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Development and validation of a scale measuring students' use of generative artificial intelligence tools

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ABSTRACT

The emergence of artificial intelligence (AI) in education, such as students' use of generative artificial intelligence (GAI) tools in academic work, has profoundly transformed the learning ecosystem, offering both promising opportunities and potential challenges. Considering that such tools are still a developing area of study in education, this paper aimed to develop a scale that can assess and describe students' practices and perspectives towards using GAI tools. Through an exploratory-sequential mixed methods design, an interview of 20 higher education students and a scoping literature review were used to generate scale items in the first phase of the study. In the second phase of the study, two pilot tests of the scale participated by 793 students were implemented. Exploratory and confirmatory factor analysis (CFA), internal consistency, and convergent validity tests were also carried out. The developed scale consists of 26 statements covering the following factors: i) research tool; ii) communication tool; iii) reliance; and iv) ethical use. The CFA model confirmed these factors, and all fit indices show that the overall structure of the scale has acceptable to good fit. The scale's psychometric properties reveal that it is valid and reliable. This scale development study implicates schools to use a structured way of assessing how students engage with GAI tools in academic settings and rethink ways to support students' learning through the responsible use of AI tools.

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1. INTRODUCTION

The rapid advancements in generative artificial intelligence (GAI) have significantly influenced various sectors, including education. GAI refers to systems capable of creating content such as text, images, and music based on large datasets and complex algorithms [1]. Tools such as chat generative pretrained transformer (ChatGPT), Google Gemini, Microsoft Co-pilot, DALL-E, and Perplexity.ai are becoming widely adopted by students, offering them a new dimension of support in generating ideas, drafting written content, solving complex problems, and enhancing creative outputs [2]. As these tools become more accessible, their integration into educational contexts is expanding rapidly, reshaping how students approach learning tasks.

This phenomenon offers a huge potential in enhancing learning experiences and promising avenues for improving student outcomes. These tools provide real-time feedback, automate repetitive tasks, and promote creativity [3], enhancing student engagement and learning efficiency. GAI has the potential to democratize access to knowledge by serving as a personalized learning assistant, catering to students' individual needs and learning styles. It allows learners to approach complex tasks more confidently and experiment and iterate with minimal friction. However, artificial intelligence (AI) ease and efficiency come with a critical caveat: the risk of overreliance and possible unethical use. The increasing dependency on AI tools raises concerns about the erosion of fundamental skills such as critical thinking, problem-solving, and independent learning [4]. As students rely more heavily on AI-generated content, there is a growing concern that the depth and rigor of their learning may diminish and that the misuse of these tools will impact their academic integrity. The need for a balanced integration of AI into education, where students can benefit from its capabilities without undermining their autonomy, has therefore emerged as a critical focus in the discourse on technology-enhanced learning [5].

While there has been a surge in research on integrating AI in education, much of the focus has been on the positive aspects, such as enhancing student engagement, personalizing learning experiences, and improving academic outcomes [6]. However, relatively little attention has been paid to the potential overreliance on GAI tools, particularly how this dependency may affect students' critical thinking, independent problem-solving, and overall learning behaviors [7]. Although some studies have explored the implications of AI in education, there is a lack of empirical data and validated instruments to measure the extent of students' reliance on GAI. Moreover, existing research often overlooks the nuanced effects of AI dependence on specific academic outcomes, cognitive skills, and long-term learning development [8]. This creates a significant gap in understanding how students interact with AI technologies and the potential risks associated with overreliance on these tools.

Given the rapid rise of GAI in educational settings, it is crucial to understand how and to what extent students use these tools for academic purposes. This gap points to the need for a standardized measurement scale to evaluate students' use of GAI in academic contexts. This will provide educators with insights for promoting responsible AI use [9]. Developing a scale to measure students' use of GAI will provide valuable insights for educators, allowing them to design strategies that maximize the benefits of AI while mitigating its potential adverse effects on student learning outcomes [2]. Such a scale can also guide the implementation of responsible AI use policies in education, helping to foster a learning environment where technology serves as an aid rather than a crutch.

