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Artificial intelligence dependency among educators: a scale development and validation study

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Abstract
This study aims to develop a valid and reliable measurement tool to assess the level of dependency on artificial intelligence (AI) among educators (teachers and academics). An exploratory sequential mixed methods design was employed. In the first phase, qualitative data were collected from 32 teachers and academics using a semi-structured interview form. Additionally, the literature review was conducted on AI dependency. Based on the findings, a 55-item pool was created. Content analysis was used for the qualitative data, while Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were used to examine and validate the factor structure of the scale, respectively. The EFA results revealed a two-factor structure comprising 32 items: Dependency in Educational Processes and Dependency in Academic Processes, explaining 69.75% of the total variance. The Cronbach's alpha reliability coefficient of the whole scale was found as 0.982. Additionally, to assess the scale's reliability, a split-half method was used by dividing the items into two groups (odd and even). The Cronbach's alpha coefficients for the first and second groups were 0.947 and 0.954, respectively, with a high and positive correlation between the two groups (r=.961). Furthermore, the Spearman-Brown coefficient was calculated as 0.980, and the Guttman split-half coefficient was also 0.980. Finally, CFA was applied on the 32-item version of the scale, and results confirmed the model with a chi-square/df ratio of 1.75 and an RMSEA value of 0.044. As a result, a valid and reliable tool was obtained to assess the dependency on AI among educators.

Keywords Artificial intelligence (AI) · AI dependency · Educators · Scale development

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1 Introduction

As the use of AI increases, human reliance on it grows, leading to a reduction in the brain's natural capacity for independent thinking. This dependency gradually diminishes human intelligence and replaces it with artificial processes. Extensive interaction with technology further pushes individuals to adopt algorithmic thinking patterns without fully comprehending the reasoning behind them. (Ahmad et al., 2023). Frequent use of AI tools reduces critical thinking skills and, through cognitive offloading, diminishes individuals' intellectual capacity, thereby allowing artificial processes to replace human intelligence (Gerlich, 2025). Consequently, this overdependence on AI contributes to a range of negative outcomes, including intellectual laziness, the spread of misinformation, a notable decline in creativity, and the erosion of both independent and critical thinking abilities (Zhang et al., 2024). Additionally, as AI becomes deeply integrated into activities such as planning and organizing, it gradually reduces the need for mental effort and thoughtful decision-making. Overreliance on AI can degrade essential professional skills and create stress in situations where physical or cognitive efforts are required (Gocen & Aydemir, 2020).

In educational institutions, the increasing reliance on AI systems has significantly altered how student records are kept and data is analyzed. Decisions are often left to automated systems, whether due to trust in technology or the convenience it provides, leading to a gradual decline in active involvement from teachers and administrative staff. As automation continues to handle academic and administrative processes, educators and staff are becoming increasingly dependent on AI, losing their cognitive engagement in decision-making tasks. This reliance on AI minimizes human participation in daily operations, reducing the necessity for traditional skills in educational settings. Consequently, teachers and administrators are gradually losing their problem-solving and critical thinking abilities, as many tasks are now performed by machines, diminishing their capacity for independent decision-making (Ahmad et al., 2023). Although prior research on the topic is limited, it is anticipated that excessive dependence on AI technology may negatively impact individuals by reducing their ability to solve problems effectively (Zhang et al., 2024).

Given the complex nature of AI dependency, there is a clear need for a specialized measurement tool to accurately assess and understand this phenomenon. In this context, studies aimed at measuring the effects of AI dependency on individuals have gained increasing importance. However, the literature still contains a limited number of studies specifically addressing AI dependency. Morales-García et al. (2024) developed and validated a scale to measure AI Dependency among university students. The scale consists of five items and is structured as a single-factor model, with all items effectively representing the construct being measured. Similarly, the same scale was adapted to Turkish culture by Savaş (2024), and findings from the Turkish sample confirmed the unidimensional structure of the scale, with high internal consistency reliability. Zhang et al. (2025) developed a scale to measure individuals' dependence on AI chatbots in daily life. Despite these initial efforts, the existing scales tend to focus on either general technology addiction or specific applications such as AI chatbots or student populations. To date, there is no comprehensive and validated instrument designed to specifically measure AI dependency among educators, including both teachers and academic staff, who increasingly integrate AI tools into their professional practices. Given the growing use of AI in instructional planning, grading, feedback, and academic management, understanding educators' levels of dependency has become essential. A context-sensitive and psychometrically sound measurement tool is therefore needed to assess how AI dependency manifests among educators, and to guide future research and policy in addressing the cognitive, emotional, and professional consequences of this emerging phenomenon. In this regard, this study aims to develop a valid and reliable scale to measure educators' dependency on AI tools. Such a tool would not only provide valuable insights into the extent of AI dependency among educators but also support strategies to prevent potential risks. In this study, AI dependency refers to the *perceived necessity* and *reliance on* AI tools, such as ChatGPT, to perform or support core teaching-related tasks. This construct goes beyond simple usage frequency and emphasizes the extent to which educators consider AI tools as indispensable for ensuring the quality, efficiency, or completeness of their academic and instructional practices. Specifically, AI dependency encompasses reliance on AI for activities such as academic writing, literature review, language editing and support, lesson planning, instructional material development, classroom activity design, and student assessment. In this sense, dependency captures two interrelated dimensions: (a) functional reliance, reflecting the degree of difficulty experienced when performing tasks without AI tools, and (b) perceived necessity, reflecting the belief that academic or pedagogical outputs would be inadequate or less effective without AI support.

2 Literature review

As an academic discipline, AI is dedicated to addressing cognitive challenges linked to human intelligence, such as learning, decision-making, and pattern recognition. Conceptually, AI serves as a framework for developing systems that can perform human-like functions, including speech recognition and language translation. These complementary viewpoints highlight AI's capacity not only to tackle real-world issues but also to reshape educational theories and methodologies (Pratiwi et al., 2025).

The integration of AI in education is evident through various tools that have become essential in modern teaching and learning environments. Canva, a graphic design platform introduced in 2013, enables educators to develop visually engaging materials to enhance instructional delivery (Widiastuti, 2024). AI-driven chatbots, such as ChatGPT (released by OpenAI in 2022) and Bard (also launched in 2022), offer personalized assistance for tasks like text generation, language translation, and tutoring (Obaidoon & Wei, 2024). Additionally, Socratic, an AI-powered educational platform acquired by Google in 2018, supports students in understanding complex concepts through interactive conversational interfaces (Lameras & Arnab, 2021). Although these technologies make education more accessible and personalized, their widespread use raises concerns about turning education into a business and limiting students' creative thinking.

The contributions of AI tools to instructional processes have been extensively discussed in the literature. Hammad (2023) and Pinzolits (2024) have emphasized that advanced AI tools and chatbots play a fundamental role in enhancing teaching and learning. AI-based technologies support instructional processes by offering teachers opportunities to better plan, implement, and evaluate their lessons (Celik et al., 2022). In particular, during collaborative tasks and activities, AI has been shown to assist teachers in monitoring students in real time and providing immediate feedback (Swiecki et al., 2019). This not only increases students' active participation in the learning process but also enables teachers to fulfill their guiding roles more effectively. AI-based automated scoring systems are also reported to assist teachers in assessment processes, helping reduce their workload and allowing them to focus on critical aspects such as timely intervention and evaluation (Kersting et al., 2014; Vij et al., 2020). Advanced AI tools like ChatGPT allow educators to offer students detailed explanations, synthesize complex information, and enrich learning experiences (Murtaza et al., 2022). These features support a more flexible and student-centered approach in teaching. In addition to reducing teachers' workload, AI plays a significant role in personalizing learning processes. Additionally, AI improves the quality of the education system and enhances the effectiveness of learning by supporting adaptive learning practices (Fitria, 2023).

