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ORIGINAL ARTICLE

Development of the GAI Dependence Scale: a validity and reliability study

*Weizhong Zhang** [1 · A,B,C,D,E,F,G], *Guangxian Leng** [1 · A,B,C,D], *Yanfeng Xu* [2 · A,B,C]

1: Fujian Polytechnic Normal University, Fuqing, China
2: Fujian Normal University, Fuzhou, China

*Weizhong Zhang and Guangxiang Leng are co-first authors.

BACKGROUND
While individuals use generative artificial intelligence (GAI) to enhance their productivity, they may also develop psychological and behavioral over-reliance on these tools. Evaluating the extent of an individual's dependence on GAI is crucial for conducting related research.

PARTICIPANTS AND PROCEDURE
The research involved 627 participants. Exploratory and confirmatory factor analysis was conducted to determine the construct validity of the scale. The results supported a structure consisting of four sub-dimensions and 19 items. The sub-dimensions are Usage Intensity, Content Dependence, Withdrawal Symptoms, and Negative Consequences.

RESULTS
Confirmatory factor analysis indicated good model fit. Significant relationships were found with the GAI Dependence Scale, AI Dependence Scale (version of six items), and Behavioral Intention Scale during the analysis of the scale's criterion validity. Cronbach's α internal consistency, and the test-retest method were used to assess the reliability of the scale. Cronbach's α internal consistency coefficient for the total score was found to be .92 for Sample 1 and .90 for Sample 2. Additionally, the test-retest reliability over a four-week interval yielded a coefficient of .81. Both coefficients are considered to indicate acceptable levels of reliability.

CONCLUSIONS
The scale is an effective and reliable tool for assessing individual dependence on GAI.

KEY WORDS
generative artificial intelligence; technology dependence; scale development; reliability and validity

CORRESPONDING AUTHOR – Weizhong Zhang, Ph.D., Fujian Polytechnic Normal University, Campus New Village, 1 Longjiang Str., Fuqing 350300, China, e-mail: 1358860312@qq.com

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BACKGROUND

As a revolutionary technology, generative artificial intelligence (GAI) is rapidly reshaping various aspects of our lives, including applications such as ChatGPT. Many researchers have extensively examined the potential and benefits of GAI across diverse domains (Dwivedi et al., 2023; Wach et al., 2023). However, alongside its rapid development, GAI has also introduced a range of challenges, underscoring its dual-edged nature. A growing body of research has highlighted an increasing dependency on GAI, which has led to concerns regarding its misuse and overreliance (Kasneci et al., 2023; King, 2023). GAI has significantly enhanced the automation of routine tasks, contributing to greater convenience and efficiency in daily life, which, in turn, may encourage individuals to develop excessive reliance on the technology (Onnasch et al., 2014). On the other hand, the "digital authority" of GAI may foster blind trust and an almost reverential attitude toward the technology (Dwivedi et al., 2021). A particularly concerning trend identified by Gao et al. (2022) is the tendency of users to unquestioningly accept GAI-generated outputs without verifying their accuracy. In addition to these issues, some scholars have examined the ethical (Liebrenz et al., 2023) and privacy concerns (Paul et al., 2023) that arise from GAI dependence. Psychological and behavioral risks linked to overreliance on GAI have also been explored. For example, studies suggest that overuse of GAI may negatively affect students' academic performance (Abbas et al., 2024), and erode their intrinsic motivation to succeed (Krou et al., 2021). Furthermore, over-dependence on GAI could undermine creativity, critical thinking, and decision-making skills, both in educators and learners, thereby potentially diminishing the overall quality of education (Ahmad et al., 2023; Chen et al., 2024; Zhang et al., 2024).

