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Research Article

# Measuring student perceptions of AI-assisted academic communication: A questionnaire development study

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**ABSTRACT**

The aim of this study is to develop a valid and reliable scale evaluating students' views on artificial intelligence (AI) supported academic communication. Knowing how students view these tools is crucial considering AI's increasing presence in the classroom. We applied a thorough approach comprising content validation, pilot research and factor analysis in addition to literature review. Initially, 40 items were created and reduced to 37 items after expert evaluation. As a result of the analysis of the data obtained from 580 participants, it was determined that the scale showed a two-factor structure as "positive dimension" and "negative dimension". Factor analyses both exploratory and confirmatory helped to establish the scale's construct validity. The scale's internal consistency reliability came out to be really strong. Based on gender and age, Bayesian statistical studies revealed no appreciable variation in students' opinions of academic communication supported by AI. The developed scale offers academics and teachers a consistent instrument to evaluate students' perception of AI technologies. This scale will help to shape plans for better integration of AI into learning environments.

**Keywords:** artificial intelligence, academic communication, scale development, student perceptions, educational technologies, Bayesian analysis

## INTRODUCTION

The rapid integration of artificial intelligence (AI) into education has changed academic communication and presents particular opportunities to improve learning environments and outcomes. AI-supported educational systems are continually evolving to provide solutions suited to students' particular demand

(Holmes et al., 2019; Ouyang et al., 2022). This method emphasizes ever more the understanding of students' impressions and interactions with these technologies. This understanding helps teachers, institutions, and legislators who wish to effectively introduce AI technologies into academic environments and manage possible challenges.

Using AI in education affects the learning process in several directions. On the one hand, AI technologies offer personalized learning paths based on big data analysis, which can reduce achievement gaps and provide individual support to students (Maghsudi et al., 2021; Shoaib et al., 2024; Taylor et al., 2024). On the other hand, the integration of AI raises ethical and privacy concerns, especially regarding data collection and analysis processes (Selwyn, 2019; Williamson et al., 2020). These contradictory elements highlight the need to know in great depth about students' perspectives on academic communication provided by AI.

Although a lot of research on AI in education is under development, the literature on standardized measuring tools to assess students' perspectives of academic communication facilitated by AI has a clear shortage. Research on several aspects of AI integration in education (Chugai & Havrylenko, 2024; Liu et al., 2024; Shalevska & Kostadinovska-Stojchevska, 2024) lacks a scale expressly meant and proven to measure these perceptions. This makes it more difficult for us to systematically assess students' ideas and create comparisons between numerous contexts.

This project is to develop and verify a scale to evaluate students' thoughts on academic communication supported by AI. This process of scale development defines the following primary causes:

- It provides academics and educators with a standard tool to assess student opinions on AI in educational settings, therefore facilitating more consistent and similar studies throughout many different institutions and countries.
- It provides in-depth insights into both positive and negative perceptions, thus helping us understand students' views on the benefits and potential risks of AI-assisted communication.
- It can inform policy decisions and educational strategies, providing information on student readiness and concerns about AI integration.
- It advances areas where student concerns must be addressed and adds to a greater conversation on the moral uses of AI in the classroom.

This scale satisfies validity and reliability standards by means of strict psychometric techniques, including content validation, pilot testing, and factor analysis. This work offers a comprehensive and valid measuring tool aimed at greatly progressing the field of AI in education and helping evidence-based decision-making processes in the implementation of AI-supported academic communication tools.

It is important to understand students' views on AI in education. This study provides information and a foundation for future research on how AI affects learning. The goal is to help educators, researchers, and policymakers understand how to use AI in education and improve students' learning experiences.

## LITERATURE REVIEW

### AI in Education

The use of AI technologies in education is profoundly transforming learning processes and pedagogical models. AI-supported instructional systems offer student-centered learning experiences, providing customized solutions tailored to individual needs (Holmes et al., 2019; Ouyang et al., 2022). These technologies both increase the academic achievement of learners and reduce manual the workload of teachers by suggesting personalized learning paths based on big data analytics (Maghsudi et al., 2021; Shoaib et al., 2024; Taylor et al., 2024). This ability of AI presents chances to decrease the accomplishment differences between students learning at different rates in education and to give every student individual help. Students' drive rises in this sense as well as learning processes get more effective.

Another critical contribution of AI-based applications in education is their innovative approaches in the design and development of instructional materials. Especially in quantitative fields such as language education and mathematics, virtual tutors and chatbots integrated into adaptive learning environments are widely used (Huang et al., 2022; Lee & Yeo, 2022). Such systems give pupils instantaneous and dynamic

feedback, therefore maximizing their learning pace and offering in-depth involvement during the learning process. These tools also point out areas in which pupils fall short and offer individualized recommendations for improvement. This function helps teachers keep closer eye on student performance and make required interventions.

The advent of AI technology into the classroom has altered educators' roles. Teachers are responsible for more than just passing on material; they also use AI systems to coordinate and manage the learning process (Holstein et al., 2019). For example, teachers are able to more accurately assess the requirements of each individual student and develop educational activities that are based on tailored learning systems that are powered by AI (Celik et al., 2022). Moreover, AI technologies save teachers more time by automating routine administrative tasks so that teachers can focus more on one-to-one interaction with students and the development of higher-order thinking skills (J. Kim et al., 2022). However, teachers have a critical role to play in the ethical use of AI systems and the evaluation of their outcomes.