As AI becomes more integrated into daily life, using it too much and relying on it heavily may reduce people's natural thinking abilities. Over time, this could weaken our ability to think clearly and solve problems on our own, as we start depending more on machines to make decisions. Constant interaction with AI tools might also lead people to think in fixed, machine-like patterns, without truly understanding what they're doing (Ahmad et al., 2023). As AI continues to take over tasks such as planning and organizing, people may use their minds less, which can reduce their skills and cause stress in situations that still require human thinking or physical effort (Gocen & Aydemir, 2020). In the field of education, similar concerns have emerged. While AI tools offer significant advantages in terms of personalized learning, improved academic outcomes, and enhanced student engagement (Vieriu & Petrea, 2025), their overuse raises important issues, especially when users begin to depend on them excessively. For instance, the over-dependence on AI dialogue systems, together with issues like AI hallucinations, plagiarism, lack of transparency, and algorithmic biases could hinder the development of critical thinking abilities (Carobene et al., 2024), and may result in negative consequences such as cognitive overload and mental fatigue (Naseer et al., 2025). Both students and teachers may begin to rely too much on these tools over time. Students may unintentionally become too reliant on AI-generated support, which could undermine their capacity to make independent, well-reasoned choices (Buçinca et al., 2021). Especially in online learning environments, AI-supported tools can reduce teacher-student interaction and weaken the human dimension of education while undertaking tasks such as presenting course material, evaluating assignments, and providing feedback (Seo et al., 2021). At the same time, within academia, especially among early-career faculty, there is an ongoing challenge of managing the demands of research, publication obligations, and teaching duties (Holmes et al., 2023). Teachers who increasingly rely on AI applications for grading and lesson planning may experience increased emotional stress, while professionals may face anxiety and pressure in critical decision-making processes. This, in turn, may reduce their involvement in the more human-centered aspects of the teaching profession and could potentially mechanize instructional practices (Naseer et al., 2025). Advanced AI-based learning management systems tend to reduce interaction between both students and teachers in educational environments, as well as shorten attention spans (Pillai et al., 2024). Consequently, it is essential for educators to adopt a critical and balanced approach to AI integration, ensuring that technological efficiency does not come at the expense of human judgment, meaningful interaction, and pedagogical authenticity.

2.1 Ethical considerations of AI dependency

Beyond the pedagogical and cognitive concerns of excessive AI use, dependency on AI tools also entails important ethical implications. One major issue relates to algorithmic bias, as AI systems trained on biased datasets may reinforce existing inequalities and produce discriminatory outcomes in assessment or decision-making processes (Ferrara, 2023). Such biases may undermine fairness and educational justice, particularly when educators rely on AI tools without critically evaluating their outputs. Additionally, Ghamrawi et al. (2024) found that some teachers believed AI could undermine teacher leadership by reducing autonomy, hindering collaboration, and relegating teachers to passive executors of preset algorithms.

Another recurring concern in the literature is the erosion of teacher autonomy. Unlike traditional assessment, where judgments and feedback are grounded in teachers' expertise and moral reasoning, AI-assisted assessment may foster dependence on algorithmic outputs. Such dependency risks diminishing teachers' capacity for ethical decision-making, encouraging a preference for technological over human-centered solutions when facing complex dilemmas. Over time, this shift may significantly alter the character of education (Lei, 2024).

Closely related is the issue of pedagogical dehumanization. As AI increasingly assumes instructional responsibilities, the relational and empathetic dimensions of education risk being overshadowed. Overuse of AI can diminish teacher-student interaction, with students turning more to intermediary tools rather than direct communication with the teacher (Aly et al., 2025). Derakhshan (2025) notes that although AI technologies can enhance learning outcomes, they risk reducing emotional engagement when they replace genuine teacher interaction. Likewise, Mahapatra (2024) emphasizes that AI feedback, if used as a substitute rather than a complement to teacher input, may leave students feeling disconnected. Together, these findings highlight the need for teachers to remain central as ethical, emotional, and pedagogical agents in AI-supported learning environments. Krullaars et al. (2023) also argue that over-reliance on AI dialogue systems may reduce students' motivation and engagement, as they might depend on AI for answers rather than actively engaging in learning.

These concerns highlight the need for robust governance frameworks. Effective integration of generative AI in education should be guided by institutional policies that define its purposes, boundaries, and conditions of use (Singh, 2024). For example, the University of Toronto has adopted a model where GenAI supports assessment processes but final decisions remain under human control, thereby ensuring accountability and quality (Guo et al., 2023).

In summary, the ethical implications of AI dependency extend beyond technical and pedagogical considerations, encompassing fairness, teacher autonomy, emotional engagement, and the authenticity of learning experiences. The literature consistently highlights that excessive reliance on AI can compromise these critical dimensions, potentially transforming education into a more mechanized and less human-centered process. By providing both a diagnostic and ethical monitoring function, the AI Dependency Scale introduced in this study offers a practical tool for educators and institutions to balance the benefits of AI with the preservation of human judgment, relational engagement, and ethical responsibility. Using this scale, educators' levels of AI dependency can be systematically assessed, enabling the identification of potential risks associated with over-reliance and the implementation of strategies to mitigate the negative effects of AI use in educational contexts.

2.2 Theoretical framework

The integration of Automation Bias Theory provides a strong conceptual grounding for the AI Dependency Scale developed in this study. Automation bias refers to the tendency of individuals to over-rely on automated systems, often accepting their outputs without sufficient scrutiny, even when contradictory evidence is available (Skitka et al., 1999). Prior research shows that users interacting with automated systems may reduce their own critical judgment and overlook potential errors, thereby exhibiting automation bias (Lyell & Coiera, 2017). More recent evidence confirms this trend in AI dialogue systems, where users often accept outputs—even when they are hallucinations—without checking their accuracy. This tendency is further reinforced by cognitive biases and heuristic processing (Gao et al., 2022). In addition to cognitive risks, recent research has highlighted ethical challenges associated with AI dependency, including misleading outputs, algorithmic biases, plagiarism, privacy breaches, and transparency concerns (Hua et al., 2024). In this study, automation bias provides a theoretical explanation for the emergence of AI dependency. Educators who tend to trust AI outputs without sufficient scrutiny are more likely to develop dependency in both instructional and academic processes, which directly corresponds to the two sub-dimensions measured by the scale. Thus, the scale not only operationalizes AI dependency in educational contexts but also offers a framework for future interventions aimed at promoting balanced and ethical AI use in teaching and research.

3 Methodology

3.1 Research design

In this study, exploratory mixed-method design, one of the mixed research designs, was employed. Mixed research methods are often preferred in many studies due to their comprehensive, exploratory, pluralistic, explanatory, creative, and complementary nature, compared to single qualitative or quantitative research models (Morse, 2003; Onwuegbuzie & Johnson, 2004). In mixed-method research designs, qualitative and quantitative methods are used together to complement the weaknesses of each approach. This integration enhances the validity and reliability of the data obtained (Creswell & Plano Clark, 2011). In this context, the exploratory mixed-method design was chosen to develop a highly valid and reliable measurement tool. This design follows a two-phase sequential structure, where qualitative data is first collected, analyzed, and examined in depth. Based on the findings from the qualitative phase, a measurement tool was developed, and quantitative data was subsequently collected and analyzed using this tool (Creswell, 2011; Creswell & Plano Clark, 2011; Fraenkel & Wallen, 2009; Tashakkori & Teddlie, 2003).

As part of the research, in the qualitative phase, interviews were conducted to determine educators' levels of AI dependency. Additionally, the literature review was conducted on AI dependency. In the quantitative phase, the developed measurement tool was administered to educators, and validity and reliability analyses were conducted, resulting in the final AI Dependency Scale.

3.2 Participants

As the research was carried out in three main phases, different participant groups were involved at each stage. In the first stage of the study, the opinions of the educators were obtained. The criterion sampling method was used to determine the participants for the interviews. This method involves including participants who meet specific predefined criteria in the research. The criteria can be based on a pre-existing list or determined by the researcher (Yıldırım & Şimşek, 2018). The primary criterion for participant selection in this study was the intensive use of AI tools. Interviews conducted with participants who met this criterion provided in-depth data on AI usage, forming the foundation of the research. The data obtained from these interviews were utilized in developing the item pool for the AI dependency measurement scale, aiming to enhance the scale's validity. In this context, the study included 32 educators (teachers and academics) who actively use AI tools. Among the participants, 77.27% ($n=25$) were male, while 22.73% ($n=7$) were female. Their years of work experience ranged from 1 to 32 years, with the most common years of work experience being 15–18 years, comprising 46.88% ($n=15$) of the participants. Regarding educational background, 81.25% ($n=26$) held a graduate degree, while 18.75% ($n=6$) had an undergraduate degree. When asked about prior AI-related training, only 12.50% ($n=4$) reported receiving formal education in this field, whereas 87.50% ($n=28$) had not received any AI-specific training. In terms of following technological developments, 87.50% ($n=28$) stated that they regularly keep up with them, while 12.50% ($n=4$) reported following them only partially. These findings indicate that the sample primarily consists of highly educated and experienced individuals who show a strong interest in technological developments but have not received formal AI education.