Currently, there is no consensus on a standardized definition of GAI dependence; the precise content and structure are still unclear. By drawing on established frameworks for internet addiction and mobile phone addiction, a preliminary conceptualization of GAI dependence can be formulated. Young (1998) defines internet addiction as the inability to control the impulse to engage in online activities, which subsequently disrupts various aspects of an individual's life. Similarly, Lei and Li (2003) characterize internet dependence as a condition in which prolonged and repetitive internet use leads to significant impairments in cognitive functions, emotional and psychological well-being, behavioral activities, and even physiological health, with individuals unable to reduce or cease their internet use despite the adverse effects. Leung (2008) defines mobile phone addiction as the excessive use of mobile phones beyond practical necessity, resulting in physiological or psychological dependence on the device. GAI dependence, as an emerging form of technological dependence, can be conceptualized as a phenomenon akin to other established forms of technological addiction. Drawing from established models of technological dependence, it can be characterized by two key components: first, an individual's inability to regulate their use of GAI tools; second, an overreliance on these tools that impairs their cognitive, emotional, and behavioral functioning. Based on these characteristics, this study defines GAI dependence as the uncontrollable overuse of GAI tools, resulting in technological dependence and subsequently leading to adverse effects on the individual's daily life and well-being.

Some studies have employed adapted technology dependence scales to assess individuals' reliance on GAI (Hu et al., 2023; Zhang et al., 2024). However, this approach may undermine the reliability of the findings. While GAI dependence can be classified as a subset of technology dependence, similar to internet and mobile phone dependence, it is crucial to recognize the essential differences between these forms of dependence. Internet and mobile phone dependence typically involve a broad range of online activities, including social media use and gaming, which have been shown to contribute to psychological issues such as anxiety and depression, as well as to impair face-to-face communication skills, leading to broader social and emotional challenges (Lozano-Blasco et al., 2022; Pan et al., 2020; Zhang et al., 2020). In contrast, the negative consequences of GAI dependence are more closely linked to cognitive development, particularly with regard to critical thinking, creativity, and decision-making, which are typically more directly associated with academic and work-related tasks (Calzada, 2024). Further research suggests that overuse of GAI may result in negative outcomes such as laziness, impaired memory, and reduced self-efficacy (Abbas et al., 2024; Zhang et al., 2024). Consequently, the distinction between GAI dependence and internet or mobile phone dependence is not only based on the objects of reliance but also on the distinct core symptoms each form of dependence presents. Zhang et al.'s (2024) adaptation of the Facebook dependence scale to assess GAI dependence may not adequately capture the unique structural aspects of GAI dependence. Therefore, it is necessary to develop an effective and reliable GAI dependence scale.

The present study employed semi-structured interviews to investigate the underlying structure of GAI dependence. Additionally, a GAI Dependence Scale was developed and subjected to rigorous testing for reliability and validity. The primary aim of this study was to offer a reliable and valid tool for assessing GAI dependence, thereby advancing research in this field.

PARTICIPANTS AND PROCEDURE

PARTICIPANTS

Sample 1. A total of 30 participants were recruited through the online survey platform Credamo to participate in semi-structured interviews exploring public perceptions of dependence on GAI technology. The sample consisted of 26 females, with an average age of 33.63 years (*SD* = 7.23).

Sample 2. A second sample of 300 participants was recruited via Credamo, with all participants passing the validity check item. The check item was included to assess whether participants had carefully read the instructions. This item requires participants to select a specific response, and if an incorrect choice is made, it suggests insufficient attention to the instructions, resulting in the exclusion of their data. Of these, 199 were female, with an average age of 30.14 years (*SD* = 7.03).

Sample 3. A third sample of 300 participants was recruited through Credamo. Three participants who failed the validity check questions were excluded, resulting in a final sample of 297 participants used for confirmatory factor analysis. This sample consisted of 206 females, with an average age of 31.14 years (*SD* = 6.66).

Retesting sample. Four weeks after data collection from Sample 3, a subsample of 100 university students was randomly selected to assess test-retest reliability. The retesting sample included 59 females, with an average age of 29.76 years (*SD* = 6.90).

Specific demographic information can be found in the Supplementary materials (Table S1).

SCALE DEVELOPMENT PROCESS AND INSTRUMENTS

Semi-structured interviews

The interviews were introduced with the question, "What specific psychological and behavioral manifestations do you think characterize individuals who are overly dependent on GAI technology?". Based on the participants' responses, the interviewer encouraged further discussion, prompting participants to reflect on their personal experiences related to GAI dependence. For example, "How do you think the emergence of GAI tools has affected your personal development? Why?".

