			
P6	I feel comfortable using AI applications in my daily life.	0.70	0.70
P7	AI systems can provide me with quick and accurate solutions for my schoolwork.	0.53	0.53
P8	I turn to AI more and more frequently to obtain information.	0.67	0.67
P11	I prefer to interact and carry out tasks with the help of AI.	0.66	0.66
P12	I believe my interaction with AI systems has significantly increased over time.	0.77	0.77
P14	I frequently use AI to solve my doubts or answer questions.	0.53	0.53
Factor 3. AI literacy			
P15	I am capable of understanding how artificial intelligence algorithms work.	0.66	0.65
P16	I can discern between objective and biased information generated by AI systems.	0.76	0.75
P17	I am able to determine the relevance of the information provided by AI.	0.65	0.65
P18	I believe I am prepared to identify possible biases or errors in the results provided by AI.	0.42	0.42

Table 5. Reliability of the SAID questionnaire dimensions

No	Factor	Number of items	Composite reliability	McDonald's omega
1	Trust in AI	3	0.71	0.71
2	Informational exclusivity with AI	6	0.81	0.81
3	AI literacy	4	0.72	0.72

recommended by authors such as Hair et al. (2021). The results for composite reliability and McDonald's omega demonstrate stronger consistency in the validity of the reported estimates, as they are considered complementary measures. The dimension of informational exclusivity with AI stands out due to its high internal consistency.

DISCUSSION

The results of the SAID questionnaire validation revealed that three of the four initially proposed dimensions demonstrate adequate goodness of fit and parsimony. The consistency of the 13 items grouped into the dimensions comprising the construct shows that the questionnaire is suitable for measuring AI dependence in secondary education populations. These dimensions are supported by the contributions of various authors who approach the measurement of AI dependence from different psychological and behavioral perspectives (**Figure 1**).

The "informational exclusivity with AI" dimension stands out for its high internal consistency ($\omega = 0.813$), indicating that students tend to rely exclusively on AI for obtaining information and completing tasks, neglecting other sources of information (Riedl, 2019). This phenomenon may be explained by the ease and speed with which AI technologies provide answers and solutions, thus fostering increasing dependence. Secondly, the "AI literacy" dimension ($\omega = 0.723$) shows that as users become more AI-literate and recognize its accuracy and relevance, they tend to turn to these technologies more often. However, this literacy also empowers users to use AI more effectively and consciously, enhancing the quality of their interaction and decision-making (Wang et al., 2022). The "trust in AI" dimension is an important component of the questionnaire's construct ($\omega = 0.715$), as it determines the extent to which users are willing to rely on these technologies in academic settings. High trust may increase dependence and limit the development of autonomous skills (Madhavan & Wiegmann, 2007), while lack of trust may hinder effective AI use.

The findings of this study are consistent with previous research exploring technological dependence on educational contexts. For example, Zhang et al. (2024) identified a significant relationship between academic self-efficacy and AI dependence, highlighting how comfort and the perception of enhanced academic

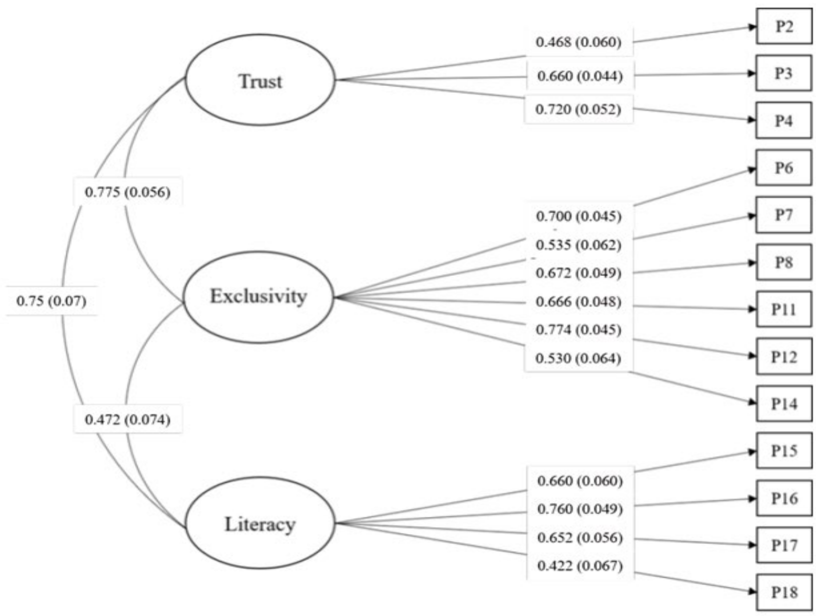

Figure 1. Factor structure and standardized values for the model (Source: Prepared by the authors using the statistical program Mplus, version 8.11)