In the second stage, a total of 330 educators, including 236 academics and 94 teachers, who use AI tools to varying degrees (rarely, frequently, or extensively), participated for EFA. Among the participants, 58.57% ($n=193$) were male, while 41.43% ($n=137$) were female. Regarding work experience, 15.71% ($n=52$) had

1–5 years of work experience, 17.14% ($n=57$) had 6–10 years, 22.86% ($n=75$) had 11–15 years, 26.43% ($n=87$) had 16–20 years, and 17.86% ($n=59$) had 21 years or more of work experience. In terms of educational background, 77.14% ($n=254$) held a graduate degree, while 22.86% ($n=76$) had a bachelor's degree. Regarding AI-related training, 20% ($n=66$) of participants had received formal education in AI, whereas 80% ($n=264$) had not. When asked about following technological developments, 60.71% ($n=200$) stated that they regularly keep up with them, while 39.29% ($n=130$) reported following them only partially.

During the CFA stage, the 32-item scale was re-administered to 216 participants for validation in CFA. 44.9% of the participants ($n=97$) were male, and 55.1% ($n=119$) were female. When examining the distribution based on work experience, 12.96% ($n=28$) had 1–5 years, 21.75% ($n=47$) had 6–10 years, 25.92% ($n=56$) had 11–15 years, 16.66% ($n=36$) had 16–20 years, and 22.68% ($n=49$) had 21 years or more of experience. In terms of educational background, 59.2% ($n=128$) had a graduate degree, while 40.8% ($n=88$) had a bachelor's degree. Regarding AI training, 25.9% of the participants ($n=56$) received training in this field, while 74.1% ($n=160$) did not receive any AI-related training. 65.7% ($n=142$) of the participants stated that they regularly follow technological developments while 34.3% ($n=74$) mentioned that they follow them to some extent.

As can be seen, the participants mainly consisted of highly educated individuals with diverse work experience, a strong interest in technological advancements, but limited formal AI training.

3.3 Data collection tools and procedures

In the scale development process, educators' perspectives on AI usage and dependency were first identified. To achieve this, a semi-structured interview form was developed by the researchers and reviewed by a panel of experts. The expert panel consisted of two experts in curriculum and instruction, two experts in qualitative research, and two experts in digital education. Based on their feedback, the interview form was revised accordingly. The final version of the interview form included eight questions, such as: *"For what purposes do you use AI tools?"* and *"Would you face difficulties in conducting your teaching activities without AI tools? If so, in which areas do you experience challenges?"* Using this finalized version, interviews were conducted in January 2025 with participants' consent, and all sessions were recorded using a voice recorder. The recorded interviews were later transcribed and analyzed. Based on the findings obtained from the interviews, the conceptual framework of the scale was constructed. The responses revealed the areas in which educators tend to be dependent on AI tools, how they integrate AI into their teaching processes, and which specific tools they use. These insights played a key role in shaping the structure and dimensions of the scale.

In parallel with the qualitative analysis, a comprehensive literature review was conducted to further support and validate the emerging themes. This review focused on prior studies related to AI use in education and AI dependency, and the dimensions that emerged from educators' views were examined in detail within the scope of the existing literature.

As a result of the qualitative data analysis and literature review, an initial item pool consisting of 62 items was developed as a 5-point Likert-type scale. Likert-type scales are widely used for assessing beliefs, opinions, and attitudes (DeVellis, 2003). Accordingly, the present scale was designed using a 5-point Likert format. Each item was rated on a five-point scale ranging from "*never = 1*", *"seldom = 2"*, *"sometimes = 3"*, *"often = 4"*, and *"always = 5"*.

After preparing the item pool, the face and content validity was qualitatively performed. To achieve this, the draft scale was submitted to a six-member expert panel, which included two experts in curriculum and instruction, two qualitative research experts, and two experts in digital education. Based on their evaluations, 13 items that did not adequately reflect AI dependency were removed from the draft. Additionally, in line with the experts' recommendations, 6 new items were added to better represent the conceptual framework. Following this expert review, the revised draft scale was piloted with 15 educators to identify any items that might be misunderstood or unclear. Based on the participants' feedback, two items were further revised to enhance clarity and prevent misinterpretation. After these final adjustments, the completed version of the scale consisting of 55 items was administered to participants via Google Forms in February 2025.

In this study, participants were asked about their use of "AI tools" in general, without restricting the scope to a specific category. Nevertheless, during the interviews, many educators specifically mentioned Generative AI tools (e.g., ChatGPT), and thus the findings predominantly reflect experiences with this category of AI applications.

3.4 Data analysis

The verbatim transcripts of the interviews conducted with educators were imported into NVivo 11, a widely used software for qualitative data analysis, and all analyses were carried out using this program. To systematically organize and describe the data while identifying recurring meaning patterns, the thematic analysis method proposed by Braun and Clarke (2006) was applied. In this process, two researchers thoroughly read the transcripts multiple times to develop familiarity with the data. The interviews were then re-examined, and key statements related to AI dependency were identified, leading to the creation of 64 initial codes. These codes were subsequently refined and grouped into broader, analytically rich themes that allowed for a comprehensive and in-depth exploration of the data. As a result of the analysis, two main themes emerged: *"Dependency in Academic Processes"* and *"Dependency in Educational Processes"*. *"Dependency in Academic Processes*" refers to AI use in research and scholarly activities such as conducting a literature review, determining a research topic, academic writing, and language enhancement. In contrast, *"Dependency in Educational Processes"* refers to the use of AI in instructional practices carried out by teachers, such as lesson planning, preparing course materials, developing course content, student assessment, preparing assignments, and in-class activities. This categorization clearly separates research-oriented academic tasks from teaching-oriented educational tasks.

The 55-item draft scale, developed based on qualitative research findings and literature review, and finalized through expert feedback, was administered to participants. Validity and reliability analyses were conducted on the collected data. To assess the construct validity of the scale, EFA was performed. Before conducting EFA, the Kaiser-Meyer-Olkin (KMO) test was used to determine the appropriateness of the dataset for factor analysis, and the Bartlett's test was conducted to assess sample adequacy. To examine the factor structure and group items with similar characteristics, the Principal Component Analysis (PCA) with Varimax Rotation was applied (Büyüköztürk, 2007; Gürbüz & Şahin, 2014). For reliability assessment, the Cronbach's Alpha internal consistency coefficient was calculated. Additionally, an independent samples t-test was performed to compare the mean scores of the upper and lower groups to determine item discrimination. Item-total correlations and inter-factor correlation analyses were also conducted. Moreover, alternative reliability measures, such as the Spearman-Brown coefficient and Guttmann split-half reliability coefficient, were calculated to further ensure internal consistency. Finally, to evaluate the fit of the factor structure with real data and test the explanatory power of the model, CFA was performed (Sümer, 2000; Özdamar, 2004).

3.5 Validity and reliability of the study

Due to the nature of thematic analysis, it is not always possible for different researchers to interpret the same data set from the exact same perspective. This challenge makes it difficult to measure inter-coder reliability (Joffe & Yardley, 2004). However, to evaluate the consistency of the analysis, codes and themes identified from four randomly selected interview transcripts were reviewed by two faculty members specializing in Educational Sciences. These faculty members are experts with prior experience in qualitative research and measurement tool development. The codes, themes, and draft scale items developed by the researchers were thoroughly examined by these experts. Based on their feedback, necessary revisions were made to ensure clarity and alignment with the study's objectives. The revision process continued until full agreement was reached among the researchers, ensuring the reliability and validity of the findings. Additionally, ethical approval for the study was obtained from the Scientific Research and Publication Ethics Committee of X University's Faculty of Social and Human Sciences.

4 Findings

The findings obtained from interviews conducted with educators were visualized and presented in Fig. 1.