Item induction, development, and content validity testing

First, the audio recordings of the semi-structured interviews were transcribed into text, resulting in a corpus of 37,665 words. Next, the collected textual information was categorized and summarized, leading to the development of 25 items, which were initially grouped into four dimensions: (1) GAI Usage Intensity, which measured the amount and frequency of GAI usage (4 items); (2) Overreliance on GAI, which assessed individuals' trust in the content generated by AI (6 items); (3) Negative Consequences of GAI Usage, which examined the negative psychological, behavioral, and social effects of frequent GAI usage (6 items); and (4) Withdrawal Symptoms from GAI Usage, which measured individuals' psychological experiences when unable to use GAI (8 items).

Following the development of the initial item pool, 30 participants were invited to evaluate the readability and clarity of the items. Based on their feedback, revisions were made, resulting in a preliminary GAI Dependence Scale consisting of 24 items. The scale employs a 7-point Likert scale, where higher scores reflect a greater level of dependence on GAI. Finally, two professors, four PhDs and eight Masters in psychology were invited to assess the content validity of the scale.

Instruments

AI Dependence Scale (version of six items). In Zhang et al.'s (2024) study, the researchers adapted the Facebook Addiction Scale developed by Andreassen et al. (2012) to measure dependence on ChatGPT using six items (7-point Likert scale). For example, "I have tried to reduce my use of GAI but have not been successful." The scale demonstrated good reliability and validity in the current study, with a Cronbach's α coefficient of .83.

Behavioral Intention (BI). BI refers to an individual's willingness and intention to use a specific technology for a defined task or purpose (Venkatesh et al., 2012). In this study, three items from Strzelecki's (2023) research were used to assess individuals' behavioral intentions toward using GAI tools. For example, "I intend to continue using GAI in the future." The scale showed good reliability, with a Cronbach's α coefficient of .74 in the current study.

DATA ANALYSIS

The current study employed descriptive statistics, item analysis, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and Pearson correlation analysis, using SPSS 21.0 and Mplus 8.1 for data analysis. Prior to data processing, skewness and kurtosis for each item were calculated. According to prevailing research, data can be regarded as approximately normally distributed when the absolute values of skewness and kurtosis are below thresholds of 2 and 7, respectively (Murtagh & Heck, 2012; Yuan & Bentler, 2001).

Item analysis

First, the total scores were ranked from low to high, with the top and bottom 27% of the scores identified as the high and low groups, respectively. Independent samples t-tests were then performed to compare the scores between the two groups for each item. Items showing significant differences between the high and low groups were considered to have adequate discriminant power (Wu, 2010). Next, the correlation between each item and the total score was assessed, and any item with a correlation below 0.40 was removed from further analysis (Wu, 2010).

Exploratory factor analysis

To assess the suitability of the data for factor analysis, the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity were conducted. The KMO value ranges from 0 to 1, with values closer to 1 indicating better suitability for factor analysis. KMO values between 0.80 and 0.90 suggest an adequate sample size, while values above 0.90 indicate a sufficient sample size for factor analysis (Field, 2024; Güler, 2021). Exploratory factor analysis was then performed using the maximum variance method. Kline (2014) recommends that the cumulative variance explained by the factors should exceed 40% to determine the factor structure of the scale. Furthermore, when selecting items for inclusion in the EFA, the eigenvalue for each factor should be at least 1.00, factor loadings for each item should be above 0.40, the difference in factor loadings between two factors should be greater than 0.10, and each factor should include at least three items (Kline, 2014).

Confirmatory factor analysis

In the CFA, model fit was assessed using the comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). A good model fit is indicated by CFI and TLI values greater than 0.90 and RMSEA and SRMR values less than 0.08 (Łaguna et al., 2023; Marsh et al., 2009). To assess the optimal factor structure, the four-factor model was compared with three competing models to determine the best-fitting model for the scale.