performance promote such dependence. Similarly, studies by Morales-García et al. (2024) and Salvi and Singh (2023) have pointed out that the accessibility and efficiency of AI tools can lead to dependence, affecting the development of skills such as inquiry and critical thinking.

Griffiths (2005) addresses several dimensions of addiction, such as salience, which functions as a key component. The study also examines mood modification, referring to the emotional changes people experience when engaging in Internet-related activities. Additionally, it includes aspects such as tolerance, withdrawal, conflict, and relapse. While the SAID questionnaire has a different focus, it shares the concern regarding how technological dependence can influence students' academic and personal lives. For instance, the "trust in AI" dimension in our study may relate to Griffiths' (2005) "salience" dimension, which describes the dominance of technology in a person's life. Similarly, Andreassen et al. (2012) developed the Bergen Facebook addiction scale, which, although addressing a different phenomenon, highlights how dependence can affect various areas of a person's life. The "informational exclusivity with AI" dimension identified in our study can be seen as a parallel to the "excessive use" dimension in the Facebook addiction scale, where users rely exclusively on one technology for their informational and social needs.

The work of Widyanto and McMurran (2004) highlights the importance of critical thinking in evaluating information. The "AI literacy" dimension in the SAID questionnaire, which focuses on individuals' ability to critically evaluate information, may be crucial in mitigating some of the negative effects identified by Widyanto and McMurran (2004), such as excessive use and lack of control. The study most closely related to AI dependence is that of Morales-García et al. (2024), who developed an AI dependence scale centered on emotional and behavioral aspects derived from DSM-5 clinical criteria and compulsive behaviors. In contrast, the SAID questionnaire incorporates educational and technological literacy dimensions, offering a broader perspective on AI use and understanding. Both questionnaires address emotional dependence: Morales-García et al. (2024) through "sense of vulnerability" and "seeking external validation," while the SAID questionnaire reflects it through "trust in AI" and "informational exclusivity with AI." Moreover, the SAID questionnaire addresses "AI literacy," a dimension absent in the work of Morales-García et al. (2024). It is worth noting that Morales-García et al.'s (2024) questionnaire is validated for university students, whereas the SAID Questionnaire is targeted at secondary education students.

CONCLUSIONS AND LIMITATIONS

Limitations and Future Implications of the Study

One of the main limitations of this study is the sample size and its representativeness. Although eight educational institutions from the Tacna Region in Peru were selected to ensure socioeconomic and cultural diversity, the results could be strengthened by including institutions from other regions or international educational contexts to improve generalizability. Additionally, the cross-sectional design of the study limits the ability to establish causal relationships between AI dependence and its effects on academic performance and skill development. It is also important to note that the self-reporting method used by students may be subject to social desirability bias and memory errors.

Furthermore, the wording of the questionnaire items was specifically designed to be answered within the context of secondary education, which may limit its applicability to other educational levels or contexts. To improve the external validity of the questionnaire, it would be useful to adapt and validate the instrument in other age groups and settings, which would allow for an assessment of whether the AI dependence dimensions identified in this study are also relevant in other populations. Another limitation of the study is the lack of analysis of concurrent and discriminant validity, which is relevant due to the high correlations between the dimensions of trust, exclusivity, and literacy. This omission is due to methodological and time constraints, as the primary focus was on internal consistency and reliability. Future research should address these forms of validity to enhance the instrument's precision through a more comprehensive design that allows for comparisons with other constructs.

The findings of this study have important implications for both future research and educational practice. In terms of research, longitudinal studies are needed to explore the evolution of AI dependence over time and its long-term impact on students' academic and personal development. These studies could be complemented by including broader subgroups of older Internet users. It would also be useful to investigate educational interventions that reduce excessive AI dependence by promoting more balanced and critical use of these technologies. Regarding educational practice, it is essential for educators and school administrators to be aware of the potential for AI dependence and adopt strategies that encourage critical and reflective use of such tools.