As shown in Fig. 1, the analysis revealed two main themes: "Dependency in Academic Processes" and "Dependency in Educational Processes." Each main theme was further divided into sub-themes: Dependency in Academic Processes includes "*Academic writing*, *literature review*, *language enhancement*, *determining a research topic*." Dependency in Educational Processes includes *"Developing course content*, *preparing course material*, *lesson planning*, *preparing in-class activities*, *preparing assignments and student assessment."* Some of the sample quotations from the interviews related to these findings are as follows:

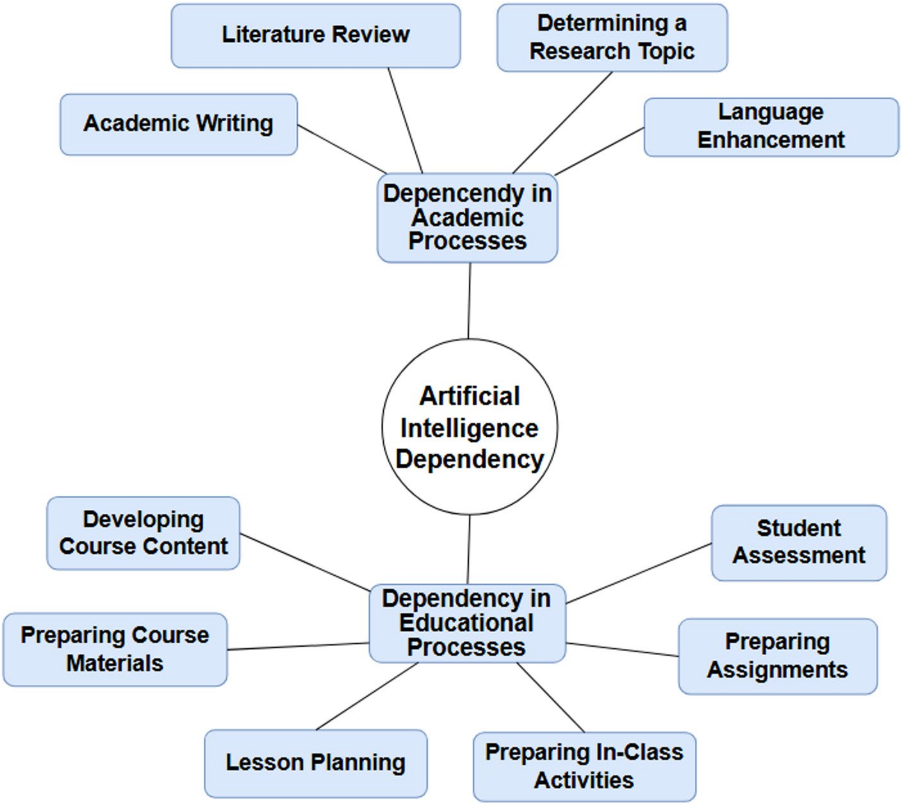

Fig. 1 Themes and sub-themes of the qualitative findings

A teacher with 15 years of work experience and a postgraduate degree expressed a high level of dependency on AI tools in processes such as literature review, academic writing, revision, developing course content, and preparation of course materials with the following statement: *"I frequently use AI tools, especially during literature reviews, for text editing and language checking while writing articles. I also benefit from AI tools when preparing presentations and teaching materials."*

An academician with 18 years of work experience described his frequent use of AI tools for research topic selection, academic writing, and preparing assignments as follows: *"Yes, I think I've started to develop a bit of a dependency. I don't want to make decisions without consulting it first. I struggle when I have to determine a research topic, format my citations to avoid plagiarism, or prepare assignments that I normally consider a burden—without using AI software."*

A teacher with 10 years of experience reported frequent use of AI tools for lesson planning, material preparation, developing course content, preparing course materials and text revision with the following statement: *"I use it frequently during the lesson planning process, while preparing educational materials, organizing content, planning the weekly topics, and for writing and editing purposes."*

An academician with 14 years of work experience shared her intense use of AI tools specifically for language support, text revision, and student assessment as follows: *"I frequently use AI tools for student evaluation, exam question preparation, writing new expressions, and checking punctuation and grammar. AI tools significantly accelerate these processes for me."*

4.1 Findings related to the construct validity of the scale

KMO and Bartlett's tests were conducted to determine the appropriateness of the obtained data for factor analysis, and the findings are presented in Table 1.

According to the data presented in Table 1, the initial factor analysis yielded a KMO value of 0.950, and the Bartlett's test result was found to be significant ($p<.01$). After repeated steps of factor analysis, the final stage revealed a KMO value of 0.949 and a significant Bartlett's test result ($p=.000$; $p<.01$). These findings indicate that the data set was appropriate for conducting factor analysis.

4.2 Findings related to EFA

The factor analysis initially started with 55 items. At each stage of the analysis, items with cross-loading values lower than 0.10 between different dimensions and item factor loadings below 0.40 were removed from the scale, and the analyses were repeated. In the final stage, a total of 23 items were excluded from the scale. The remaining 32 items explained 69.75% of the total variance. The total variance explained table of the scale is presented in Table 2.

According to the Rotated Component Matrix presented in Table 2, two sub-dimensions of the scale were identified. The total eigenvalue of the first sub-dimension was 18.621, explaining 58.190% of the variance. The second sub-dimension had a total eigenvalue of 3.699, accounting for 11.560% of the variance. After the rotation procedure, the total eigenvalue of the first sub-dimension was calculated as 13.333, explaining 41.665% of the variance, while the second sub-dimension had an eigenvalue of 8.987, explaining 28.085% of the variance. The combined total variance explained by these two sub-dimensions was determined to be 69.75%. In social sciences, a variance explanation rate above 40% is considered acceptable in terms of

Table 1 KMO and Bartlet test results

Scale	N	KMO	Chi-Square	df	p
Initial	330	0.950	10844.149	1485	0.000**
Final	330	0.949	5551.206	496	0.000**

**$p<.001$

Table 2 Total variance explained values of the scale

	Initial Eigen values			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% Variance	% Cumulative	Total	% Variance	% Cumulative	Total	% Variance	% Cumulative
1	18.621	58.190	58.190	18.621	58.190	58.190	13.333	41.665	41.665
2	3.699	11.560	69.750	3.699	11.560	69.750	8.987	28.085	69.750

the scale's representational power (Çokluk et al., 2014). In addition, a Scree Plot was examined to support the determination of the number of factors, which is presented in Fig. 2.

To assist in determining the number of factors, the Scree Plot was examined. It was observed that from the second point onward, the contribution of the components to the explained variance declined, and the curve followed a horizontal trajectory. Therefore, the number of factors in the scale was determined to be two. The factor loadings of the remaining 32 items in the scale are presented in Table 3.

As shown in Table 3, the Artificial Intelligence Dependency Scale consists of 32 items and two sub-dimensions. The first sub-dimension, *dependency on educational processes*, includes 18 items, with factor loadings ranging from 0.755 to 0.884. The second sub-dimension, *dependency on academic processes*, consists of 14 items, with factor loadings between 0.561 and 0.826. The fact that all items have factor loadings above 0.40 indicates that the items have sufficient factor loadings. Moreover, when examining the item-total correlations of the items in the scale, no item has a negative correlation or a correlation below 0.20, further supporting the consistency of the scale.