Reliability and validity test

Reliability was assessed using Cronbach's α coefficient and test-retest reliability. Cronbach's α was evaluated using two samples (Sample 1 and Sample 2, $n = 597$). Test-retest reliability was assessed by asking 100 participants (based on the voluntary principle) to complete the same measure four weeks after the initial administration, and correlating the results with the first measurement. In addition, correlations between the GAI Dependence Scale and the AI Dependence Scale (version of six items) and the Behavioral Intention Scale were calculated in this study to test criterion-related and predictive validity. A reliability coefficient greater than .70 is considered acceptable, while a coefficient greater than .90 indicates excellent reliability (Groth-Marnat, 2009).

RESULTS

The result showed that skewness ranged between −1.29 and 0.64 and kurtosis ranged between −1.39 and 3.33. Accordingly, it was concluded that the data obtained from the samples met the normality assumptions.

ITEM ANALYSIS

The results of the item analysis indicated that all items showed significant differences between the high and low score groups (*ps* < .05). The item-total correlation analysis revealed that all items had significant correlations with the total score (*ps* < .05). However, the correlation coefficients for Items 1 and 4 were 0.29 and 0.33, respectively, which were below the threshold of 0.40. Consequently, these items were excluded from the scale, resulting in a final set of 23 items, with correlation coefficients ranging from 0.44 to 0.79.

EXPLORATORY FACTOR ANALYSIS

An EFA was conducted on data from Sample 2 ($n = 300$). The KMO value was 0.93, and Bartlett's test of sphericity yielded a χ^2 value of 4634.88, with $p < .001$, indicating that the data were suitable for factor analysis. Using principal component analysis with varimax rotation, factors were extracted based on an eigenvalue greater than 1. Four factors were retained, explaining a cumulative variance of 68.60%. During the analysis, Items 18, 11, 21, and 19 exhibited cross-loadings across dimensions. Each item was sequentially removed, and EFA was rerun after each deletion. Based on the updated factor structure, subsequent items were removed, resulting in a final set of 19 items. The cumulative variance explained by the four factors was 71.32% (Table 1).

Based on theoretical considerations and the content of the items, the four factors were labeled as follows: Intensity of Use (3 items), Content Dependency (5 items), Withdrawal Symptoms (5 items), and Negative Consequences (6 items).

CONFIRMATORY FACTOR ANALYSIS

The results of the CFA demonstrate that the four-factor model not only meets established psychometric

Table 1

Results of exploratory factor analysis

Items	Factor loading			
	1	2	3	4
I'm lazy in thinking and solving problems on my own due to the frequent use of GAI.	0.89			
I'm less creative due to the frequent use of GAI.	0.88			
After using AI frequently, I become lazy in memorizing or learning new things.	0.86			
Overusing GAI makes me lack confidence in completing tasks independently when GAI is unavailable.	0.85			
Overusing GAI has a negative impact on my learning and work.	0.80			
I spend less time solving problems with others collaboratively after using AI.	0.75			
I feel uncomfortable if I am not allowed to use GAI.		0.86		
I feel frustrated, irritable, or anxious if I am not allowed to use GAI.		0.82		
It feels as if I have lost my intimate friend if I am forbidden to use GAI.		0.82		
I would be unable to complete tasks perfectly if I were not allowed to use GAI.		0.75		
I feel tired when solving problems on my own, but energized when using GAI to solve them.		0.65		
I often copy the content generated by GAI without any changes.			0.80	
I replicate content generated by GAI to save time.			0.75	
I completely trust the information provided by GAI.			0.75	
GAI provides more comprehensive information, so I always prioritize using content generated by GAI.			0.72	
Compared to my own answers, I usually prefer the responses generated by GAI.			0.71	
I use GAI more frequently.				0.84
I use GAI more impulsively.				0.80
I intend to increase my usage of GAI to enhance performance.				0.68
Eigenvalue	6.78	4.06	1.57	1.14
Variance %	24.77	43.16	60.14	71.32

criteria but also provides a better fit compared to the three competing models (Table 2). The four-factor model's fit indices include χ^2/df = 2.93, TLI = 0.94, CFI = 0.93, RMSEA = 0.08, and SRMR = 0.07, with all factor loadings exceeding 0.62 ($p < .001$), indicating a robust and reliable factor structure.

