Contemporary Educational Technology, 2025, **17**(3), ep579
ISSN: 1309-517X (Online)

OPEN ACCESS **Research Article**

Pre-service science teachers' perception on using generative artificial intelligence in science education

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Citation: Ishmuradova, I. I., Zhdanov, S. P., Kondrashev, S. V., Erokhova, N. S., Grishnova, E. E., & Volosova, N. Y. (2025). Pre-service science teachers' perception on using generative artificial intelligence in science education. *Contemporary Educational Technology, 17*(3), ep579. https://doi.org/10.30935/cedtech/16207

ARTICLE INFO

Received: 3 Oct 2024
Accepted: 19 Mar 2025

ABSTRACT

The development of generative artificial intelligence (AI) has started a conversation on its possible uses and inherent difficulties in the field of education. It becomes essential to understand the perceptions of pre-service teachers about the integration of this technology into teaching practices as AI models including ChatGPT, Claude, and Gemini acquire popularity. This investigation sought to create a valid and trustworthy instrument for evaluating pre-service science teachers' opinions on the implementation of generative AI in educational settings related to science. This work was undertaken within the faculty of education at Kazan Federal University. The total number of participants is 401 undergraduate students. The process of scale development encompassed expert evaluation for content validity, exploratory factor analysis, confirmatory factor analysis, and assessments of reliability. The resultant scale consisted of four dimensions: optimism and utility of AI in science education, readiness and openness to AI integration, AI's role in inclusivity and engagement, and concerns and skepticism about AI in science education. The scale demonstrated robust psychometric properties, evidenced by elevated reliability coefficients. Cluster analysis unveiled distinct profiles of pre-service teachers based on their responses, encompassing a spectrum from enthusiastic participants to skeptical disengaged individuals. This study provides a comprehensive instrument for evaluating pre-service teachers' perceptions, thereby informing teacher education programs and professional development initiatives regarding the responsible integration of AI. Recommendations entail the validation of the scale across varied contexts, the exploration of longitudinal changes, and the investigation of subject-specific applications of generative AI in science education.

Keywords: generative artificial intelligence, science education, scale development, pre-service teacher's perceptions

INTRODUCTION

The rapid evolution of generative artificial intelligence (AI) has sparked discussions about their applications and repercussions, as well as new paths in education. Models such as ChatGPT, Gemini, and Claude illustrate generative AI, a class of strong deep learning systems able to produce human-like material across various modalities (Michel-Villarreal et al., 2023; Su & Yang, 2023). These AI systems have attracted interest to educators and academics looking at their capabilities to improve teaching, learning, and evaluation processes (Baidoo-Anu & Owusu Ansah, 2023; Rasul et al., 2023; Shumiye, 2024).

Generative AI raises difficulties even if it delivers exciting educational possibilities, including tailored learning experiences and automated content development (Bhutoria, 2022; Kumar et al., 2023). These address issues on accuracy, bias, academic integrity, and the evolving position of human teachers (Alasadi & Baiz, 2023; Michel-Villarreal et al., 2023). Consequently, encouraging AI literacy among their students and guiding teachers to use these tools properly have taken front stage (Zastudil et al., 2023). Since they will shape the course of education ahead, pre-service teachers' opinions on introducing generative AI into classrooms are rather important. Though various studies have looked at pre-service teachers' thoughts on AI and technology integration generally (Istenic et al., 2021; Yang & Chen, 2023), a thorough instrument is needed to evaluate their particular views of generative AI in scientific education.

Although the literature contains several scale studies on the application of generative AI, none of them particularly assesses pre-service science education teachers' opinions on this technology. The particular traits of science education, such as laboratory work, scientific process skills, design and analysis of experiments, could call for various approaches to the use of generative AI. Generative AI use rates might not accurately represent these specific circumstances in science education. For instance, generic scales may not be sufficient to handle problems including the usage of generative AI in science studies or the use of AI-based simulations in teaching science concepts. Thus, creating a scale including products unique to science education will help us to more precisely and in depth evaluate pre-service teachers' opinions of the application of generative AI in this field. Such a scale can better evaluate pre-service teachers' preparedness, expose the benefits and drawbacks of utilizing generative AI in science education, and help to create more successful plans for generative AI inclusion in curricula. Finally, we think that the study on this topic will benefit greatly from the creation of a generative AI perspective scale unique for science education. By attaining these objectives, the study can enrich the comprehension of pre-service teachers' preparedness and apprehensions, guiding teacher training programs and initiatives for professional growth to facilitate the responsible integration of generative AI in science classrooms.

LITERATURE REVIEW

Generative Artificial Intelligence

Generative AI refers to a class of deep learning models and techniques that are capable of generating new human-like content such as text, images, audio, or other modalities (Kaldaras et al., 2024; Michel-Villarreal et al., 2023; Su & Yang, 2023). Generative AI uses deep learning to not only analyze existing data but also create new outputs that mimic patterns found in training data (Cevallos et al., 2023). With the announcement of OpenAI ChatGPT for open use in November 2022, generative AI became more known to everyone (Rasul et al., 2023).

There are many generative AIs available for public use. ChatGPT 3.5 and ChatGPT 4 versions are trained by OpenAI. Google trained the model, previously called Bard, with larger data and launched the model called Gemini. There are also models called Claude offered by Antropic.

Claude itself is defined as the following:

> "Sure, I'm an AI model created by Anthropic to engage in open-ended dialogue and assist with a variety of tasks. I use large language models and machine learning to understand and generate human-like responses. My knowledge spans a wide range of topics which allows me to converse, analyze information, answer questions, write content, and solve problems. However, I'm not connected to the Internet–my training data cutoff is from August 2023 so I may not have fully up-to-date information on recent events after that point. I'm an artificial general intelligence aimed at being helpful, honest and harmless in our interactions" (03/19/2024).

ChatGPT 4.0 is defined itself as the following:

> "I am a generative AI developed by OpenAI, built on the GPT (generative pre-trained transformer) architecture. My abilities stem from extensive training on a diverse dataset, which includes a wide range of internet text, books, and articles, enabling me to understand and generate human-like text. OpenAI, an AI research and deployment company, aims to ensure that artificial general intelligence benefits all of humanity. I'm designed to interact, answer questions, create content, and assist with a variety of text-based tasks. Ethical use and safety are paramount, with continuous updates enhancing my performance and safety measures" (03/19/2024).

Gemini is described itself as follows:

> "I am Gemini, a large language model created by Google AI. I am trained on a massive dataset of text and code, allowing me to generate text, translate languages, and answer your questions in an informative way. Think of me as a super-powered student who's devoured a vast library of information. I can communicate and create new things based on the knowledge I've gleaned from this immense dataset" (03/19/2024).