After determining the remaining items and their respective dimensions in the scale, 27% upper and lower groups were formed in order to assess the validity of the scale, and the data were analyzed using an independent samples t-test. The analysis

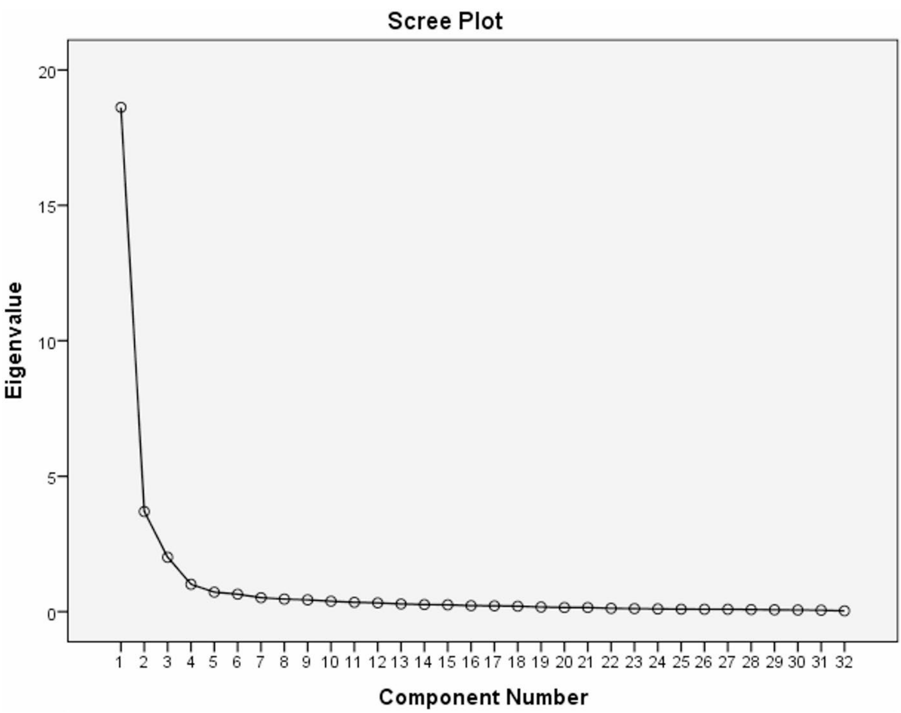

Fig. 2 Scree Plot Graph

Table 3 Factor loadings of the AI dependency scale

Item No	Rotated Component Matrix	Component Matrix	Item-Total Correlation
A1	0.884	0.856	0.814
A2	0.865	0.876	0.841
A3	0.844	0.872	0.839
A4	0.834	0.868	0.835
A5	0.833	0.798	0.757
A6	0.832	0.845	0.808
A7	0.828	0.828	0.789
A8	0.825	0.773	0.730
A9	0.820	0.836	0.801
A10	0.817	0.835	0.799
A11	0.815	0.855	0.820
A12	0.814	0.830	0.792
A13	0.813	0.857	0.824
A14	0.811	0.772	0.728
A15	0.809	0.830	0.795
A16	0.802	0.850	0.816
A17	0.777	0.855	826
A18	0.755	0.819	0.787
B1	0.826	0.675	0.687
B2	0.826	0.697	0.710
B3	0.808	0.637	0.647
B4	0.798	0.755	0.765
B5	0.786	0.694	0.702
B6	0.770	0.692	0.702
B7	0.762	0.703	0.710
B8	0.737	0.663	0.672
B9	0.721	0.520	0.530
B10	0.716	0.663	0.672
B11	0.593	0.516	0.519
B12	0.586	0.752	0.748
B13	0.566	0.565	0.563
B14	0.561	0.583	0.577

results for the items under the dependency on educational processes dimension are presented in Table 4.

When the upper and lower 27% groups were compared for the 18 items in the Dependency in Educational Processes sub-dimension of the AI Dependency Scale, a statistically significant difference was found in favor of the upper group for all items at the $p<.001$ level. Regarding the Dependency in Academic Processes sub-dimension of the scale, responses from participants in the upper and lower groups were compared using an independent samples t-test, and the results are presented in Table 5.

As shown in Table 5, a statistically significant difference was found in favor of the upper group for all items at the $p<.001$ level.

Table 4 Reliability analysis of upper and lower groups for the dependency in educational processes sub-dimension

Items	Group	*N*	X	SD	t	df	*p*
A1	Upper	89	2.97	1.05	10.473	176	0.00**
	Lower	89	1.07	0.27			
A2	Upper	89	2.94	1.01	11.554	176	0.00**
	Lower	89	1.02	0.16			
A3	Upper	89	3.34	0.99	14.175	176	0.00**
	Lower	89	1.02	0.16			
A4	Upper	89	2.92	0.99	10.987	176	0.00**
	Lower	89	1.07	0.27			
A5	Upper	89	2.97	1.21	9.350	176	0.00**
	Lower	89	1.07	0.27			
A6	Upper	89	2.78	1.04	10.024	176	0.00**
	Lower	89	1.05	0.22			
A7	Upper	89	2.94	1.13	10.551	176	0.00**
	Lower	89	1.00	0.00			
A8	Upper	89	2.65	1.16	8.743	176	0.00**
	Lower	89	1.00	0.00			
A9	Upper	89	3.18	1.00	12.700	176	0.00**
	Lower	89	1.05	0.22			
A10	Upper	89	3.21	0.90	12.591	176	0.00**
	Lower	89	1.15	0.43			
A11	Upper	89	3.15	0.88	13.820	176	0.00**
	Lower	89	1.07	0.27			
A12	Upper	89	2.81	1.00	10.788	176	0.00**
	Lower	89	1.02	0.16			
A13	Upper	89	3.13	1.16	10.786	176	0.00**
	Lower	89	1.05	0.22			
A14	Upper	89	2.89	1.41	7.951	176	0.00**
	Lower	89	1.05	0.22			
A15	Upper	89	2.86	1.11	10.042	176	0.00**
	Lower	89	1.02	0.16			
A16	Upper	89	3.13	0.99	11.757	176	0.00**
	Lower	89	1.13	0.34			
A17	Upper	89	3.02	1.12	10.131	176	0.00**
	Lower	89	1.10	0.31			
A18	Upper	89	2.73	1.05	9.358	176	0.00**
	Lower	89	1.07	0.27			

**p<.01

In order to determine the reliability of the scale, the Cronbach's alpha reliability coefficient was calculated for both subdimensions and the entire scale, and the results are presented in Table 6.

As seen in Table 6, Cronbach's alpha reliability coefficient was calculated as 0.982 for Dependency in Educational Processes while it was found as 0.948 for Dependency in Academic Processes sub-dimension. The Cronbach's alpha coefficient for the entire scale was calculated as 0.975. In the field of social sciences, a Cronbach's alpha value above 0.70 is considered an acceptable level of reliability (Nunnally &

Table 5 Reliability analysis results of upper and lower groups for the dependency in academic processes sub-dimension

Items	Group	*N*	X	SD	t	df	*p*
B1	Upper	89	3.52	1.05	11.712	176	0.00**
	Lower	89	1.28	0.51			
B2	Upper	89	3.65	0.96	11.227	176	0.00**
	Lower	89	1.42	0.75			
B3	Upper	89	3.60	1.07	9.979	176	0.00**
	Lower	89	1.50	0.72			
B4	Upper	89	3.50	1.00	12.740	176	0.00**
	Lower	89	1.23	0.43			
B5	Upper	89	3.44	1.15	9.437	176	0.00**
	Lower	89	1.36	0.71			
B6	Upper	89	3.36	1.02	11.326	176	0.00**
	Lower	89	1.23	0.54			
B7	Upper	89	3.31	1.04	10.777	176	0.00**
	Lower	89	1.31	0.47			
B8	Upper	89	3.15	1.00	11.557	176	0.00**
	Lower	89	1.15	0.36			
B9	Upper	89	3.81	0.89	8.415	176	0.00**
	Lower	89	1.81	1.15			
B10	Upper	89	3.10	1.06	10.691	176	0.00**
	Lower	89	1.13	0.41			
B11	Upper	89	3.73	1.05	7.703	176	0.00**
	Lower	89	1.92	0.99			
B12	Upper	89	3.00	0.95	11.590	176	0.00**
	Lower	89	1.10	0.31			
B13	Upper	89	3.18	1.11	8.069	176	0.00**
	Lower	89	1.47	0.68			
B14	Upper	89	2.94	1.13	6.884	176	0.00**
	Lower	89	1.34	0.87			

$^{**}p<.01$

Table 6 Reliability statistics of the scale

Dimensions	Item Number	Cronbach Alpha
Dependency in Educational Processes	18	0.982
Dependency in Academic Processes	14	0.948
Total	32	0.975

Bernstein, 1994). Accordingly, it can be stated that both the subdimensions and the entire scale are highly reliable.

Additionally, the Spearman-Brown coefficient and the Guttman Split-Half coefficient—both alternative methods for assessing reliability—were employed, and the findings are presented in Table 7.