Conclusions

The SAID Questionnaire makes a significant contribution to both the field of education and psychology by offering a validated tool to assess AI dependence among secondary school students. This study provides strong empirical evidence for an emerging construct that helps capture students' perceptions of AI use and dependence. It identifies three dimensions: "trust in AI," "informational exclusivity with AI," and "AI literacy," which together offer insight into how these dimensions contribute to AI-dependent behaviors in educational settings.

The identification of these dimensions enables the design of more targeted interventions to mitigate the potential negative effects of AI dependence on students' academic and social development. In this sense, the study's results open new lines of research and application in educational psychology by providing an empirical framework to better understand the cognitive and behavioral mechanisms associated with technological dependence in adolescents, who represent a particularly vulnerable group.

Based on the findings, it is recommended that educators implement concrete pedagogical strategies such as guided debates on the limits of using tools like ChatGPT, comparative writing exercises between human-produced and AI-generated texts, and activities focused on source verification and critical analysis of automated responses. These practices help students develop evaluation, argumentation, and autonomy skills, counteracting the tendency to delegate complex thinking to automated systems. It is also suggested that schools implement digital literacy programs that explicitly address the role of AI as a support tool rather than a substitute for cognitive effort. For policymakers, the results of this study highlight the need to establish national guidelines to regulate the integration of AI-based technologies into educational systems, including protocols to monitor excessive use, equitable access criteria, and continuous teacher training mechanisms that promote a balanced relationship between students and technology.

The findings underscore the importance of balanced AI use in education, promoting both its effectiveness and the development of autonomous skills. Future research should explore the long-term implications of this dependence and develop educational strategies to mitigate its negative effects. The conscious and critical integration of AI into educational environments is essential to ensure that these technologies serve as supportive tools rather than substitutes for independent learning.

Author contributions: RG: conceptualization, methodology, software, data curation, writing – original draft, writing – review & editing, visualization; **WB:** methodology, formal analysis, investigation, writing – original draft, writing – review & editing; **JM:** supervision, validation, resources, writing – review & editing; **LA:** investigation, data curation, writing – review & editing. All authors approved the final version of the article.

Funding: This article was funded by National University Jorge Basadre Grohmann.

Acknowledgments: The authors would like to thank National University Jorge Basadre Grohmann for all the facilities provided.

Ethics declaration: This study was approved by the Institutional Ethics Committee of the National University Jorge Basadre Grohmann on April 19, 2023 (Approval Code: 2023-010-CEIUNJBG). All participants were informed about the objectives of the research and written consent was obtained from parents or legal guardians, as well as the assent of the students. Confidentiality was guaranteed through the anonymization of personal data and the secure storage of the information collected. Only the research team had access to the data, which were used exclusively for academic purposes.

Declaration of interest: The authors declared no competing interest.

Data availability: Data generated or analyzed during this study are available from the authors on request.

REFERENCES

Adiguzel, T., Kaya, M., & Cansu, F. (2023). Revolutionizing education with AI: Exploring the transformative potential of ChatGPT. *Contemporary Educational Technology, 15*(3), Article ep429. https://doi.org/10.30935/cedtech/13152

Andreassen, C. S., Torsheim, T., Brunborg, G. S., & Pallesen, S. (2012). Development of a Facebook addiction scale. *Psychological Reports, 110*(2), 501–517. https://doi.org/10.2466/02.09.18.PR0.110.2.501-517

Bartlett, M. S. (1951). A further note on tests of significance in factor analysis. *British Journal of Psychology, 4*, 1–2. https://doi.org/10.1111/j.2044-8317.1951.tb00299.x

Bryman, A. (2016). *Social research methods* (5th ed.). Oxford University Press.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access, 8*, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

Costello, A. B., & Osborne, J. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment Research & Evaluation, 10*(1), Article 7. https://doi.org/10.7275/jyj1-4868

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches*. SAGE.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108–116.