While existing research has extensively explored the positive implications of GAI in education—such as enhancing student engagement, personalizing learning experiences, and improving academic outcomes—there remains a significant gap in understanding the potential risks associated with overreliance on these tools. This study is among the first to systematically develop and validate a standardized measurement scale that quantifies students' dependency on GAI in academic contexts. Unlike prior research, which largely focuses on AI benefits, this study critically examines its influence on essential cognitive skills, including critical thinking, independent problem-solving, and long-term learning behaviors.

The novelty of this research lies in its empirical approach to assessing AI reliance, addressing the lack of validated instruments to measure students' interactions with GAI. By establishing a data-driven scale, this study provides a framework for educators and policymakers to better understand students' AI usage patterns and to design interventions that promote responsible and balanced AI integration in learning. Furthermore, this research bridges the gap between AI potential benefits and its unintended consequences, ensuring that educational technology serves as a tool for enhancement rather than replacement of fundamental learning skills.

The primary purpose of this study is to develop and validate a scale that measures students' reliance on GAI in educational contexts. This scale aims to provide a standardized tool for educators and researchers to assess the extent to which students depend on AI for academic tasks and the potential impact this reliance may have on their learning experiences. By establishing the construct validity, the study ensures that the scale is grounded in empirical data, reflecting students' real-world interactions with AI in an educational context. The ultimate goal is to equip educators with actionable insights to promote responsible and balanced use of AI in education, ensuring that students benefit from the responsible use of these tools without compromising essential cognitive and academic skills.

2. LITERATURE REVIEW

2.1. Generative artificial intelligence in education

GAI tools are designed to generate content autonomously, ranging from text, images, and even code, based on user prompts. ChatGPT, developed by OpenAI, is a text-based GAI that can hold conversations, answer questions, write essays, and provide detailed explanations across a wide range of subjects. DALL-E, also by OpenAI, generates images based on textual descriptions, making it useful for visual content creation [10]. In educational contexts, GAI tools are increasingly used by students for various academic tasks. ChatGPT has become a popular tool for assisting with essay writing, summarizing complex texts, generating study guides, and even providing feedback on drafts [11]. Students can use these tools for quick problem-solving by asking questions related to math, science, or any subject matter and receiving detailed explanations in real time. GAI tools also assist with content creation in digital art, design, and media production, where students may use DALL-E to visualize concepts or create original graphics for projects [12].

The rise of these AI systems signals a shift in the traditional approaches to education. These tools provide immediate, on-demand student support, often as supplemental learning aids that complement classroom instruction [13]. GAI tools are particularly beneficial for self-directed learners who want to explore concepts beyond classroom hours or require additional resources to understand complex topics.

2.2. Student interaction with generative artificial intelligence tools

GAI tools in education reshape students' learning behaviors, influencing autonomy, problem-solving abilities, and time management [12]. These tools offer personalized support, often acting as on-demand tutors or creative partners, which can significantly impact how students approach learning. GAI tools enable students to take greater control of their learning experiences by providing instant feedback and resources. These tools can clarify concepts or solve problems without waiting for instructor feedback. Also, they help students tackle complex academic problems by providing solutions, explanations, and even step-by-step guidance [14]. This capability enhances problem-solving skills by offering alternative methods or perspectives students may not have considered. For instance, a student struggling with a math problem might input it into ChatGPT [15], which can offer the answer and an explanation of the steps involved. These tools also show greater engagement from students. Compared to students who did not utilize it, those who did showed a 25% improvement in their grades and a 30% increase in class involvement. Furthermore, compared to manual assessments, the tool's assessment precision was 95%, indicating great consistency [16]. However, frequently using these GAI tools for problem-solving may lead to a superficial understanding of concepts because students might focus on obtaining quick answers rather than engaging in deeper critical thinking. Integrating GAI tools in education marks a transformative shift in learning practices, offering students personalized, on-demand support across various academic disciplines. The impact of GAI on education hinges on how well students balance the convenience of AI-generated solutions with meaningful engagement in learning processes.

3. METHOD

The scale development process in this study used an exploratory sequential mixed-methods design. It is a sequential design that uses qualitative methods of gathering and analyzing data, followed by quantitative approaches [17]. The first phase, which focuses on item conceptualization and writing, warrants that the researchers have an adequate and comprehensive understanding of the construct by interviewing students and analyzing relevant documents and literature. The second phase involves statistical scale validation using factor analysis, internal consistency, and convergent validity tests.