According to the data in Table 7, the items in the developed scale were divided into two groups as odd- and even-numbered items. The Cronbach's alpha reliability

Table 7 Correlation results between the sub-dimensions and the entire scale

Cronbach Alpha		*N* of Items	Correlation Between Forms	Gutman Split Half Coefficient	Spearman-Brown Coefficient	
Part 1	Part 2				Equal Length	Unequal Length
0.947	0.954	32	0.961	0.980	0.980	0.980

coefficient was calculated as 0.947 for the first group and 0.954 for the second group. These values indicate that both groups have high and comparable internal consistency. A strong and positive correlation was found between the two groups (r=.961). Additionally, the split-half reliability coefficients were also quite high, with Spearman-Brown at 0.980 and Guttman at 0.980. These results suggest that the developed scale has a high level of reliability. In order to evaluate the consistency between the sub-dimensions and the entire scale, a correlation analysis was conducted between the sub-dimensions and the entire scale. The results are presented in Table 8.

There was a strong positive correlation between the entire scale and the dependency in educational processes (r=.932, p<.001) sub-dimension, as well as between the entire scale and dependency in academic processes (r=.881, p<.001) sub-dimension. Furthermore, a strong positive correlation was found between the sub-dimensions (r=.649, p<.001). These results indicate a high level of consistency between the sub-dimensions and the entire scale.

4.3 Findings related to CFA

In this study, CFA was conducted to evaluate the construct validity of the AI Dependency Scale. The analysis examined the t-values and found no critical warnings for any of the items. Upon reviewing the factor loadings of the model, it was determined that all items in each sub-dimension had factor loadings above 0.30. The diagram showing the unstandardized solutions of the model is presented in Fig. 3.

In the model developed within the scope of the study, the Chi-Square/df (χ^2/df) value was calculated as 1325.04/463 = 2.86. Additionally, the RMSEA value was found to be 0.065. Both the Chi-Square/df ratio and the RMSEA value fall within acceptable threshold levels, indicating an adequate model fit. To further improve the model fit, modification indices were reviewed, and four suggested modifications that offered the greatest improvement were implemented. Accordingly, within the Dependency in Academic Processes sub-dimension, modifications were made between item

Table 8 Inter correlations for the AI dependency scale

Dimensions	Dependency in Educational Process	Dependency in Academic Process	Total
Dependency in Educational Processes	1	0.649**	0.932**
Dependency in Academic Processes		1	0.881**
Total			1

**p<.01

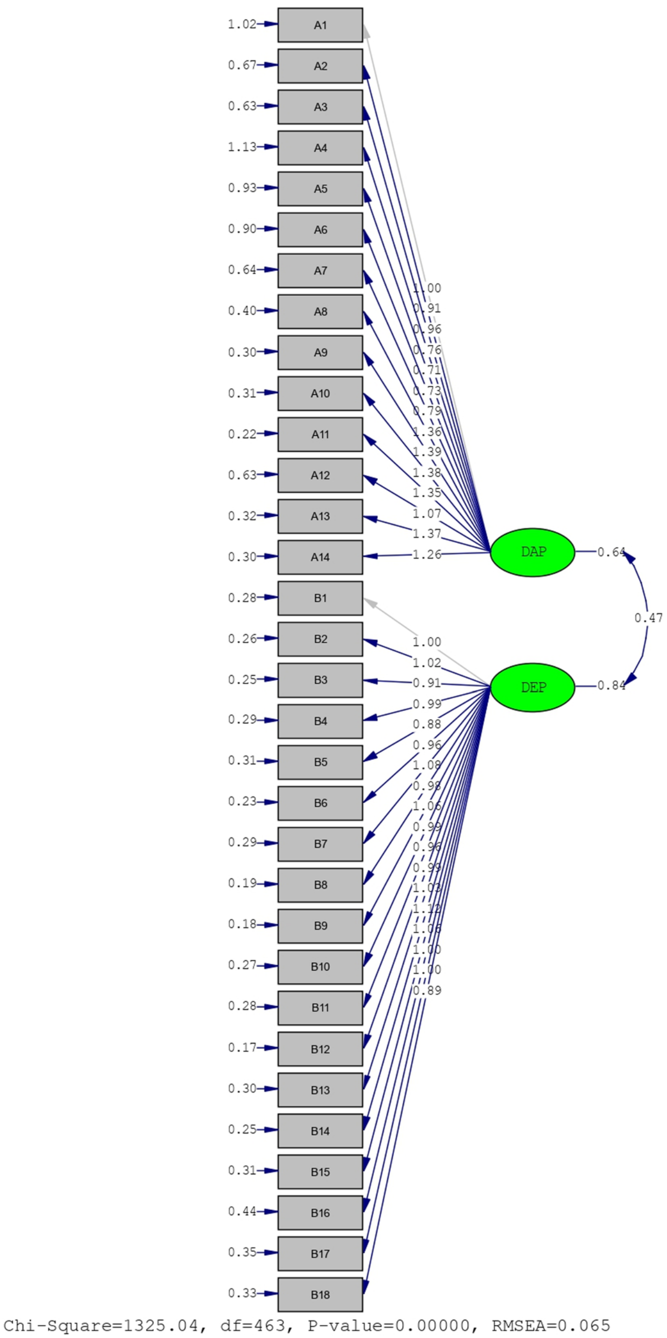

Fig. 3 Unstandardized CFA Diagram

A7 and A6, as well as between item A9 and A8. Similarly, in the Dependency in Educational Processes sub-dimension, modifications were applied between item B15 and B13, and between item B17 and B16. Following these adjustments, the diagram presenting the standardized solutions of the revised model is shown in Fig. 4.

As seen in Fig. 3, after the modifications, the Chi-Square/df value of the model was calculated as 806.29/459 = 1.75. Additionally, the RMSEA value was found to be 0.044. These values, along with the indicators of the model fit providing evidence for the construct validity of the scale, are presented in Table 9.

It was determined that the scale demonstrated excellent fit in six indices and acceptable fit in another six indices. These results indicate that the model developed for the two sub-dimensions and the entire structure of the scale is valid and statistically sound. After all analyses were completed, an AI Dependency Scale consisting of 32 items and two sub-dimensions, was developed (Appendix-1). The items of the scale, its sub-dimensions, and the characteristics of these sub-dimensions are presented in Table 10.

The AI Dependency Scale for Educators consists of two sub-dimensions. The Dependency in Academic Processes sub-dimension includes 14 items (Items 1–14), with no reverse-scored items. The minimum score that can be obtained from this sub-dimension is 14, and the maximum score is 70. The Dependency in Educational Processes sub-dimension consists of 18 items (Items 15–32), with no reverse-scored items. The minimum score for this sub-dimension is 18, while the maximum is 90. In total, the scale includes 32 items, and scores range from 32 to 160. A higher score obtained from the scale indicates a higher level of dependency on AI tools.

5 Discussion

This study aimed to develop a valid and reliable measurement tool to assess artificial AI dependency among educators. Employing an exploratory sequential mixed-methods design, the study successfully developed the Artificial Intelligence Dependency Scale for Educators, consisting of two sub-dimensions—*Dependency in Educational Processes* and *Dependency in Academic Processes*—with a total of 32 items. The scale development process was grounded in both in-depth qualitative interviews and a comprehensive literature review, ensuring content relevance and conceptual integrity.

The findings from the EFA revealed a two-factor structure explaining 69.75% of the total variance, while the CFA results confirmed the model fit, with key indices such as χ^2/df (1.75), RMSEA (0.044), and CFI (0.96) indicating an excellent fit. Reliability analyses demonstrated very high internal consistency, with a Cronbach's alpha of 0.975 for the entire scale, and values of 0.982 and 0.948 for the educational and academic sub-dimensions, respectively. Additional reliability metrics—including split-half coefficients (Spearman-Brown = 0.980; Guttman = 0.980) and strong inter-factor correlations—further validated the internal consistency and stability of the scale.