However, the use of AI in education raises ethical and privacy concerns. Integration of AI technology into education calls for the gathering and analysis of vast volumes of data on learning processes, which generates important problems including data privacy and security (Selwyn, 2019; Williamson et al., 2020). Reducing such ethical issues depends much on openness about the gathering of personal data of students and the uses for which it will be applied. Furthermore, AI systems must be designed and applied in compliance with the impartiality principle; else, they run the danger of causing discriminatory policies directed against students. Consequently, strict observance of ethical values and data security guidelines is necessary during the evolution and execution of AI uses. In this context, raising awareness and actively involving relevant stakeholders (teachers, students, parents, and policy makers) in the process is of great importance.

AI technologies offer various advantages in education such as individualized learning, providing interactive feedback and developing educational materials. Nonetheless, including AI into the learning process could help students to go through more in-depth and long-lasting education. In terms of lesson planning and evaluation, AI also helps educators to operate more precisely and quickly. Nonetheless, the sustainable and dependable integration of these technologies into educational processes depends on following the required rules and measures on the ethical use of them and data security.

## AI in Academic Communication

The integration of AI in higher education is transforming learning processes by shaping academic communication, especially through tools such as ChatGPT, and providing students with support in areas such as writing and vocabulary development. This review brings together the findings of recent research to assess higher education students' perceptions and attitudes towards AI tools within ethical, cultural and disciplinary contexts.

Much of the recent research uses mixed methods, combining qualitative (interviews, focus groups) and quantitative (surveys, statistical analyses) data to gain an in-depth understanding of student attitudes. These methods offer a more nuanced understanding of the advantages and limitations of AI tools in the academic context. For example, studies conducted in North Macedonia, China and Ukraine (Chugai & Havrylenko, 2024; Shalevska & Kostadinovska-Stojchevska, 2024), while generating a generally positive perception of AI's capacity to improve academic tasks, also raise concerns about ethical issues such as academic integrity and data privacy.

The literature often discusses the view of AI tools as useful instruments for raising academic performance and productivity. In writing processes and improving learning results, students usually find them useful (Adiguzel et al., 2023; Chugai & Havrylenko, 2024; Liu et al., 2024; Shalevska & Kostadinovska-Stojchevska, 2024). Ethical issues include over-reliance on AI tools, prejudices toward AI outputs, and possible negative impacts on critical thinking ability arise, nevertheless (Avsheniuk et al., 2024; Chugai & Havrylenko, 2024; Sánchez-Reina et al., 2024). This suggests that institutional standards have to be correctly created to satisfy these hazards (Zhou et al., 2024).

Moreover, the study emphasizes the need for cultural and disciplinary settings in influencing student opinions about AI. Studies show that acceptance and faith in AI technology are much influenced by cultural backgrounds and some academic fields. Research on variances between domains and cross-cultural studies

on AI integration and application, for example, highlight different points of view on these issues hinting that these elements are crucial in shaping student attitudes (Chugai & Havrylenko, 2024; Ma et al., 2024). This study provides a balanced view of AI's role in higher education, highlighting both its potential to assist academic communication and the necessity to manage the ethical concerns that come with it. As AI technologies improve and become more prevalent in educational settings, a more in-depth understanding of these dynamics is required to optimize their integration and address the ethical implications.

## Students' Perception of AI in Academic Communication

Students' perceptions of AI-supported academic communication have a significant impact on their learning experiences; these perceptions directly affect their level of involvement in the learning process, frequency of contact, and overall success, influencing motivation and learning outcomes. These perceptions definitely influence students' interpersonal dynamics, learning outcomes, and level of engagement. Although AI tools used in education are considered useful in terms of enhancing learning processes, providing personalized support and promoting student engagement. However, there are also several challenges, such as limited features and concerns about social boundaries. These perceptions significantly influence how students interact with AI and to what extent they are able to utilize its potential in their learning process. AI teaching assistants increase student engagement and satisfaction by providing timely feedback and personalized support in online education (Kim et al., 2020; Palasundram et al., 2019; Sayed et al., 2023; Seo et al., 2021). In academic writing courses, AI tools help students in planning and drafting processes, making the learning process more engaging and less monotonous (Utami et al., 2023). By helping students to create cogent and thorough arguments, AI-supported scaffolding systems help to strengthen academic writing abilities (M. K. Kim et al., 2022; Putri Erito, 2023).

By adjusting to particular student demands, AI systems offer tailored learning experiences that help to raise academic achievement. For instance, the usage of chatbots in Ghana's higher education system gives students quick comments, therefore improving the efficiency of the learning process and promoting academic success by raising students' motivation (Essel et al., 2022; Hu, 2022). By offering cognitive and social presence as well as raising students' happiness and involvement, AI coaches in language learning help to improve learning outcomes (Wang et al., 2024).