Generative AI has evolved beyond simply producing human-like responses, now capable of diverse tasks such as creating videos (Leiker et al., 2023), generating images, designing diagrams (Krishna Suryadevara, 2020), writing computer code (Rudolph et al., 2023), and solving mathematical problems (Poola & Božić, 2023). However, despite their impressive capabilities, these systems are not without errors. They can produce factual errors, inconsistent outputs, and may amplify biases present in their training data (Baidoo-Anu & Owusu Ansah, 2023; Bender et al., 2021). Popular generative AI systems like ChatGPT, Gemini, and Claude are known to potentially produce content containing errors or reflecting certain biases. As this technology rapidly advances, it presents both significant opportunities and potential risks, leading to growing concerns about its societal impact. So, there are more and more calls for responsible development based on AI ethics (Cooper, 2023; Liebrenz et al., 2023) in order to get the most out of generative AI while minimizing the bad things that might happen.

Generative Artificial Intelligence in Education

The emergence of generative AI has opened up new possibilities and sparked discussions regarding its potential applications in education. Researchers have begun to explore how large language models, generative adversarial networks, and other generative techniques can be leveraged to improve teaching, learning, and assessment. One of the prominent topics is the use of generative AI as an educational support tool. AI writing assistants like Claude or ChatGPT show promise in providing feedback to help students improve their writing skills (Mohamed, 2023). Generative models can also dynamically generate explanations, examples, and practice questions tailored to individual student needs (Bhutoria, 2022; Kumar et al., 2023; Zhang & Aslan, 2021). Chen et al. (2023) claim that timeliness, scalability, and the capacity to offer real-time feedback and boost student engagement are the key advantages of pedagogical chatbots. According to Langran et al. (2024), all stakeholders must play an urgent role in the ethical and fair use of AI, and teacher educators in particular must be at the forefront to guide this process correctly. This, in a sense, emphasizes the necessity of the use and integration of generative AI technologies in education.

For instructors, generative AI can potentially save time and improve personalization by automating the creation of educational content such as assessments, course materials, or coding exercises (Baidoo-Anu & Owusu Ansah, 2023; Kohnke et al., 2023; Ruiz-Rojas et al., 2023). AI-generated characters, scenarios, and dialogues could enable more immersive simulations for medical, language, or business education (Bakkum et al., 2023; Spaniol & Rowland, 2023; Vallis et al., 2023). However, challenges remain regarding the reliability, safety, and ethical implications of generative AI in education (Alasadi & Baiz, 2023). Concerns have been raised about risks such as factual errors, increased bias, and academic dishonesty (Michel-Villarreal et al., 2023). Preparing instructors to implement these technologies responsibly while improving students' AI literacy are key priorities (Wilton et al., 2022; Zastudil et al., 2023). Even while generative AI has the potential to provide insightful explanations, particularly for some concepts, its integration with conventional teaching techniques needs to be carefully studied and calibrated (Lee & Song, 2024).

Pre-Service Teachers' Perception of Using Generative Artificial Intelligence in Education

The rapid emergence and adoption of generative AI in educational settings has brought to the forefront a crucial discussion about the skills and knowledge that educators need to effectively incorporate this technology into their teaching practices. Generative AI, with its ability to create content, answer questions, and even simulate complex scenarios, offers unprecedented opportunities for enhancing the learning experience. However, it also presents challenges that educators must be prepared to address. Recent studies have highlighted the specific competencies that teachers need to develop in order to harness the potential of generative AI while minimizing its risks (Alasadi & Baiz, 2023; Nyaaba et al., 2024; Zhang & Villanueva, 2023).

As discussions on the use of AI in teacher education grow, it has attracted the attention of experts in the field of technological pedagogical content knowledge for teachers, especially in K-12 education. Generative AI tools such as ChatGPT can help teachers design courses and impart content knowledge by supporting technology integration (Cun & Huang, 2024).

The acceptance and perceptions of these educators, like other instructional technologies, are pivotal for the widespread adoption of generative AI tools (Baytak, 2023). Particularly, the attitudes of pre-service teachers towards the inclusion of generative AI in educational settings are vital, underscoring the need for a deep understanding of their perspectives on this innovative technology.

Research into the attitudes of pre-service teachers towards AI and its incorporation into education has been fruitful. A study by Nyaaba et al. (2024) highlighted a significant uptick in awareness and use of generative AI tools, such as OpenAI's ChatGPT, Google Bard, and DALLE, among future educators in Ghana. This trend underscores a growing recognition of the relevance and applicability of generative AI in educational contexts.

Further researchers, such as those by Yang and Chen (2023) and Zhang et al. (2023), delved into pre-service teachers' intentions to employ AI-powered chatbots for educational objectives. Findings suggest that these intentions are largely driven by the perceived usefulness and ease of utilizing AI technologies, with usefulness exerting a more profound influence on their adoption decisions. A study was conducted examining EFL pre-service teachers' experiences of generative AI (Söğüt, 2024). The author emphasizes the pedagogical benefits of AI in the EFL writing process, such as providing instant and personalized feedback and reducing inequalities by providing equal access to information.

Contrastingly, the adoption of social robots in educational spheres has encountered resistance from pre-service teachers, who find their application "unacceptable" due to concerns over the robots' social intelligence capabilities within classroom settings (Istenic et al., 2021). This resistance highlights a nuanced perspective among future educators, indicating varying levels of receptivity towards different types of educational technology applications.

Using Generative Artificial Intelligence in Science Education

Verma et al. (2023) assert that it is premature to predict the potential impact of these generative language models on us as science teacher educators. Generative AI is implemented in the field of science education, as it is in the field of general education. Improved student success came from using generative AI, sometimes known as Synthesia, as a sophisticated teaching tool in laboratory research. Joseph (2023) claims that the findings point to students finding Synthesia AI movies to be helpful in clarifying laboratory experiment knowledge. At the secondary school level, the integration of AI technology into scientific classrooms has been shown to improve student involvement and academic achievement. Customized learning experiences tailored to the particular needs of every student have been shown by intelligent tutoring systems and adaptive learning systems to be effective (Okunade, 2024). Cooper's (2023) analysis of ChatGPT's responses to queries in scientific education highlights its remarkable ability to imitate human-like responses. According to Cooper (2023), ChatGPT's comments mostly matched the primary research themes found in the literature.