For the scale development, items were generated based on the interview data of 20 higher education students selected purposively and a review of existing literature on GAI. Interview questions focus on how students use GAI tools in their academic work, their personal experiences using these tools, and the considerations they take into account. Forty statements in Likert scale format were drafted, and an online version of the instrument was administered to the respondents. For the first run of pilot testing, 506 higher education students in three universities located in Manila, Philippines, were involved in the study. The inclusion criteria set by the researchers in finalizing the survey respondents are: i) the participants should be full-time university students for at least one year and ii) they should be using GAI tools in their academic work for the last six months. In the second run of pilot testing, 287 higher education students participated in the online survey. The profile of the 813 respondents is shown in Table 1. In examining the psychometric properties of the scale, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), internal consistency test, and convergent validity test were carried out. The researchers observed ethical considerations to safeguard participants' rights and welfare during the conduct of the study.

Table 1. Demographics of the respondents

Profile		Frequency	Percentage (%)
Gender	Female	522	64.21
	Male	291	35.79
Total		813	100.00
Specialization	Education	302	37.15
	Business	260	31.98
	Communication	251	30.87
Total		813	100.00

4. RESULTS

The researchers collected evidence of the construct validity of the scale. EFA was carried out to reduce the number of items in the initial scale to identify underlying variables or factors that explain the relationship between the observed variables [18]. This process aided the researcher in focusing on fewer items that explain the structure by regrouping the observed variables into smaller and more meaningful clusters rather than taking into account a large number of items that may not be relevant to the study [19].

Assumptions tests in using EFA were tested, and the results reveal that the sample size is adequate for EFA through the Kaiser-Meyer-Olkin (KMO) test with a value of 0.965. A KMO value greater than 0.80 demonstrates sample adequacy for factor analysis. Barlett Sphericity test result was significant ($\chi2$=12560.760; $p<0.05$), which means that the pilot test data is suitable for EFA as the correlation matrix of the variables in the dataset diverges significantly from the identity matrix [20].

Out of 40 statements from the initial scale, 26 were retained because they have a factor loading of at least 0.40. A factor loading of less than 0.40 means that the correlation of the item with the factor is weak and must be removed from the scale [21]. Upon exploring the common themes supported in the literature, the first factor is initially described as a “research tool” consisting of seven statements (1-7). The second generated factor is called the “communication tool,” where six items are loaded under this factor (statements 8-13). Eight statements clustered in the third factor (statements 14-21) which was described as “perceived reliance.” The last factor is clustered under the factor “ethical use,” with five statements loading in this factor (statements 22-26). The uniqueness value for each statement was presented which describes the variance that is measured by the item that cannot be accounted for by common factors is represented by the uniqueness value. A low uniqueness value, which is closer to zero, is generally desirable. The variable aligns well with the identified factors, strengthening the overall factor model [18].

Table 2 shows the results of the EFA of the GAI usage scale for students, highlighting the factor loadings and the underlying structure of the scale. The SS loadings is the sum of the squared loading, which is used to determine the value of each factor. All loading greater than 1 implies that the factor can be kept for further analysis [19] since higher factor loading shows that it explains a greater proportion of the total variance in the data. The cumulative percentage of variance is 59.8%, which is acceptable since the suggested percent of variance is 50-60% for EFA [22]. The presented data reflects how well a variable contributes to measuring the underlying construct the factor represents.