The qualitative findings highlighted that educators increasingly rely on AI tools for academic writing, literature reviews, lesson planning, content development, and

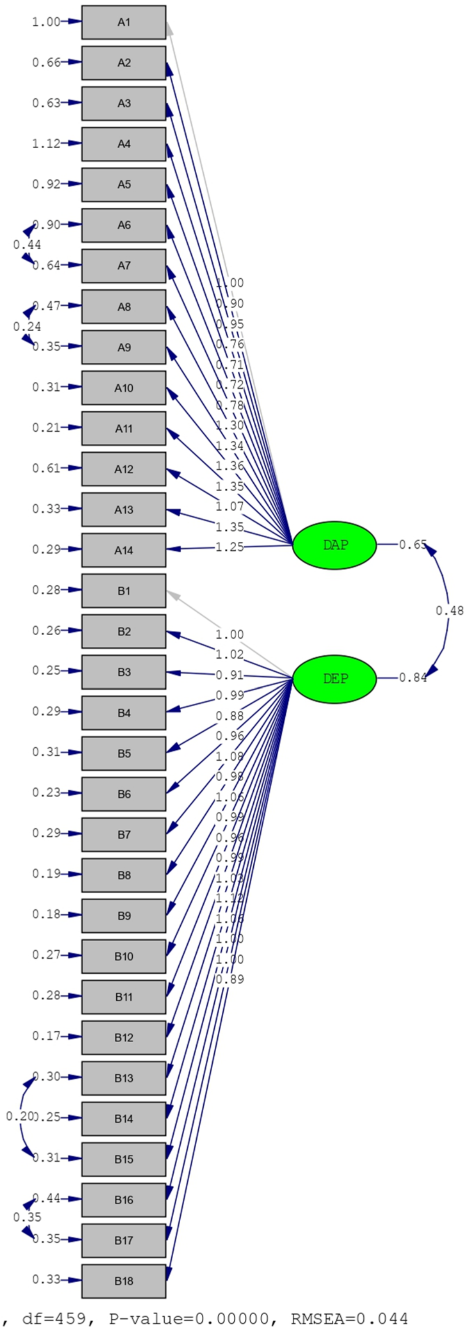

Fig. 4 Standardized estimates of the CFA model

Table 9 Fit indices used in scale adaptation studies and the model fit of the scale *

Fit Index	Good Fit Index Values	Acceptable Fit Index Values	Values of the Scale	Fit Evaluation
[1]χ^2/sd	$0 \leq \chi^2/sd \leq 2$	$2 < \chi^2/sd \leq 3$	1.75	Excellent
[2]AGFI	0.90≤AGFI≤1.00	0.85≤AGFI≤0.90	0.89	Acceptable
[3]GFI	0.95≤GFI≤1.00	0.90≤GFI≤0.95	0.91	Acceptable
[3]CFI	0.95≤CFI≤1.00	0.90≤CFI≤0.95	0.96	Excellent
[3]NFI	0.95≤NFI≤1.00	0.90≤NFI≤0.95	0.96	Excellent
[3]NNFI (TLI)	0.95≤NNFI≤1.00	0.90≤NNFI≤0.95	0.97	Excellent
[3]RFI	0.95≤RFI≤1.00	0.90≤RFI≤0.95	0.93	Acceptable
[3]IFI	0.95≤IFI≤1.00	0.90≤IFI≤0.95	0.97	Excellent
[4]RMSEA	0.00≤RMSEA≤0.05	0.05≤RMSEA≤0.08	0.04	Excellent
[4]SRMR	0.00≤SRMR≤0.05	0.05≤SRMR≤0.10	0.07	Acceptable
[5]PNFI	0.95≤PNFI≤1.00	0.50≤PNFI≤0.95	0.88	Acceptable
[6]PGFI	0.95≤PGFI≤1.00	0.50≤PGFI≤0.95	0.76	Acceptable

*(Baumgartner & Homburg, 1996;[3] Bentler, 1980;[3] Bentler & Bonett, 1980;[4] Browne & Cudeck, 1993; Byrne, 2010;[5] Hu & Bentler, 1999; İlhan & Çetin, 2014;[1] Kline, 2011;[3] Marsh et al., 2006;[6] Meyers et al., 2006;[2] Schermelleh-Engel & Moosbrugger, 2003)

Table 10 Sub-dimensions, items, and characteristics of the AI dependency scale

Sub-dimension	Items	Reverse Item	Minimum Score	Maximum Score
Dependency in Academic Processes	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14	No	14	70
Dependency in Educational Processes	15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32	No	18	90

student assessment. These insights align with the growing integration of AI in educational settings, but also underscore the potential risks of over-dependence on such tools. The scale, therefore, fills a significant gap in the literature by offering a psychometrically sound instrument specifically designed to assess AI dependency among educators, a population that had not previously been the focus of targeted measurement efforts.

In the literature, the contributions of AI tools to academic processes have been demonstrated in various studies. For example, Khalifa and Albadawy (2024) analyzed 24 studies as part of a systematic review and identified six key areas where AI supports academic writing and research. These areas include *"facilitating idea generation and research design*, *improving content and structure*, *supporting literature review and synthesis*, *enhancing data management and analysis*, *assisting with editing*, *review*, *and publishing processes*, and *aiding communication*, *dissemination*, *and ethical compliance*."

It is also emphasized that AI tools are particularly effective in identifying gaps in the literature (Vatansever et al., 2021; Roumengas et al., 2023). Furthermore, these tools contribute to the formulation of research hypotheses (Khalifa & Albadawy, 2024) and improve the quality and efficiency of content creation and organization in academic research (Giglio & Costa, 2023; Lee & Choi, 2023; Ghorashi et al., 2023; Ingley & Pack, 2023; Semrl et al., 2023; Khlaif et al., 2023). AI tools, especially ChatGPT, are noted to significantly enhance productivity and quality in scientific article writing (Huang & Tan, 2023). These tools support the writing process through functions such as text expansion, outline development, and writing style improvement. Additionally, their predictive text capabilities accelerate the writing process by suggesting technical terms and providing support in academic writing (Dwivedi et al., 2023). Moreover, AI tools are considered effective in writing review articles, helping create comprehensive overviews of existing research (Huang & Tan, 2023). Particularly during the literature review and synthesis process, AI plays a critical role in increasing efficiency and depth (Golan & Shalev, 2023). In addition, AI-powered writing software enhances writing style by correcting grammatical errors, which is especially advantageous for non-native English-speaking academics (Giglio & Costa, 2023).

In conclusion, the AI Dependency Scale for Educators is a rigorously developed instrument that offers researchers, policymakers, and educational institutions a reliable means of measuring the extent to which educators depend on AI technologies in their professional practices. This tool may serve as a foundation for future studies exploring the cognitive, behavioral, and pedagogical implications of AI use, and can inform the development of guidelines or interventions aimed at promoting balanced and critical AI integration in educational contexts.

6 Conclusion

This study presents a newly developed scale designed to measure educators' dependency on AI tools. Utilizing an exploratory sequential mixed-methods design, the research identified two primary factors—*Dependency in Academic Processes* and *Dependency in Educational Processes*—based on interviews with academics and teachers. The validity and reliability of the scale were analyzed, and the results of the factor analyses confirmed its construct validity, demonstrating that the scale is a robust tool for evaluating educators' dependency on AI tools.

The contributions of AI tools to academic and instructional processes are increasingly recognized by educators, leading to a growing dependency on these technologies. However, the literature also highlights potential negative effects of AI overuse, such as cognitive overload, mental fatigue, and diminished critical thinking skills. Therefore, it is essential for educators to use AI tools consciously and in a balanced manner, ensuring that the human element remains central to pedagogical processes. In this context, the study makes a significant contribution to the literature by offering a reliable instrument to measure educators' AI dependency. Future research may expand on these findings by testing the validity of the scale across different educational levels and cultural contexts. Additionally, increasing the number of qualitative studies exploring both the benefits and potential drawbacks of excessive AI use in education will help raise awareness and promote more responsible integration of AI in educational settings.

7 Theoretical and practical contributions

The findings of this study offer both theoretical and practical contributions. Theoretically, it expands the understanding of AI dependency by identifying its key dimensions—dependency in educational processes and dependency in academic processes—and by conceptualizing how this dependency manifests in educators' daily practices. Beyond its use for researchers and policymakers, the scale also has practical implications for educators and educational institutions. Practically, the study provides a validated and reliable measurement tool that can be directly used in various research and institutional contexts.

This AI Dependency Scale enables researchers to measure the level of reliance on AI tools among educators, such as how frequently and to what extent teachers use AI for lesson planning, material development, or student assessment, and how academics depend on AI for tasks like academic writing, literature reviews, and research topic selection. For example, a researcher could use this scale to compare AI dependency levels between early-career and senior educators, or between different academic disciplines.