Furthermore, an analysis of the classification of biology and chemistry questions in the ChatGPT 3.5 undergraduate level textbook based on Bloom's taxonomy revealed a significant level of agreement between GPT-taxonomy and human-taxonomy (Hwang et al., 2023). This demonstrates that generative AI technology can aid science educators in structuring course content. Cooper (2023) suggests that educators can utilize ChatGPT for creating science lessons, rubrics, and quizzes, while emphasizing the importance of reviewing and adapting the AI-generated content to suit their specific teaching requirements.

In particular, the potential to revolutionize education, including science education and science teacher education, is present with the emergence of generative language models, such as ChatGPT, which provide personalized learning experiences, adaptive assessments, and virtual tutors (Verma et al., 2023). Nevertheless, the utilization of generative AI in education poses challenges, including concerns about AI-generated errors and the potential for misuse (Baidoo-Anu & Owusu Ansah, 2023). While emphasizing the potential of AI in education, it points out that the unequal use of these technologies could exacerbate inequalities in education. Additionally, it emphasizes that those providing science education should focus on developing AI literacy to ensure that these technologies can be used fairly and transformative (Verma et al., 2023). It is crucial to equip science teachers with the necessary skills to ethically and judiciously harness these powerful tools, emphasizing the need for further research and curriculum development in this area (Karampelas, 2025; Nyaaba & Zhai, 2024; Okunade, 2024).

Some scale development studies have been conducted on the application of AI in education. In the context of Turkey, Karaoglan Yilmaz and Yilmaz (2020) devised a measure to assess the level of adoption of generative AI methodologies among university students. The scale development process was executed using the UTAUT model as its foundation. The preparation of the items was based on the subscales of 'performance expectancy', 'effort expectancy', 'facilitating conditions', and 'social impact'. Exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and reliability analysis were conducted to assess the scale's validity and reliability. The study conducted by Baidoo-Anu and Owusu Ansah (2023) introduced the students' ChatGPT experiences scale. The researchers devised the scale items for the investigation. An assessment was conducted on a sample of 441 university students from Ghana. EFA and CFA analyses were performed on the acquired data. A number of research (Chan & Hu; 2023; Treglia & Tomassoni, 2024; Wood & Moss, 2024) have employed questionnaires as an alternative to valid and reliable scales for assessing students' views and opinions.

METHODOLOGY

The study aims to develop a valid and reliable instrument to measure pre-service science teachers' perceptions regarding the use of generative AI in science education and to examine their perceptions (**Appendix A**). To achieve this, we focused on staying within the established stages of developing the scale (as shown in **Figure 1**). Based on the data from the psychometric analyses, which were the final stage of the scale development process, we investigated the perceptions of pre-service science teachers at the faculty of pedagogy of the Kazan Federal University on the topic of 'generative use of AI in science education' using cluster analysis.

Data Collection Tool and Process

The construction of the item pool and the comprehensibility

The scale development process was followed based on the diagram shown in **Figure 1**. A thorough literature review was conducted to scrutinize publications on the application of AI in the domain of

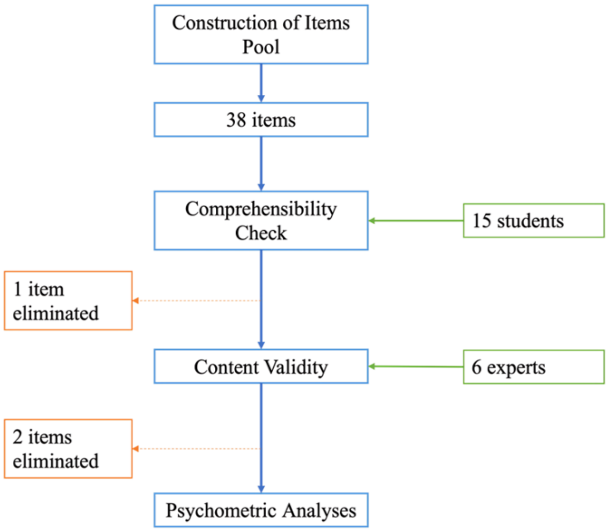

Figure 1. Scale development process (Source: Elaborated by the authors)

educational instruction. This examination informed the selection and adaptation of relevant items to tailor them specifically to the field of science education. The preliminary version of the scale consisted of 38 items. These items were then pilot-tested for comprehensibility with a cohort of 15 students, comprising five students each from the disciplines of physics education, chemistry education, and biology education. The feedback from these students indicated that, with the exception of one item, they found the items to be comprehensible and within their cognitive grasp. The exception pertained to the statement, "I'm uncertain how to evaluate the accuracy and reliability of content created for science lessons," which participants found ambiguous in terms of whether it referred to all content or specifically to AI-generated content. To alleviate this confusion and enhance clarity, the item was revised to, "I am uncertain about how to evaluate the accuracy and reliability of AI-generated content for science lessons." This modification was aimed at refining the scale to more precisely capture the constructs being measured.

Content validity

The items were subjected to a content validity assessment by soliciting expert opinion. The scale was circulated among six experts, who were carefully chosen based on their specialization in the field of science education and educational technologies. The panel included two experts in general science education, one in physics education, two in biology education, and one in chemistry education. These experts evaluated each item based on a binary scale: 1 for "appropriate" and 0 for "not appropriate". The item content validity index (I-CVI) was calculated for each item, with a possible range from 1 (indicating unanimous agreement) to 0.50 (indicating lower levels of agreement).

According to Yusoff (2019), the minimum acceptable I-CVI is 0.83 when engaging six experts in the evaluation process. Consequently, two items – "I believe that artificial intelligence has the potential to enhance education" with an I-CVI of 0.67 and "I am optimistic about the long-term benefits of integrating AI into educational systems" with an I-CVI of 0.50 – were excluded from the scale due to their failure to meet the threshold.

After these exclusions, the revised scale's I-CVI values ranged between 1 and 0.83, signifying a high level of expert agreement on the content validity of the remaining items. The scale content validity index/average (S-CVI/Ave), a measure of the overall validity of the scale items, was calculated to be 0.98, while the scale content validity index/universal agreement (S-CVI/UA) was determined to be 0.86. These indices reflect a robust consensus on the appropriateness of the scale's content. Given these satisfactory content validity evaluations, the process advanced to the subsequent psychometric analyses.

Sample

The study was implemented within the faculty of education at Kazan Federal University. The rationale for selecting senior students lies in the premise that their domain knowledge and experience are considerably developed, making them representative subjects for this research. The participants are prospective science education teachers, thereby providing pertinent insights into the instructional utility of AI in their future profession. The demographic composition of the sample revealed that 74.8% identified as female, while 25.2% identified as male.