Table 2. EFA of the GAI usage scale for students

Statements	Factor				Uniqueness
	1	2	3	4	
1. I use AI tools to find answers to specific problems I encounter in class.	0.720				0.301
2. I use AI tools to get helpful advice about getting things done in school.	0.709				0.479
3. I use AI tools to find relevant materials and sources for my study.	0.622				0.418
4. I use AI tools to look for outlines for academic presentation and reporting.	0.592				0.471
5. I use AI tools to support my hypothesis.	0.514				0.543
6. I use AI tools to generate creative ideas for school tasks and projects.	0.473				0.525
7. I use a variety of AI tools to research ideas and facts.	0.466				0.332
8. I use AI tools to improve the clarity of my statements in written or oral communication.		0.713			0.346
9. I use AI tools to find the right words for written or oral communication.		0.681			0.317
10. I use AI tools to improve the grammatical structure of my statements in written or oral communication.		0.676			0.357
11. I use AI tools to write essays and reports.		0.597			0.368
12. I use AI tools to determine the most appropriate way of expression for a given context.		0.585			0.382
13. I refine the tone and style of my writing using AI tools.		0.512			0.320
14. I depend on AI tools because it enhances my learning.			0.741		0.388
15. I use AI tools to answer questions in our test when there are opportunities.			0.712		0.359
16. I use AI tools regardless of what others perceive about it.			0.684		0.382
17. I prefer to use AI tools over traditional methods for my study.			0.642		0.377
18. I use AI tools to complete school tasks efficiently.			0.626		0.399
19. I depend on AI tools to confirm facts learned from peers, teachers, or other online sources.			0.617		0.218
20. I prefer to use AI tools over traditional methods for my study.			0.608		0.466
21. I use AI tools to complete school tasks efficiently.			0.551		0.361
22. I observe transparency and accountability while using AI tools.				0.833	0.293
23. I engage in efforts to address ethical challenges associated with using AI tools.				0.812	0.277
24. I continuously reflect and self-assess my use of AI tools in my studies.				0.773	0.428
25. I know when not to use AI tools in school.				0.723	0.394
26. I use AI tools responsibly in my study.				0.705	0.357

Note: ‘Maximum likelihood’ extraction method was used in combination with a ‘varimax’ rotation

Table 3 shows the EFA factor loadings and variances, identifying the key components contributing to the scale's structure. CFA was conducted to confirm the identified factors of the scale measuring how students use GAI tools in schools [23]. Figure 1 presents the CFA model, and Table 3 summarizes how each item contributes to the measurement of the specified factors. Looking at the standardized coefficients of the items for each factor, it shows that all items have a relatively strong relationship with the factor they measure: research tool (β=0.802-0.930), communication tool (β=0.723-0.848), reliance (β=0.733-0.821), and ethical use (β=0.720-0.781). All p-values are less than 0.05, meaning all relationships are statistically significant. Table 3 provides more information about the CFA model.

Table 3. EFA factor loadings and variances

Factor	Name	SS loadings	% of variance	Cumulative (%)
1	Research tool	7.49	18.7	18.7
2	Communication tool	6.42	16.1	34.8
3	Reliance	5.90	14.8	49.6
4	Ethical use	4.10	12.2	61.8