Davis, R. A., Flett, G. L., & Besser, A. (2004). Validation of a new scale for measuring problematic internet use: Implications for pre-employment screening. *CyberPsychology & Behavior, 5*(4). https://doi.org/10.1089/109493102760275581

Deckker, D., & Sumanasekara, S. (2025). A systematic review of the impact of artificial intelligence, digital technology, and social media on cognitive functions. *International Journal of Research and Innovation in Social Science, 9*(3), 134–154. https://doi.org/10.47772/IJRISS.2025.90300011

Deng, X., & Yu, Z. (2023). A meta-analysis and systematic review of the effect of chatbot technology use in sustainable education. *Sustainability, 15*(4), Article 2940. https://doi.org/10.3390/su15042940

Field, A. (2018). *Discovering statistics using IBM SPSS statistics* (5th ed.). SAGE.

Garcia, R. A., Mayta, N. A., Bartesaghi, W. M., & Llapa, M. P. (2024). Exploration of ChatGPT in basic education: Advantages, disadvantages, and its impact on school tasks. *Contemporary Educational Technology, 16*(3), Article ep511. https://doi.org/10.30935/cedtech/14615

Gerlich, M. (2025). Herramientas de IA en la sociedad: Impactos en la descarga cognitiva y el futuro del pensamiento crítico [AI tools in society: Impacts on cognitive offloading and the future of critical thinking]. *Societies, 15*(1), Article 6. https://doi.org/10.3390/soc15010006

Grassini, S. (2023). Development and validation of the AI attitude scale (AIAS-4): A brief measure of general attitude toward artificial intelligence. *Frontiers in Psychology, 14*. https://doi.org/10.3389/fpsyg.2023.1191628

Griffiths, M. (2005). A 'components' model of addiction within a biopsychosocial framework. *Journal of Substance Use, 10*(4), 191–197. https://doi.org/10.1080/14659890500114359

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)*. SAGE. https://doi.org/10.1007/978-3-030-80519-7

Hamal, O., Faddouli, N., Harouni, M., & Lu, J. (2022). Artificial intelligent in education. *Sustainability, 14*(5), Article 2862. https://doi.org/10.3390/su14052862

Hemmer, P., Westphal, M., Schemmer, M., Vetter, S., Vossing, M., & Satzger, G. (2023). Human-AI collaboration: The effect of AI delegation on human task performance and task satisfaction. In *Proceedings of the 28th International Conference on Intelligent User Interfaces* (pp. 453–463). ACM. https://doi.org/10.1145/3581641.3584052

Hu, B., Mao, Y., & Kim, K. J. (2023). How social anxiety leads to problematic use of conversational AI: The roles of loneliness, rumination, and mind perception. *Computers in Human Behavior, 145*, Article 107760. https://doi.org/10.1016/j.chb.2023.107760

Ilyas, M. (2022). Emerging role of artificial intelligence. *Journal of Systemics, Cybernetics and Informatics, 20*(6), 58–65. https://doi.org/10.54808/jsci.20.06.58

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons, 61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Kaiser, H. F. (1970). A second generation Little Jiffy. *Psychometrika, 35*(4), 401–415. https://doi.org/10.1007/BF02291817

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika, 39*(1), 31–36. https://doi.org/10.1007/BF02291575

Kapus, K., Nyulas, R., Nemeskéri, Z., Zádori, I., Muity, G., Kiss, J., Feher, A., Fejes, É., Tibold, A., & Fehér, G. (2021). Prevalence and risk factors of Internet addiction among Hungarian high school students. *International Journal of Environmental Research and Public Health, 18*(13), Article 6989. https://doi.org/10.3390/ijerph18136989

Keshishi, N., & Hack, S. (2023). Emotional intelligence in the digital age: Harnessing AI for students' inner development. *Journal of Perspectives in Applied Academic Practice, 11*(3), 172–175. https://doi.org/10.56433/jpaap.v11i3.579

Kim, K., Yoon, Y., & Shin, S. (2024). Explainable prediction of problematic smartphone use among South Korea's children and adolescents using a machine learning approach. *International Journal of Medical Informatics, 186*, Article 105441. https://doi.org/10.1016/j.ijmedinf.2024.105441

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.