RELIABILITY ANALYSIS

The internal consistency of the scale was assessed by calculating Cronbach's α coefficients for two independent samples, which were .92 for Sample 1 and .90 for Sample 2. Additionally, the test-retest reliability over a four-week interval yielded a coefficient of .81, both of which are considered to be acceptable levels of reliability.

VALIDITY ANALYSIS

Correlation analysis (Table 3) revealed that the correlations between the four dimensions and the total score of GAI dependence ranged from 0.59 to 0.89 ($p < .001$), demonstrating strong associations. The intercorrelations among the four dimensions ranged

Table 2

Results of confirmatory factor analysis (n = 297)

Model	χ^2/df	TLI	CFI	RMSEA	SRMR
Unifactor	13.19	0.53	0.59	0.20	0.16
Two-factor	9.03	0.69	0.73	0.16	0.21
Three-factor	3.71	0.90	0.91	0.10	0.08
Four-factor	2.93	0.94	0.93	0.08	0.07

Table 3

Results of correlation analysis (n = 297)

	1	2	3	4	5	6	7
1. Intensity of Use	–						
2. Content Dependency	0.55***	–					
3. Withdrawal Symptoms	0.54***	0.61***	–				
4. Negative Consequences	0.20**	0.25***	0.56***	–			
5. GAI Dependency	0.59***	0.72***	0.89***	0.78***	–		
6. AID	0.54***	0.57***	0.83***	0.67***	0.87***	–	
7. Behavioral Intention	0.46***	0.45***	0.36***	−0.06	0.31***	0.30***	–

Note. ** $p < .01$, *** $p < .001$; AID – total score of AI Dependence Scale (six-item version).

from 0.20 to 0.61 ($p < .01$), which were lower than the correlations between each dimension and the total score, suggesting robust structural validity of the questionnaire. Further, the correlations between the dimensions and the total score of GAI dependence with the AI Dependence Scale (version of six items) ranged from 0.54 to 0.87 ($p < .001$), supporting good criterion-related validity. In terms of predictive validity, all dimensions, except for the Negative Consequences dimension, showed significant correlations with the intention to continue using the GAI (ranging from 0.31 to 0.46), further confirming the questionnaire's capacity to predict user behavior.

DISCUSSION

STRUCTURE OF THE GAI DEPENDENCE SCALE

The current study employed EFA to identify the factor structure of the GAI Dependence Scale. The results revealed a four-factor model consisting of Usage Intensity (3 items), Content Dependence (5 items), Withdrawal Symptoms (5 items), and Negative Consequences (6 items), which together accounted for 71.32% of the total variance. CFA further confirmed that the four-factor model demonstrated satisfactory fit indices, surpassing the fit of one-factor, two-factor, and thThe GAI Dependence Scale exhibits both conceptual parallels and essential distinctions when compared to previous scales measuring internet addiction or mobile phone dependence. In established instruments, dimensions such as usage intensity, withdrawal symptoms, and negative consequences are consistently identified as core components, reflecting shared features of technological dependency (Caplan, 2002; Chen et al., 2003; Lei & Yang, 2007). However, a critical theoretical advancement of the current scale lies in its specific operationalization tailored to GAI interaction. While compulsive internet use often manifests as generalized, aimless online browsing and problematic smartphone use is associated with specific mobile applications (Lozano-Blasco et al., 2022; Pan et al., 2020), GAI dependence is primarily characterized by task-oriented engagement with creative and conversational AI systems. Consequently, the unique manifestations within each dimension differ substantively. For instance, the Withdrawal Symptoms dimension assesses declines in confidence, task-related anxiety, and negative emotional responses when GAI is unavailable. The Negative Consequences dimension focuses on risks specific to GAI overuse, such as cognitive outsourcing, diminished intrinsic motivation, and uncritical acceptance of AI-generated content. Furthermore, the uniquely identified Content Dependence dimension directly captures excessive trust in GAI outputs, a feature not salient in traditional technology dependence scales. Although the scale developed in this study exhibits a strong correlation with the adaptation by Zhang et al. (2024), the aforementioned theoretical and content distinctions suggest that their adapted scale may not fully capture the unique psychological and behavioral signature of GAI dependence. In contrast, the GAI Dependence Scale developed in the current study offers a more nuanced, valid, and comprehensive tool for evaluating this emerging form of technological dependency.