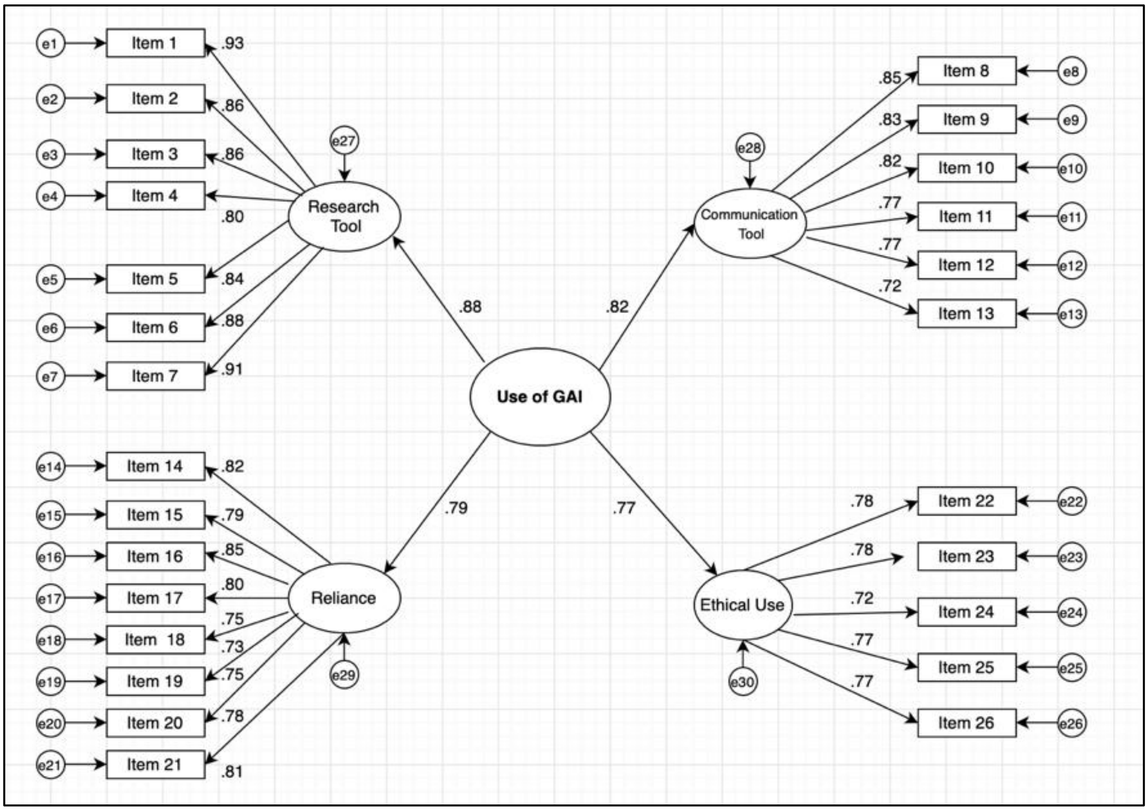

Figure 1. CFA of a scale measuring students' usage of GAI

Table 4 shows the CFA results, demonstrating the model fit indices and factor loadings for the scale measuring students' usage of GAI tools. CFA was employed to confirm the model fit of the scale structure initially identified using EFA. The different measurement models of CFA (χ^2/df=3.51, comparative fit index (CFI)=0.932, Tucker-Lewis's index (TLI)=0.916, root mean square error of approximation (RMSEA)=0.031 and standardized root mean square residual (SRMR)=0.044) confirmed the structure of the scale. The CFA results confirmed the seven factors for the model.

The range of acceptable fit indices for CFA models does not have a universal threshold and varies among scholars and sources. For the ratio χ^2/df, the desired value is ≤3 but any value <5 can be accepted [24]. For CFI and TLI, the value considered a great fit is CFI/TFI>0.95, but a value greater than 0.80 is generally accepted [25]. Also, the desired value for RMSEA and SRMR is <0.05, and a value <0.10 is a moderately good fit [26]. Overall, the model is generally acceptable based on the given indices.

Table 4. CFA of a scale measuring students' usage of GAI tools

Factor	Item	Estimate	SE	β	z	p
Research tool	1	0.916	0.080	0.930	11.47	<0.001
	2	1.018	0.090	0.864	11.37	<0.001
	3	0.839	0.076	0.863	11.04	<0.001
	4	0.626	0.060	0.802	10.48	<0.001
	5	0.775	0.070	0.841	11.03	<0.001
	6	0.816	0.073	0.878	11.11	<0.001
	7	1.022	0.070	0.913	11.18	<0.001
Communication tool	8	1.211	0.061	0.848	9.40	<0.001
	9	1.018	0.068	0.832	9.67	<0.001
	10	0.839	0.090	0.824	10.81	<0.001
	11	0.626	0.084	0.770	11.73	<0.001
	12	0.775	0.084	0.769	11.26	<0.001
	13	0.816	0.073	0.723	10.57	<0.001
Reliance	14	0.859	0.076	0.821	11.29	<0.001
	15	1.062	0.094	0.793	11.25	<0.001
	16	0.746	0.068	0.800	10.93	<0.001
	17	0.500	0.050	0.749	9.98	<0.001
	18	0.903	0.081	0.733	11.17	<0.001
	19	1.151	0.010	0.753	11.52	<0.001
	20	0.839	0.076	0.778	11.00	<0.001
	21	0.849	0.075	0.806	11.30	<0.001
Ethical use	22	1.015	0.073	0.781	10.43	<0.001
	23	0.989	0.081	0.777	9.98	<0.001
	24	0.944	0.011	0.720	9.65	<0.001
	25	1.012	0.090	0.767	9.54	<0.001
	26	0.891	0.058	0.771	10.05	<0.001

Legend: SE–standard error of the estimate; β(beta)-standardized factor loading; z–z-value; p–p-value

Table 5 shows the CFA model fit indices, indicating the overall goodness-of-fit for the scale measuring students' usage of GAI tools. The average variance extracted (AVE) is a statistical measure of a scale's convergent validity, indicating how closely different measures of the same construct are related. The AVE represents the average variance in a scale's items that the measured construct can explain. It is calculated by squaring each item's standardized factor loadings, adding them together, and dividing the total by the number of items on the scale. AVE values range from 0 to 1, with higher values indicating stronger convergent validity [27].