To ensure the robustness of the psychometric evaluation, the collected data set was randomly divided into two distinct groups. This was conducted to facilitate two separate but complementary statistical analyses: EFA and CFA. Accordingly, data from 202 individuals were used for EFA to uncover potential underlying factor structures without biasing the analysis with preconceived notions. In contrast, the CFA employed data from 199 individuals to test the hypothesis that a relationship between observed variables and their underlying latent constructs exists. This bifurcation of the sample allowed for a comprehensive validation of the scale's factor structure.

Data Analysis

Since the scale items were not presented as a definite structure, it was first determined whether the scale had sub-dimensions by performing EFA (Williams et al., 2010). Then, the CFA method was applied to determine whether these sub-dimensions were valid in different samples (Thompson, 2004). The data analysis commenced with psychometric computations, initiating with an EFA to identify potential latent constructs within the survey instrument. Prior to the EFA, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and the Bartlett's test of sphericity were conducted to ascertain the factorability of the data. Given the preference for orthogonal factor structures, the Varimax rotation technique was selected due to its efficacy in producing non-correlated dimensions (Watkins, 2018; Williams et al., 2010; Yong & Pearce, 2013).

The subsequent phase involved a CFA, which allowed for the hypothesis testing of the factor structure proposed by the EFA. During the CFA, indices such as the Chi-square to degrees of freedom ratio ($\chi^2/df < 3$), comparative fit index (CFI) (> 0.90), Tucker-Lewis index (TLI) (> 0.90), standardized root mean square residual (SRMR) (< 0.08), and root mean square error of approximation (RMSEA) (< 0.08) were meticulously examined to assess model fit. Also, factor loadings were checked to make sure that the relationships between the variables that were seen and their corresponding latent constructs were strong and important (Brown, 2015; Jackson et al., 2009).

The third stage of analysis was dedicated to assessing the reliability of the scale and its subscales. Internal consistency reliability was estimated using Cronbach's alpha for the EFA dataset and McDonald's omega coefficient for the CFA dataset. the statistical software Jamovi was used for EFA, CFA, and reliability analysis.

In the fourth and final phase of analysis, a cluster analysis was performed on the entire sample to explore the distinct profiles of pre-service science teachers based on the dimensions of the scale. This involved grouping the participants into clusters to discern patterns in their responses. The procedure for the cluster analysis and the visualization of data were facilitated by the software Tableau, which provided a powerful means of interpreting complex data sets and uncovering substantive insights into the collective orientations of the students within the clusters.

FINDINGS

Descriptive

Table 1 shows the means, which range from 2.59 to 3.96; most entries have means more than 3. They show quite good reactions. Usually ranging from 1.1 to 1.3, standard deviations indicate very moderate variation in responses across items. Based on their skewness and kurtosis values, all objects can be regarded as having a normal distribution. The kurtosis values run from –0.90 to 0.58; the skewness values span –1.11 to 0.35. These values are within reasonable bounds for supposing normalcy (usually for skewness and kurtosis between –2 and +2). Further supporting the hypothesis of normalcy are the rather tiny and consistent standard errors (SE) for both skewness and kurtosis across items. The correlation value between the items varies between –0.082 and 0.948. While the minimum score is 1, the maximum score is 5 for each item.

Table 1. Descriptive statistics for each item

Items	Mean	SD	Minimum	Maximum	Skewness	Skewness SE	Kurtosis	SE
AI_1	2.59	1.28	1	5	0.35	0.17	−0.90	0.34
AI_2	3.23	1.17	1	5	−0.26	0.17	−0.52	0.34
AI_3	3.62	1.14	1	5	−0.59	0.17	−0.33	0.34
AI_4	3.89	1.13	1	5	−0.84	0.17	−0.04	0.34
AI_5	3.85	1.11	1	5	−0.75	0.17	−0.14	0.34
AI_6	3.85	1.13	1	5	−0.85	0.17	0.07	0.34
AI_7	3.53	1.32	1	5	−0.56	0.17	−0.76	0.34
AI_8	3.70	1.11	1	5	−0.82	0.17	0.17	0.34
AI_9	3.80	1.12	1	5	−0.83	0.17	0.10	0.35
AI_10	3.96	1.15	1	5	−1.11	0.17	0.58	0.34
AI_11	3.89	1.17	1	5	−0.95	0.17	0.18	0.34
AI_12	3.84	1.22	1	5	−0.94	0.17	0.02	0.34
AI_13	3.86	1.17	1	5	−0.92	0.17	0.12	0.34
AI_14	3.46	1.23	1	5	−0.42	0.17	−0.68	0.34
AI_15	3.19	1.26	1	5	−0.22	0.17	−0.82	0.34
AI_16	3.43	1.20	1	5	−0.46	0.17	−0.57	0.34
AI_17	3.21	1.21	1	5	−0.09	0.17	−0.80	0.34
AI_18	3.25	1.25	1	5	−0.24	0.17	−0.76	0.34
AI_19	3.24	1.19	1	5	−0.17	0.17	−0.66	0.34
AI_20	3.36	1.25	1	5	−0.31	0.17	−0.84	0.34
AI_21	3.51	1.10	1	5	−0.52	0.17	−0.14	0.34
AI_22	2.99	1.20	1	5	−0.11	0.17	−0.67	0.34
AI_23	3.23	1.23	1	5	−0.21	0.17	−0.73	0.34
AI_24	2.96	1.17	1	5	−0.08	0.17	−0.60	0.34
AI_25	2.81	1.23	1	5	0.08	0.17	−0.88	0.35
AI_26	3.63	1.12	1	5	−0.68	0.17	−0.01	0.34
AI_27	3.43	1.16	1	5	−0.57	0.17	−0.21	0.34
AI_28	3.63	1.13	1	5	−0.70	0.17	−0.01	0.34
AI_29	3.53	1.13	1	5	−0.55	0.17	−0.17	0.34
AI_30	3.43	1.10	1	5	−0.49	0.17	−0.17	0.34
AI_31	3.41	1.13	1	5	−0.58	0.17	−0.19	0.34
AI_32	3.55	1.12	1	5	−0.55	0.17	−0.25	0.34
AI_33	3.51	1.14	1	5	−0.47	0.17	−0.34	0.34
AI_34	3.49	1.13	1	5	−0.49	0.17	−0.24	0.34
AI_35	3.69	1.14	1	5	−0.71	0.17	−0.03	0.34
AI_36	3.58	1.09	1	5	−0.54	0.17	−0.10	0.34
AI_37	3.64	1.14	1	5	−0.67	0.17	−0.05	0.34

Note: SD: Standard deviation; SE: Standard error.