Lage, L., Egidio, A., & Spear, A. L. (2023). Digital dependence in organizations: Impacts on the physical and mental health of employees. *Clinical Practice and Epidemiology in Mental Health, 19*. https://doi.org/10.2174/17450179-v19-e230109-2022-17

Lee-Won, R. J., Herzog, L., & Park, S. G. (2015). Hooked on Facebook: The role of social anxiety and need for social assurance in problematic use of Facebook. *Cyberpsychology, Behavior, and Social Networking, 18*(10). https://doi.org/10.1089/cyber.2015.0002

Levy, J., & Varela, J. (2006). *Modelización con estructuras de covarianzas en ciencias sociales: Temas esenciales, avanzados y aportaciones especiales* [Modeling with covariance structures in social sciences: Essential and advanced topics and special contributions] (1st ed.). Netbiblo.

Li, C. H. (2016) Confirmatory factor analysis with ordinal data: Comparing robust maximum likelihood and diagonally weighted least squares. *Behavior Research Methods, 48*, 936–949. https://doi.org/10.3758/s13428-015-0619-7

Liu, Z. (2022). The evolution of artificial intelligence and its collaboration with brain science. *Highlights in Science, Engineering and Technology, 1*, 31–39. https://doi.org/10.54097/hset.v1i.424

Ma, N., Khynevych, R., Hao, Y., & Wang, Y. (2025). Effect of anthropomorphism and perceived intelligence in chatbot avatars of visual design on user experience: Accounting for perceived empathy and trust. *Frontiers in Computer Science, 7*. https://doi.org/10.3389/fcomp.2025.1531976

Madhavan, P., & Wiegmann, D. A. (2007). Similarities and differences between human-human and human-automation trust: An integrative review. *Theoretical Issues in Ergonomics Science, 8*(4), 277–301. https://doi.org/10.1080/14639220500337708

Meerkerk, G.-J., Van Den Eijnden, R. J. J. M., & Garretsen, H. F. L. (2006a). Predicting compulsive Internet use: It's all about sex! *CyberPsychology & Behavior, 9*(1), 95–103. https://doi.org/10.1089/cpb.2006.9.95

Meerkerk, G.-J., Van Den Eijnden, R. J. J. M., Vermulst, A. A., & Garretsen, H. F. L. (2006b). The compulsive Internet use scale (CIUS): some psychometric properties. *CyberPsychology & Behavior, 12*(1), 1–6. https://doi.org/10.1089/cpb.2008.0181

Morales-García, W., Sairitupa-Sanchez, L., Morales-García, S. B., & Morales-García, M. (2024). Development and validation of a scale for dependence on artificial intelligence in university students. *Frontiers in Education, 9*. https://doi.org/10.3389/feduc.2024.1323898

Okello, H. T. (2023). Analyzing the impacts of artificial intelligence on education. *IAA Journal of Education, 9*(3), 8–13. https://doi.org/10.59298/IAAJE/2023/2.10.1000

Poulton, A., & Hester, R. (2019). Transition to substance use disorders: Impulsivity for reward and learning from reward. *Social Cognitive and Affective Neuroscience, 15*, 1182–1191. https://doi.org/10.1093/scan/nsz077

Riedl, M. O. (2019). Human-centered artificial intelligence and machine learning. *Human Behavior and Emerging Technologies, 1*, 33–36. https://doi.org/10.1002/hbe2.117

Rietveld, T., & van Hout, R. (1993). *Statistical techniques for the study of language and language behaviour*. De Gruyter Mouton. https://doi.org/10.1515/9783110871609

Robson, C., & McCartan, K. (2016). *Real world research* (4th Ed.). John Wiley & Sons.

Salvi, R., & Singh, R. (2023). Artificial intelligence and human society. *International Journal of Social Science and Human Research, 6*(9), 5441–5445. https://doi.org/10.47191/ijsshr/v6-i9-13

Sayyad, W., Mali, D., & Mistry, M. (2020). Smartphone usage and its addiction among undergraduate nursing students. *Indian Journal of Forensic Medicine & Toxicology, 14*(4), 3838–3843. https://doi.org/10.37506/ijfmt.v14i4.12229

Schepman, A., & Rodway, P. (2020). Initial validation of the general attitudes towards artificial intelligence scale. *Computers in Human Behavior Reports, 1*, Article 100014. https://doi.org/10.1016/j.chbr.2020.100014