Table 6 shows the convergent validity and reliability indices, demonstrating the internal consistency and construct validity of the scale's factors. The AVE is especially important in convergent validity because it ensures that the items on a scale measure the same underlying construct. A high AVE indicates that the items are more strongly related to one another than other constructs, implying that they measure the same construct. In general, a value of 0.5 or higher indicates good convergent validity, though the specific threshold may vary depending on the context and measure used. All components have AVE values greater than 0.50, demonstrating the scale's construct convergent validity. In addition, all reliability indices ($\alpha \geq 0.70$) are acceptable, which shows the scale items have an acceptable internal consistency.

Table 5. CFA model fit indices of the scale measuring students' usage of GAI tools

Model fit index	Measurement model	Recommendation
Chi-square/df ratio	3.510	Acceptable fit
CFI	0.932	Acceptable fit
TLI	0.916	Acceptable fit
RMSEA	0.031	Good fit
SRMR	0.044	Good fit

Table 6. Convergent validity and reliability indices of the factors of the scale measuring students' usage of GAI tools

Factors	AVE	Cronbach alpha
Research tools	0.732	0.822
Communication tools	0.717	0.836
Reliance	0.794	0.913
Ethical use	0.664	0.840

5. DISCUSSION

The emergence of AI tools in education, such as using GAI tools by students and teachers, has caused a learning ecosystem shift worldwide. Despite the ubiquitous discussions about the topic, great depth of inquiry is required to understand the practices of school stakeholders in using GAI and its impact on the teaching and learning process. There is tension about whether GAI is beneficial or unfavorable among students and teachers. Students' usage and practices towards these tools are still a grey area and a developing area of study. The present study examined how students use GAI in their academic work. These inputs were used in developing a valid and reliable assessment of students' practices in using GAI.

Both qualitative and quantitative data reveal that students' usage of GAI can be best described using four factors: i) research tool; ii) communication tool; iii) reliance; and iv) ethical use. The study's results discussed a comprehensive analysis of how students use GAI tools across these four key factors. These factors emerged from the EFA and the CFA, validating the scale structure that measures students' engagement with GAI.

The EFA identified 26 significant items from the original 40 statements, regrouped into four meaningful factors with sufficient loadings. The cumulative percentage of variance these factors explain is 61.8%, suggesting that they provide a robust explanation of the relationships among the observed variables. The factor loadings presented in the EFA were all greater than 0.40, which meets the threshold for retaining items, and the uniqueness values indicate that the variables align well with the identified factors, further strengthening the model.

Factor 1, research tool, accounted for 18.7% of the variance, emphasizing how students use AI for academic tasks like finding information, generating ideas, and supporting hypotheses. The high loadings for this factor suggest a strong reliance on AI for research-related activities, reflecting its growing importance in academic contexts. AI supports students in locating information efficiently, generating ideas, and organizing their research, leading to a more streamlined academic process. For example, AI has been shown to enhance information retrieval and hypothesis generation by assisting students in refining their search strategies and identifying relevant literature [28].

Factor 2, communication tool, explained 16.1% of the variance, focusing on how students use AI to enhance written and oral communication. This includes improving grammar, style, and clarity, highlighting the role of AI in refining communication skills. The items under this factor had consistently strong factor loadings, indicating that students significantly engage with AI tools to enhance their communicative abilities. AI-powered writing assistants significantly improve the quality of student writing by offering real-time feedback on grammatical errors, sentence structure, and coherence [29]. Moreover, AI tools also contribute to refining oral communication skills, offering students personalized feedback and opportunities to practice presentations [30]. The consistent high-factor loadings suggest that AI is crucial in helping students enhance their communication capabilities across various contexts.