Exploratory Factor Analysis

In EFA, the maximum likelihood extraction method was employed, in conjunction with a varimax rotation. The factor loading threshold was set at 0.5. The analysis was reiterated after removing the second, third and 15th items from the scale, as their factor loadings fell below the critical value. Bartlett's test of sphericity (χ^2 = 6760, df = 561, p < .001) and KMO measure of sampling adequacy (0.922) indicated that the data were suitable for factor analysis. Parallel analysis was used to determine the optimal number of factors to retain.

As illustrated by the scree plot, the scale items clustered into four distinct factors (**Figure 2**).

Factor 1 subsumed 13 items, with factor loadings ranging from 0.65 to 0.87 (as shown in **Table 2**). An examination of the constituent items revealed that this factor encapsulated statements reflecting optimism regarding the positive potential of AI to enhance various facets of science education, such as problem-solving, critical thinking, and the comprehension of complex concepts. Additionally, it encompassed the belief in the role of AI in augmenting the efficiency of educational content creation. Consequently, this factor was labeled "*optimism and utility of AI in science education*". The items loading onto factor 1 accounted for 28.27% of the scale's variance.

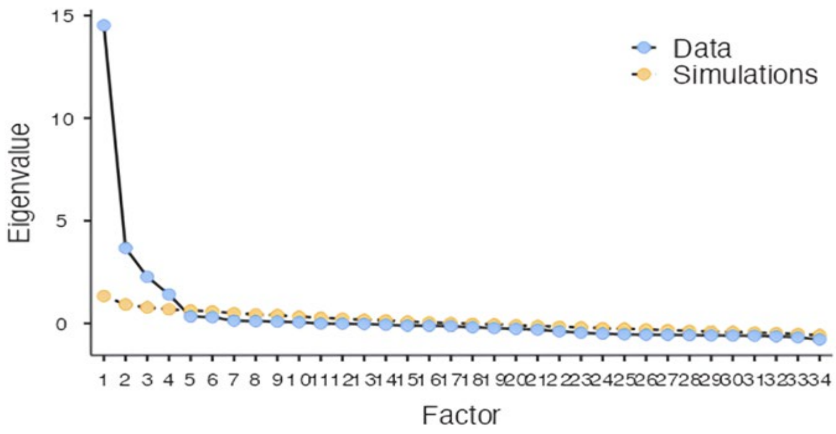

Figure 2. Scree plot (Source: Elaborated by the authors)

Table 2. Factor loading

Items	Factor 1	Factor 2	Factor 3	Factor 4	Uniqueness
AI_37	0.872				0.1401
AI_35	0.864				0.1788
AI_32	0.842				0.1810
AI_33	0.836				0.2198
AI_36	0.835				0.1971
AI_34	0.828				0.2154
AI_27	0.806				0.2498
AI_26	0.794				0.2607
AI_29	0.791				0.2360
AI_31	0.785				0.3218
AI_30	0.778				0.2965
AI_28	0.764				0.3074
AI_21	0.650				0.4488
AI_13		0.927			0.0688
AI_11		0.926			0.0760
AI_12		0.926			0.0661
AI_10		0.854			0.2063
AI_9		0.681			0.4721
AI_5		0.648			0.5114
AI_6		0.644			0.4786
AI_8		0.640			0.5013
AI_7		0.638			0.4944
AI_4		0.623			0.4704
AI_14		0.531			0.6246
AI_19			0.844		0.2693
AI_17			0.806		0.3221
AI_16			0.718		0.4219
AI_18			0.699		0.4888
AI_20			0.663		0.5439
AI_22				0.852	0.1822
AI_24				0.795	0.2325
AI_25				0.684	0.4562
AI_23				0.618	0.3233
AI_1				0.548	0.6284
Variance extracted (%)	28.27	20.93	9.14	9.04	

Factor 2 comprised 11 items, with factor loadings ranging from 0.53 to 0.93. The items subsumed within this factor reflected educators' preparedness, willingness to learn, and confidence in integrating AI into science teaching practices. This factor expressed recognition of the transformative role of AI in the future of education and a proactive stance on engaging with AI. Therefore, it was termed "*readiness and openness to AI integration*". The items loading onto factor 2 explained 20.93% of the scale's variance.

Table 3. Model indices for perception

Model	χ^2/df (< 5)	CFI (> 0.9)	TLI (> 0.9)	SRMR (< 0.8)	RMSEA (< 0.8)	RMSEA 95% CI
Initial model	1,686/521 = 3.23	0.837	0.825	0.0709	0.1060	0.100–0.112
Final model	1,039/504 = 2.06	0.925	0.917	0.0611	0.0731	0.067–0.079

Note: CI: Confidence interval.

Factor 3 consisted of 5 items, with factor loadings ranging from 0.66 to 0.84. This factor encapsulated the belief that AI can enhance the accessibility and engagement of science education, particularly for diverse students and individuals with disabilities or learning differences. It suggested that AI tools can personalize learning experiences and increase student engagement. Consequently, this factor was labeled "*AI's role in inclusivity and engagement*". The items loading onto factor 3 accounted for 9.14% of the scale's variance.

Factor 4 subsumed 5 items, with factor loadings ranging from 0.59 to 0.85. This factor delineates concerns regarding the potential negative impacts of utilizing AI in education, such as exacerbating inequalities in education, diminishing the role of human teachers, issues pertaining to privacy and data rights, and the potential to facilitate plagiarism. Therefore, this factor was termed "*concerns and skepticism about AI in science education*". The items loading onto factor 4 explained 9.04% of the scale's variance.

In summation, all items demonstrated compatibility with the relevant scale. Cumulatively, these items accounted for 67.4% of the scale's variance.

Confirmatory Factor Analysis

The Initial model is a model without any modification (as shown in **Table 3**). For the initial model, the Chi-square to degrees of freedom ratio (χ^2/df) is 3.23. This value falls below the recommended threshold of 5, indicating a reasonable fit between the hypothesized model and the observed data. However, CFI and TLI values are 0.84 and 0.83, respectively, both of which are below the acceptable fit benchmark of 0.9, suggesting that the model could be improved. SRMR value is 0.07, which is within the acceptable range (below 0.08) and indicates a good fit. RMSEA is 0.11 with a 90% confidence interval ranging from 0.10 to 0.11, exceeding the preferred maximum of 0.08, which suggests a mediocre fit. So, we applied modifications recommended by the software. In the final model, there is a notable improvement across all indices. The χ^2/df ratio has decreased to 2.06, suggesting a better fit than the initial model. CFI and TLI have both increased to 0.93 and 0.92, respectively, surpassing the 0.9 threshold and indicating a good fit between the model and the data. SRMR has decreased to 0.06, which is an excellent fit. RMSEA has also improved to 0.07, with a narrower 90% confidence interval of 0.07 to 0.079, reflecting a better fit than the initial model, though it is still slightly below the ideal cut-off. Overall, the final model exhibits a superior fit compared to the initial model, as demonstrated by all indices meeting or coming close to their respective criteria for a good fitting model. This indicates that the final model is a better representation of the data regarding the perception being modeled.