Sinitaru, L. (2022). Addiction as a feeling of unfreedom. In *Proceedings of the Materials of the National Scientific Conference with International Participation "Problems of Social and Human Sciences and Modernization of Education"* (pp. 85–92). https://doi.org/10.46728/c.v1.25-03-2022.p85-92

Sotero, L., Ferreira da Veiga, G., Carreira, D., Portugal, A., & Relvas, A. P. (2020). Adicción a Facebook y adultos emergentes: La influencia de variables sociodemográficas, comunicación familiar y diferenciación del self [Facebook addiction and emerging adults: The influence of sociodemographic variables, family communication, and self-differentiation]. *Escritos de Psicología–Psychological Writings, 12*(2), 81–92. https://doi.org/10.24310/espsiescpsi.v12i2.9986

Steyvers, M., & Kumar, A. (2023). Three challenges for AI-assisted decision-making. *Perspectives on Psychological Science, 19*(5), 722–734. https://doi.org/10.1177/17456916231181102

Suh, W., & Ahn, S. (2022). Development and validation of a scale measuring student attitudes toward artificial intelligence. *Sage Open, 12*(2). https://doi.org/10.1177/21582440221100463

Trabelsi, Z., Alnajjar, F., Ambali, M. M., Gochoo, M., & Ali, L. (2023). Real-time attention monitoring system for classroom: A deep learning approach for student's behavior recognition. *Big Data and Cognitive Computing, 7*(1), Article 48. https://doi.org/10.3390/bdcc7010048

Velicer, W. F., & Fava, J. L. (1998). Affects of variable and subject sampling on factor pattern recovery. *Psychological Methods, 3*(2), 231–251. https://doi.org/10.1037/1082-989X.3.2.231

Vicente-Escudero, J. L., Saura-Garre, P., López-Soler, C., Martínez, A., & Alcántara, M. (2019). Mobile and internet addiction in adolescents and their relationship with psychopathological problems and protective variables. *Escritos de Psicología, 12*(2), 103–112. https://doi.org/10.24310/espsiescpsi.v12i2.10065

Vinichenko, M. V., Nikiporets-Takigawa, G. Y., Chulanova, O. L., & Ljapunova, N. V. (2021). Threats and risks from the digitalization of society and artificial intelligence: Views of generation Z students. *International Journal of Advanced and Applied Sciences, 8*(10), 108–115. https://doi.org/10.21833/ijaas.2021.10.012

Wang, B., Patrick, P. L., & Yuan, T. (2022). Measuring user competence in using artificial intelligence: Validity and reliability of artificial intelligence literacy scale. *Behaviour & Information Technology, 42*(9), 1324–1337. https://doi.org/10.1080/0144929X.2022.2072768

Widyanto, L., & McMurran, M. (2004). The psychometric properties of the Internet addiction test. *Cyber Psychology & Behavior, 7*(4), 443–450. https://doi.org/10.1089/cpb.2004.7.443

Xu, D. (2023). ChatGPT opens a new door for bioinformatics. *Quantitative Biology (Beijing, China), 11*, 204–206. https://doi.org/10.15302/j-qb-023-0328

Yanai, H., & Ichikawa, M. (2006). Factor analysis. *Handbook of Statistics, 26*, 257–296. https://doi.org/10.1016/S0169-7161(06)26009-7

Yankouskaya, A., Liebherr, M., & Ali, R. (2025). Can ChatGPT be addictive? A call to examine the shift from support to dependence in AI conversational large language models. *Human-Centric Intelligent Systems, 5*, 77–89. https://doi.org/10.1007/s44230-025-00090-w

Zhang, S., Zhao, X., Zhou, T., & Kim, J. H. (2024). Do you have AI dependency? The roles of academic self-efficacy, academic stress, and performance expectations on problematic AI usage behavior. *International Journal of Educational Technology in Higher Education, 21*, Article 34. https://doi.org/10.1186/s41239-024-00467-0

Zhuo, T. Y., Huang, Y., Chen, C., & Xing, Z. (2023). Red teaming ChatGPT via jailbreaking: Bias, robustness, reliability and toxicity. *arXiv*. https://doi.org/10.48550/arXiv.2301.12867