PSYCHOMETRIC INDICATORS OF THE GAI DEPENDENCE SCALE

This study followed the standard procedures of psychometrics to ensure the scientific rigor and validity of the scale. During the scale development phase, a pool of items was created through semi-structured interviews. These items were assessed for readability and then submitted to experts for further evaluation of content validity. The GAI Dependence Scale demonstrated good internal consistency, with Cronbach's α coefficients of .92 and .90 in two different samples. The test-retest reliability was .81. In addition, the study evaluated the scale's construct validity, criterion-related validity, and predictive validity, with results indicating that the four-factor model of the GAI Dependence Scale is structurally stable and exhibits good validity. In general, the development procedures and evaluation criteria of the scale is in accordance with the psychometric standards established in previous research (Groth-Marnat, 2009; Wu, 2010).

THEORETICAL CONTRIBUTIONS AND PRACTICAL IMPLICATIONS

At the theoretical level, this scale provides a specialized conceptual framework for understanding new forms of dependency within human-computer interaction. It distinguishes itself from traditional scales measuring internet addiction (Lozano-Blasco et al., 2022) or problematic smartphone use (Pan et al., 2020) by shifting the focus from generalized media use to the specific psychological investment in generative and conversational AI systems. This aligns with the current research trend moving from "technology use" to "technology relationships." For instance, recent studies on AI attachment (Kasturiratna & Hartanto, 2026) explore users' emotional bonds with AI, while the Content Dependence dimension revealed by our scale offers a complementary perspective from the angle of cognitive trust. Simultaneously, negative attitudes towards generative AI-assisted writing (Yang et al., 2025) may be potentially linked to the Negative Consequences dimension in this study, together depicting the complex landscape of GAI's double-edged sword effect in educational settings. Integrating these latest findings with the present research contributes to building a more comprehensive theoretical model of GAI impact, encompassing cognitive, affective, and behavioral dimensions.

At the practical level, this scale offers an assessment foundation for promoting positive and healthy technological adaptation in educational and life contexts. Firstly, for educators and administrators, the scale can be used to screen for potential risks of excessive GAI reliance among student populations. This enables the targeted design of digital literacy education to cultivate students' critical use of AI-generated content (Dwivedi et al., 2021), which resonates with the central thesis regarding thoughtful technology integration in Technology and Learning (Sage & Matteucci, 2024). Secondly, the sub-dimensions of the scale can guide personalized intervention: for users with high Usage Intensity, guidance on time management can be provided, while for those with strong Content Dependence, training in fact-checking and independent thinking needs reinforcement. Finally, at the broader socio-technical development level, continuously tracking the levels and patterns of GAI dependence can provide empirical evidence for formulating relevant technology ethics guidelines and optimizing product design aimed at mitigating negative consequences, thereby fostering a human-centered path for artificial intelligence development.

LIMITATIONS

First, this study developed a GAI Dependence Scale intended for the general population; however, due to limitations in the recruitment process, the sample's occupational and age distribution was not sufficiently balanced. Future research should focus on enhancing sample diversity and validating the scale in different populations. Second, while the GAI Dependence Scale has proven effective for Chinese participants in a Chinese-language context, its validity needs to be tested in other linguistic and cultural environments. Third, during the semi-structured interviews used to establish the item pool, only participants with experience using GAI were invited to participate, which makes it difficult to confirm whether true GAI-dependent individuals were involved, and whether other important aspects were overlooked. Lastly, given the potential limitations of the subjective reporting method used in this study, future research should incorporate other assessment methods, such as third-party evaluations, to improve the reliability and comprehensiveness of the findings.

Supplementary materials are available on the journal's website.

Disclosures

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