Table 4 displays the results of a CFA for a series of indicators related to four different factors. The CFA results show that all the indicators have statistically significant loadings on their respective factors ($p < 0.01$). The estimates are high, and the SEs are low across all factors, suggesting that the hypothesized factor structure fits the observed data well. This strong and significant relationship between the indicators and their respective factors indicates a well-specified measurement model.

Reliability

Table 5 presents reliability statistics for a scale measuring four dimensions of attitudes toward AI in science education. Both Cronbach's alpha and McDonald's omega are used to assess internal consistency, which indicates how closely related a set of items are as a group. The "*optimism and utility of AI in science education*" dimension shows extremely high internal consistency, with both Cronbach's alpha and McDonald's omega values at 0.98. This suggests that the items within this dimension are very reliable and measure the construct consistently. For "*readiness and openness to AI integration*," Cronbach's alpha is 0.95 and the McDonald's omega is 0.95. These values are also very high, indicating excellent reliability and suggesting that the items are well correlated and collectively represent this dimension accurately. The dimension "*AI's role in inclusivity and engagement*" has slightly lower, yet still strong, internal consistency, with a Cronbach's alpha of 0.87 and a McDonald's omega of 0.88. These values suggest that the items are reliably measuring the intended

Table 4. Factor loading based on CFA

Factor	Indicator	Estimate	Standard error	Z	p
Factor 1	AI_21	0.796	0.0677	11.74	< .001
	AI_26	0.957	0.0636	15.04	< .001
	AI_27	0.988	0.0657	15.05	< .001
	AI_28	0.946	0.0648	14.60	< .001
	AI_29	0.993	0.0627	15.84	< .001
	AI_30	0.948	0.0619	15.30	< .001
	AI_31	0.902	0.0659	13.69	< .001
	AI_32	1.011	0.0613	16.49	< .001
	AI_33	1.019	0.0622	16.38	< .001
	AI_34	0.991	0.0627	15.79	< .001
	AI_35	1.006	0.0631	15.94	< .001
	AI_36	0.971	0.0603	16.10	< .001
	AI_37	1.033	0.0623	16.58	< .001
Factor 2	AI_4	0.841	0.0699	12.03	< .001
	AI_5	0.825	0.0690	11.96	< .001
	AI_6	0.853	0.0693	12.32	< .001
	AI_7	0.967	0.0822	11.75	< .001
	AI_8	0.839	0.0685	12.26	< .001
	AI_9	0.863	0.0685	12.60	< .001
	AI_10	1.040	0.0640	16.24	< .001
	AI_11	1.043	0.0654	15.94	< .001
	AI_12	1.080	0.0692	15.60	< .001
	AI_13	1.041	0.0659	15.81	< .001
	AI_14	0.710	0.0819	8.67	< .001
Factor 3	AI_16	0.911	0.0757	12.03	< .001
	AI_17	1.043	0.0726	14.36	< .001
	AI_18	0.891	0.0810	10.99	< .001
	AI_19	0.946	0.0735	12.87	< .001
	AI_20	0.779	0.0861	9.04	< .001
Factor 4	AI_1	0.734	0.0860	8.53	< .001
	AI_22	1.071	0.0677	15.81	< .001
	AI_23	0.972	0.0746	13.03	< .001
	AI_24	1.037	0.0667	15.55	< .001
	AI_25	0.911	0.0777	11.73	< .001

Table 5. Reliability coefficient each dimension

Dimension	Cronbach's alpha	McDonald's omega
Optimism and utility of AI in science education	0.975	0.975
Readiness and openness to AI integration	0.951	0.953
AI's role in inclusivity and engagement	0.873	0.875
Concerns and skepticism about AI in science education	0.878	0.885
Total	0.954	0.958

construct. "*Concerns and skepticism about AI in science education*" also shows strong internal consistency, with Cronbach's alpha at 0.88 and McDonald's omega at 0.89. This indicates that the items within this dimension are consistently measuring the same underlying construct. The total scale, representing all dimensions combined, has a Cronbach's alpha of 0.96 and a McDonald's omega of 0.96, indicating exceptional overall reliability and suggesting that the scale as a whole is a very dependable measure of attitudes towards AI in science education. In summary, all dimensions show strong internal consistency, confirming that the scale is reliable in measuring educators' attitudes towards various aspects of AI in science education.

Cluster Analysis

The distribution of the scale's dimensions is presented in **Figure 3**. Examining the scatterplot patterns, it is clear that there is a positive correlation between utility, readiness, and engagement across all clusters. However, concerns are less positively correlated with these variables, especially in cluster 1 and cluster 4. This indicates that higher perceptions of utility, readiness, and engagement do not necessarily align with greater concerns. The trend is particularly noticeable in cluster 4, where all scores are low, signifying either a lack of engagement or interest in AI for education. Subsequently, cluster analysis has been conducted.

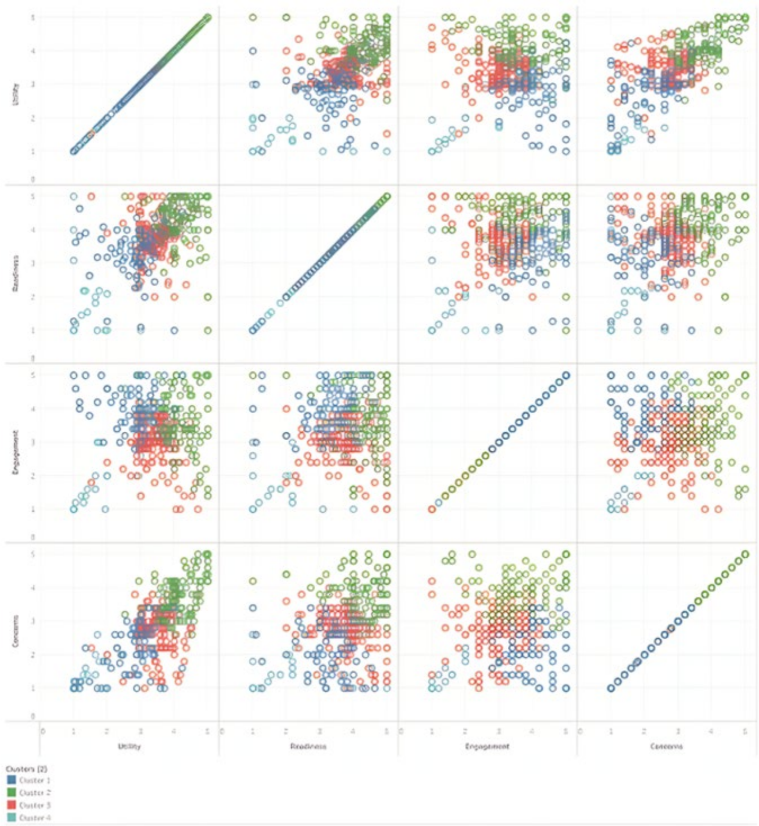

Figure 3. Scatter plot among dimension (Source: Elaborated by the authors)