Factor 3, reliance, captured 14.8% of the variance and emphasized students' growing dependence on AI tools for learning and academic performance. This factor is noteworthy as it reflects both the efficiency AI provides and potential over-reliance, where students prefer AI tools over traditional methods for studying and confirming facts. The high factor loadings here indicate that AI tools have become indispensable for many students, raising important considerations about critical thinking and independent learning. Students may increasingly rely on AI to validate facts and complete tasks rather than develop analytical skills [31]. While AI tools undoubtedly improve learning outcomes by providing quick access to information, their overuse can diminish the importance of traditional learning methods and reduce opportunities for critical engagement with the material [32].

Lastly, factor 4, ethical use, which explained 12.2% of the variance, is pivotal as it encapsulates students' awareness and practice of responsible AI usage. This factor includes items like transparency, accountability, and ethical challenges, with strong loadings showing that students are conscious of the ethical implications of using AI. However, it may be a developing area. Ethical concerns such as data privacy, bias in AI algorithms, and the misuse of AI for academic dishonesty have been highlighted as areas requiring more attention in educational contexts [33]. Studies demonstrate that while students are becoming more conscious of ethical considerations [34], their understanding of AI responsible use is still evolving, necessitating further educational efforts.

The CFA results confirmed the validity of the four-factor structure with acceptable fit indices (χ^2/df=3.51, CFI=0.932, TLI=0.916, RMSEA=0.031, and SRMR=0.044). These values align with scholarly recommendations, further supporting the reliability of the identified factors. High standardized coefficients (ranging from 0.723 to 0.930) across all factors confirm the strong relationships between the items and their respective factors, reinforcing the construct validity of the scale. The findings underscore the multi-dimensional nature of students' use of GAI tools, highlighting areas of academic application, communication, reliance, and ethical responsibility, with potential implications for further research and educational practice.

6. CONCLUSION

The study comprehensively explains how students engage with GAI tools across four dimensions: research, communication, reliance, and ethical use. The validation process demonstrates the robustness of the identified factors, showing that these dimensions offer a meaningful explanation of students' interactions with AI in academic settings. The cumulative variance of the factors suggests that these domains capture significant aspects of student behavior with GAI, emphasizing its pivotal role in modern education. The strong factor loadings further underscore the model's validity, especially in research and communication areas, where AI has been shown to enhance students' academic work and communicative competencies.

The findings have significant implications for educational practice, particularly how AI is integrated into learning environments. The increasing reliance on AI tools for research and communication highlights the need for educators to guide students in balancing the efficiency offered by AI with the development of critical thinking and independent learning skills. While beneficial, the substantial reliance on AI for academic tasks raises concerns about over-dependence, which could hinder students' ability to engage in deeper cognitive processes without technological support. Similarly, the emphasis on ethical use suggests that, while students are becoming more aware of the responsibilities associated with AI, much work remains to be done to improve their understanding of transparency, accountability, and ethical challenges in AI use.

In conclusion, this study's findings contribute to the growing discourse on AI in education by shedding light on the multi-dimensional engagement of students with GAI tools. The research suggests the need for balanced AI integration strategies in curricula that leverage AI strengths in enhancing academic performance and fostering students' ethical use and critical independence. Future studies could further explore the long-term effects of AI reliance on learning outcomes and develop frameworks that encourage responsible and effective AI usage in academic settings. These results can inform educators, policymakers, and technologists as they design and implement AI-driven educational tools that support holistic student development.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial, personal, or professional interests that could have influenced the work reported in this paper. Authors state no conflict of interest.

INFORMED CONSENT

The protection of privacy is a legal right that must not be breached without individual informed consent. In cases where the identification of personal information was necessary for scientific reasons, we obtained full documentation of informed consent, including written permission from all individuals prior to their inclusion in this study.

ETHICAL APPROVAL
The research involving human participants in this study complied with all relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration. Ethical approval was obtained from the University Research Ethics Committee of Far Eastern University prior to conducting the interviews.

DATA AVAILABILITY
The data that support the findings of this study are available from the corresponding author [AB], upon reasonable request. Due to privacy and ethical considerations, the data are not publicly available.

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