Beyond its use for researchers and policymakers, the scale also has practical implications for educators and educational institutions. Teachers can use the scale as a self-assessment tool to reflect on their own reliance on AI in both instructional and academic tasks, which may raise awareness of potential over-dependence. In addition, educational institutions and policymakers can use the scale in needs assessments to identify areas where professional development is required, such as training programs that foster critical, ethical, and balanced AI integration in teaching and research practices. Furthermore, the scale can serve as a foundation for future research that investigates how high levels of AI dependency may affect critical thinking, decision-making, creativity, or job satisfaction in educational environments.

In summary, this study not only introduces a new conceptually grounded and psychometrically strong scale but also provides a practical tool for understanding and addressing the benefits and risks of AI integration in education.

8 Limitations

This study has certain limitations regarding cultural and contextual factors. The data were collected exclusively from educators in Türkiye, and the resulting scale therefore reflects the perspectives and practices of this specific context. While the qualitative interviews consistently revealed two main dimensions of AI dependency—academic processes and educational processes—it is possible that different themes might emerge in other cultural or educational settings. For this reason, the generalizability of the scale to non-Turkish or non-Western contexts remains uncertain. Future research should validate the scale across diverse cultural and institutional contexts to ensure its broader applicability.

Appendix

Table 11 Artificial Intelligence Dependency Scale

Please consider your level of dependency on artificial intelligence while answering the items below. Never (1) – Rarely (2) – Sometimes (3) – Often (4) – Always (5)
1. Yapay zekâ araçları olmadan akademik yazılarımı tamamlamanın daha uzun süreceğini düşünürüm. *(I believe it would take longer to complete my academic writing without AI tools.)*
2. Yapay zekâ araçları kullanmadan akademik yazılarımın yetersiz olacağını düşünürüm. *(I think my academic writing would be inadequate without using AI tools.)*
3. Akademik yazılarımda yapay zekâ araçlarından aldığım öneriler olmadan yazım sürecini tamamlamakta zorlanırım. *(I find it difficult to complete the writing process without suggestions from AI tools in my academic writing.)*
4. Alanyazın araştırması öncesinde konu hakkında bilgi sahibi olmak için yapay zekâ araçlarına başvururum. *(I use AI tools to gain background knowledge about a topic before conducting a literature review.)*
5. Yapay zekâ araçlarının sağladığı kaynak önerilerine göre alanyazın araştırması yaparım. *(I conduct literature reviews based on resource suggestions provided by AI tools.)*
6. Yapay zekâ araçlarına başvurmadığımda, alanyazın araştırmasının eksik olacağını düşünürüm. *(I think my literature review will be incomplete without consulting AI tools.)*
7. Yapay zekâ araçlarına başvurmadan alanyazın araştırması yaparken kendimi yetersiz hissederim. *(I feel inadequate when conducting a literature review without using AI tools.)*
8. Akademik yazılarımı yapay zekâ araçlarının dil kontrolü desteği olmadan tamamlamakta zorlanırım. *(I find it difficult to complete my academic writing without AI tools' language support.)*
9. Akademik yazılarımı yapay zekâ araçlarının yazım kontrolü desteği olmadan tamamlamakta zorlanırım. *(I find it difficult to finish my academic writing without the spelling and grammar support of AI tools.)*
10. Akademik yazılarımın hatasız olabilmesi için yapay zekâ araçlarının geri bildirimine ihtiyaç duyarım. *(I need feedback from AI tools to ensure my academic writing is error-free.)*
11. Yapay zekâ araçlarını kullanmadığımda akademik yazılarımdaki dil ve yazım hatalarını fark edemeyeceğimi düşünürüm. *(I believe I wouldn't notice language and grammar errors in my academic writing without AI tools.)*
12. Yapay zekâ araçlarının önerileri olmadan araştırma konusu belirlemekte zorlanırım. *(I find it difficult to determine a research topic without suggestions from AI tools.)*
13. Yapay zekâ araçları olmadan özgün bir araştırma konusu seçmekte zorlanırım. *(I find it difficult to choose an original research topic without using AI tools.)*
14. Yapay zekâ araçlarına başvurmadan araştırma konusu belirlediğimde araştırmamın niteliksiz olacağını düşünürüm. *(I think my research will lack quality if I choose the topic without using AI tools.)*
15. Yapay zekâ araçlarına başvurmadığımda nitelikli ders içerikleri oluşturmakta zorlanırım. *(I find it difficult to create high-quality course content without AI tools.)*
16. Yapay zekâ araçlarına başvurmadığımda eksiksiz ders içerikleri oluşturmakta zorlanırım. *(I find it difficult to develop comprehensive course content without using AI tools.)*
17. Yapay zekâ araçları olmadan, ders içeriği oluşturmam gerektiğinde ne yapacağımı bilemem. *(Without AI tools*, *I don't know where to start when I have to create course content.)*
18. Yapay zekâ araçları olmadan ders materyalleri hazırlamakta zorlanırım. *(I find it difficult to prepare course materials without AI tools.)*
19. Yapay zekâ araçları olmadan öğretim materyalleri geliştirmeye çalıştığımda, materyalin niteliksiz olacağını düşünürüm. *(I feel that the instructional materials I develop without AI tools will lack quality.)*

Table 11 (continued)

Please consider your level of dependency on artificial intelligence while answering the items below. Never (1) – Rarely (2) – Sometimes (3) – Often (4) – Always (5)
20. Yapay zekâ araçlarının sunduğu içerikler olmadan, ders materyalleri geliştiremem. *(I cannot develop course materials without the content provided by AI tools.)*
21. Ders planı hazırlarken yapay zekâ araçlarına başvurmadığımda, planın eksik olacağı endişesi taşırım. *(I worry that my lesson plan will be incomplete without consulting AI tools.)*
22. Ders planı hazırlarken, yapay zekâ araçlarını kullanmadan ilerlemekte zorlanırım. *(I find it difficult to progress in lesson planning without using AI tools.)*
23. Yapay zekâ araçlarının önerilerine başvurmazsam ders planlarımın niteliksiz olacağını düşünürüm. *(I believe my lesson plans would lack quality without suggestions from AI tools.)*
24. Sınıf içi etkinlikleri hazırlarken yapay zekâ araçları olmadan karar vermekte zorlanırım. *(I find it hard to make decisions when preparing in-class activities without AI tools.)*
25. Sınıf içi etkinlikleri hazırlarken, yapay zekâ araçlarının önerileri olmadan fikir üretmekte zorlanırım. *(I find it difficult to generate ideas for in-class activities without suggestions from AI tools.)*
26. Yapay zekâ araçlarını kullanmadan hazırladığım sınıf içi etkinliklerin yetersiz olacağını düşünürüm. *(I believe that in-class activities I prepare without AI tools will be inadequate.)*
27. Ödev hazırlarken yapay zekâ araçları olmadan ödev hazırlamaya çalıştığımda, ödevlerin yeterince ilgi çekici olmayacağını düşünürüm. *(When preparing assignments without AI tools, I think they will not be engaging enough.)*
28. Yapay zekâ araçlarından destek almadan hazırladığım ödevlerin yeterince kapsamlı olmayacağını düşünürüm. *(I believe assignments prepared without AI support will not be comprehensive enough.)*
29. Yapay zekâ araçları olmadan hazırladığım ödevlerin, öğrencilerin ihtiyaçlarına uygun olmamasından endişe duyarım. *(I worry that assignments prepared without AI tools may not meet students' needs.)*
30. Öğrenci başarısını/performansını değerlendirirken, yapay zekâ araçlarından aldığım geri bildirimlere başvurmadan objektif değerlendirmeler yapamayacağımı düşünürüm. *(I feel I cannot make objective assessments of student performance without feedback from AI tools.)*
31. Öğrenci performansını değerlendirirken yapay zekâ araçlarına başvurmadığımda, ölçütlere uygun değerlendirmeler yapıp yapamadığımdan emin olamam. *(I am unsure if my assessment aligns with the criteria when I do not use AI tools for assessing student performance.)*
32. Yapay zekâ araçları olmadan öğrenci değerlendirmelerini doğru bir şekilde yapamayacağımı düşünürüm. *(I believe I cannot accurately assess students without AI tools.)*

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Data availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate All participants were volunteers who had agreed to participate in the research study. They were told they could withdraw from the research at any time. There are no ethical issues or conflicts of interest emanating from this study.

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