Table 6. Dimension average based on clusters

Clusters	N	Utility	Readiness	Engagement	Concerns
Cluster 1	65	2.70	3.26	4.05	2.08
Cluster 2	120	4.27	4.33	3.87	3.94
Cluster 3	194	3.39	3.76	2.99	2.77
Cluster 4	22	1.50	1.82	1.55	1.46

In a structure with four classes, the between-group sum of squares is calculated to be 44.92, the within-group sum of squares is 41.77, and the total sum of squares is 86.69. The relatively high between-group sum of squares, when compared to the within-group sum of squares, suggests that the clusters are well-differentiated, and the responses of individuals within each cluster are quite consistent. This indicates that the analysis was effective in revealing significant patterns in the data.

As shown in **Table 6**, cluster 1, consisting of 65 individuals, shows moderate average scores on "*optimism and utility of AI in science education*" and "*readiness and openness to AI integration*" (around 2.71 and 3.26, respectively), high on "*AI's role in inclusivity and engagement*" (4.05), but low on "*concerns and skepticism about AI in science education*" (2.08). This suggests that members of cluster 1 see some utility and are somewhat ready for AI in education and are highly engaged with AI. However, "*concerns and skepticism about AI in science education*" states that they are worried. This group can be called "*the enthusiastic engagers*".

Cluster 2, the largest with 120 individuals, has high average scores across "*optimism and utility of AI in science education*" and "*readiness and openness to AI integration*" (above 4.26 and 4.32), slightly lower on "*AI's role in inclusivity and engagement*" (3.87), and the highest average score on "*concerns and skepticism about AI in science education*" (3.94). Members of this cluster appreciate the utility of AI and are ready to integrate it, are somewhat less engaged than cluster 1, and have low concerns about AI. This group can be called "*the optimists*".

Cluster 3 has the most individuals, 194, with moderately high scores on "*optimism and utility of AI in science education*" and "*readiness and openness to AI integration*" (approximately 3.39 and 3.76), a lower score on "*AI's role in inclusivity and engagement*" (3.00), and moderate "*concerns and skepticism about AI in science education*"

(2.77). This cluster seems to recognize the utility of AI and feels fairly ready but is less engaged and moderately concerned compared to cluster 2. This group can be called "*the pragmatic acceptors*".

Cluster 4, with only 22 individuals, scores very low across all dimensions (1.5 on "*optimism and utility of AI in science education*", 1.82 on "*readiness and openness to AI integration*", 1.55 on "*AI's role in inclusivity and engagement*", and 1.46 on "*concerns and skepticism about AI in science education*"). This cluster is the most skeptical or least convinced about the benefits of AI in education, showing low engagement, and readiness, indicating a general disengagement from AI in education. Also, their level of concern is very high. This cluster can be called "*the skeptical detached*".

DISCUSSION

The findings from this study provide valuable insights into pre-service science teachers' perceptions of utilizing generative AI in science education. EFA revealed a four-factor structure, highlighting the multidimensional nature of these perceptions.

The initial factor, denoted as "*optimism and utility of AI in science education*," mirrors the participants' trust in the favorable capabilities of AI to improve various facets of science education, such as problem-solving, critical thinking, and grasping intricate concepts (Michel-Villarreal et al., 2023; Ruiz-Rojas et al., 2023). This factor also encompasses the perceived function of AI in enhancing the efficiency of educational content creation (Baidoo-Anu & Owusu Ansah, 2023; Kohnke et al., 2023), aligning with existing literature on the potential advantages of generative AI in education.

The second factor, titled "*readiness and openness to AI integration*," epitomizes the readiness, eagerness to learn, and assurance of pre-service educators in incorporating AI into their forthcoming teaching methodologies. This factor resonates with the discoveries of Zhang et al. (2023), which emphasized the impact of perceived usefulness and ease of use on the intentions of pre-service educators to employ AI technology.

The third factor, known as "*AI's role in inclusivity and engagement*," encapsulates the notion that AI can enrich accessibility and involvement in science education, particularly for diverse learners and individuals with disabilities or diverse learning styles (Joseph, 2023; Okunade, 2024). This factor aligns with the literature highlighting AI's potential to tailor learning experiences and elevate student engagement (Chen et al., 2023; Kumar et al., 2023).

The fourth factor, termed "*concerns and skepticism about AI in science education*," signifies concerns about the potential adverse effects of AI in education, including exacerbating disparities, diminishing the role of human educators, privacy and data rights issues, and the likelihood of enabling plagiarism (Alasadi & Baiz, 2023; Michel-Villarreal et al., 2023; Wilton et al., 2022). This factor underscores the necessity to tackle these concerns and establish responsible AI integration practices in education (Cooper, 2023; Liebrenz et al., 2023).

The verification of the factor structure through CFA and reliability evaluations confirmed the robustness of the scale in assessing the perceptions of prospective science educators towards generative AI in science education. The elevated reliability coefficients (Cronbach's alpha and McDonald's omega) suggest that the scale consistently evaluates the intended constructs.

The cluster analysis revealed four distinct profiles of pre-service science teachers based on their responses to the scale dimensions. The "*enthusiastic engagers*" cluster demonstrated high engagement with AI but had concerns about its implementation. The "*optimists*" cluster showed high optimism, readiness, and low concerns, aligning with the findings of Yang and Chen (2023) on pre-service teachers' intentions to utilize AI technology. The "*pragmatic acceptors*" cluster recognized the utility of AI but had moderate levels of engagement and concerns. Finally, the "*skeptical detached*" cluster exhibited low levels of engagement, readiness, and optimism, reflecting a general disengagement from AI in education, potentially linked to the negative stance observed by Istenic et al. (2021) towards social robots in education.

This study makes an important contribution to the science education literature by developing and validating a comprehensive scale to measure pre-service science teachers' perceptions of generative AI in science education. The four-factor structure identified through psychometric analyses (EFA and CFA) provides a nuanced understanding of how future science educators view AI integration and encompasses the dimensions of optimism and utility, readiness and openness, inclusiveness and engagement, and concerns and skepticism. In contrast to previous research that sometimes focused on individual aspects of AI in education, this multimodal approach provides a more comprehensive perspective. Moreover, cluster analysis reveals diverse profiles of pre-service teachers ranging from enthusiastic participant to skeptical detached, thereby providing a perceptive study of the many attitudes within the cohort. Addressing the concerns and skepticism identified in this study, while capitalizing on the optimism and readiness of pre-service teachers, can facilitate the responsible integration of generative AI in science education (Nyaaba & Zhai, 2024; Okunade, 2024). This study addresses a significant gap in the existing research by providing a reliable and valid tool specifically developed for science education. This tool can be used to guide professional development initiatives, inform teacher preparation programs, and influence policies for the responsible incorporation of AI in scientific classrooms. By elucidating the complex interplay among their perspectives, this work establishes the foundation for targeted interventions and curriculum modifications that can better prepare the next generation of scientific instructors for the AI-enhanced learning environment.

CONCLUSION

This study developed a valid and reliable scale to measure pre-service science teachers' perceptions of utilizing generative AI in science education. The scale captured four key dimensions: optimism and perceived utility, readiness for integration, beliefs about inclusivity and engagement, and concerns and skepticism. Cluster analysis revealed distinct profiles of pre-service teachers based on these dimensions.

It is important to note that the study's findings should be interpreted within the context of its limitations, such as the sample being drawn from a single university and the potential influence of socio-cultural factors on perceptions. Future research could explore the generalizability of these findings across different educational settings and investigate the longitudinal impacts of pre-service teacher training on the adoption and implementation of generative AI in science classrooms. In the study, scale development processes were followed. However, the limitation of the study is that the sample group was selected from a certain university based on convenience sampling. Future researchers will be able to test the validity and reliability of the scale and check the validity in the context of different cultures by differentiating the sample. Another difficulty encountered in the study is the lack of a science-specific scale that measures pre-service science teachers' perceptions of AI. Therefore, it was not possible to determine the similar result criteria of the scale by comparing the results

As generative AI evolves rapidly in education, understanding pre-service teachers' perceptions is crucial for responsible integration. This scale offers a robust tool to inform teacher education initiatives aimed at harnessing AI's potential while addressing concerns. Proactive efforts in this area can enhance science learning experiences for students in the AI-driven future.

Author contributions: Izida I. Ishmuradova: conceptualization, data curation, methodology, writing – original draft, writing – review & editing; **Sergei P. Zhdanov:** conceptualization, formal analysis, methodology, writing – review & editing; **Sergey V. Kondrashev:** conceptualization, formal analysis, methodology, writing – original draft; **Natalya S. Erokhova:** conceptualization, formal analysis, writing – review & editing; **Elena E. Grishnova:** formal analysis, writing – original draft, writing – review & editing; **Nonna Y. Volosova:** methodology, writing – original draft. All authors approved the final version of the article.

Funding: The authors received no financial support for the research and/or authorship of this article.

Ethics declaration: The authors declared that this study was conducted in accordance with the principles outlined in the 1964 Declaration of Helsinki, ensuring that all research involving human participants was performed with the highest ethical standards. Ethical approval for this study was obtained from Kazan Federal University. Participants were informed that their involvement in the study was entirely voluntary and that they had the right to withdraw from the study at any time without any consequences. This assurance was provided to respect and protect the autonomy and rights of all participants.

Declaration of interest: The authors declare no competing interest.

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

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APPENDIX A: PERCEPTION OF GENERATIVE AI IN SCIENCE EDUCATION

Table A1. Perception of generative AI in science education

No	Perception
AI_01	I am uncertain about how to evaluate the accuracy and reliability of AI-generated content for science lessons.
AI_02	I feel confident in my ability to use AI applications to facilitate science content.
AI_03	I believe that AI technologies can help students better understand complex scientific concepts.
AI_04	I think AI has potential to nourish scientific thinking in science education.
AI_05	I am concerned about the potential for generative AI to spread misinformation or biased content in science education.
AI_06	Generative AI tools can help generate feedback to support students understanding of complex scientific concepts.
AI_07	Generative AI has the potential to increase students' creative thinking skills in science.
AI_08	I feel adequately prepared to integrate AI technologies into my future science teaching practices.
AI_09	I think AI has the potential to enhance students' problem-solving skills in science.
AI_10	I believe generative AI tools can enhance science learning by generating customized educational content.
AI_11	Using generative AI could save me time in creating instructional materials and lesson plans for science classes.
AI_12	Generative AI has the potential to increase students' critical thinking skills in science.
AI_13	Generative AI tools could help make abstract scientific concepts more concrete and understandable for students.
AI_14	Integrating generative AI into lessons could be too technologically challenging for me.
AI_15	I think that AI will fundamentally change the way we teach and learn in the future.
AI_16	I am willing to explore new teaching methods that involve AI in science education.
AI_17	I believe that teacher training programs should include coursework on using AI in education.
AI_18	I need more training to feel comfortable using generative AI tools effectively in my future science classroom.
AI_19	I am actively seeking opportunities to learn about AI applications in science education.
AI_20	I see AI as a valuable tool for improving teaching science practices.
AI_21	I am open to incorporating AI-based tools and technologies into my future science teaching practices.
AI_22	I am confident in my ability to effectively integrate generative AI tools into my future science teaching practices.
AI_23	I believe generative AI will play a significant role in transforming science education in the coming years.
AI_24	I perceive AI as a means to foster inquiry-based learning in science classrooms.
AI_25	I believe that AI has the potential to make science more accessible to diverse learners.
AI_26	Generative AI can make science lessons more engaging by creating interactive simulations or visualizations.
AI_27	Generative AI could be useful for creating accessible science materials for students with disabilities or learning differences.
AI_28	I believe that integrating AI into science education can lead to improved student engagement.
AI_29	I am excited about the potential of generative AI to create personalized learning experiences for students in science classes.
AI_30	I have concerns about student privacy and data rights when using generative AI in the classroom.
AI_31	I fear that AI may exacerbate existing educational inequalities rather than alleviate them.
AI_32	I worry that relying too much on AI could diminish the role of human teachers in the classroom.
AI_33	I am pessimistic about the role of AI in revolutionizing education.
AI_34	Using generative AI for writing assignments could promote plagiarism among students.
AI_35	I perceive AI as a tool that can help students develop a deeper understanding of scientific concepts.
AI_36	Generative AI could automate routine tasks (e.g., grading and content creation), allowing me to focus more on high-quality teaching.
AI_37	I am optimistic about the long-term benefits of integrating AI into educational systems.