Despite the advantages of AI-powered tools, learners express various concerns about the capacity of AI to meet all their needs. For example, they expressed the need for more comprehensive features for editing specific language texts (Utami et al., 2023). The use of AI in online learning can affect student-instructor interactions, raising concerns about social boundaries and the potential for monitoring (Seo et al., 2021). Although AI-generated avatars in educational content are preferred by some students for lecturing, others question their effectiveness (Vallis et al., 2024). Koć-Januchta et al. (2020) assert that students' engagement with AI features requires training and reinforcement to optimize their learning experiences

When students see AI tools as beneficial and simple to use, they are more likely to trust them. This is consistent with the technological acceptance paradigm, which emphasizes perceived usefulness and simplicity of use as important drivers of technology adoption. In the context of intelligent personal assistants, students' trust in these tools is closely related to how these tools enhance learning experiences and their capacity to provide personal support (Choi et al., 2024).

Effective communication about the limits and capabilities of AI can also influence trust. Saying anything about AI performance, for instance, either positively or negatively could affect pupils' belief in these tools (Kim & Song, 2023). The sense of connection with others through AI tools, i.e., the sense of social presence, is an important factor in building trust. Students who feel a stronger sense of social presence tend to trust and use these tools more (Choi et al., 2024).

While these factors are important, the cultural and educational context in which AI tools are used also needs to be considered. For example, some cultures value group work more than individual work, and this may determine how AI tools can be adapted to meet these cultural expectations. For example, in Indonesia, students' confidence in AI tools is also influenced by their ability to meet specific language requirements, such as editing text in Indonesian (Utami et al., 2023).

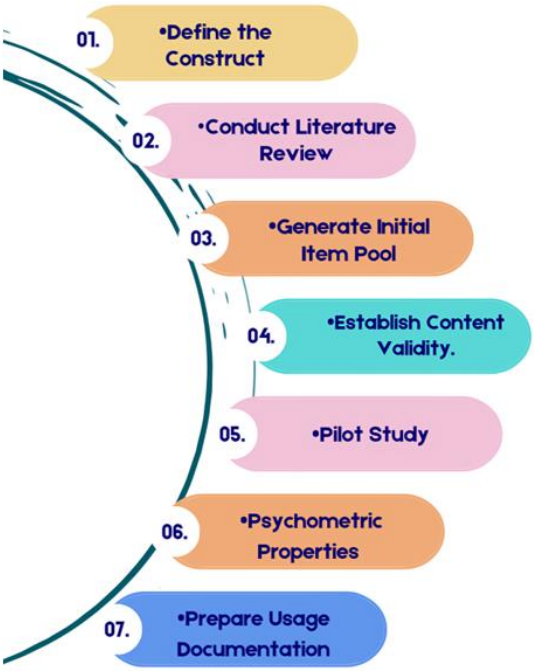


**Figure 1.** Development process of scale (Source: Created by the authors)

In conclusion, the existing literature reveals the multifaceted impact of AI-supported academic communication on student perceptions. While research emphasizes the potential of AI technologies to enhance learning processes and improve academic performance, it also raises ethical concerns, data privacy and possible negative impacts on critical thinking skills. Research in this field is challenging to methodically compare and evaluate without a consistent instrument assessing students' opinions on AI-supported academic communication. Development of a legitimate and trustworthy scale is obviously necessary to close this discrepancy. Such a scale would provide valuable information to educators, policy makers and researchers to more effectively plan and manage the integration of AI technologies into educational settings. It would also enable longitudinal studies to understand how student perceptions change in different cultural contexts and over time. By summarizing the existing body of knowledge on AI-supported scholarly communication, this literature review provides a solid foundation for the scale development process that this study aims at.

## METHODOLOGY

Since the study is a scale development study, the steps described in **Figure 1** were followed. Each step is explained shortly:

1. **Define the construct:** At this point, the psychological construct—that which has to be measured—is precisely specified. While first introducing the idea of construct validity, Cronbach and Meehl (1955) underlined the need for a clear and exact specification of a construct. According to MacKenzie et al. (2011), construct identification not only offers conceptual clarity but also shapes the foundation for next validity assessments of the scope.
2. **Conduct literature review:** Hinkin (1998) underlined the need for a thorough literature research in pointing up the advantages and drawbacks of current scales as well as in building a conceptual foundation for the new scale. Cooper et al. (2018) stated that a systematic literature review plays an important role in understanding the different dimensions of the construct and related concepts.
3. **Generate initial item pool:** DeVellis (2016) emphasized the importance of developing a broad set of items covering all aspects of the construct when creating an item pool. Clark and Watson (1995) emphasized the importance of using clear, understandable and appropriate language for the target audience in item writing.

4. **Establish content validity:** Yusoff (2019) suggested using expert opinions and calculating the content validity ratio to assess content validity. Polit and Beck (2006) emphasized the importance of assessing content validity with qualitative and quantitative methods.
5. **Pilot study:** van Teijlingen and Hundley (2001) and Johanson and Brooks (2010) stated that pilot studies play a critical role in testing the comprehensibility of scale items and identifying potential implementation problems.
6. **Psychometric properties:** Reliability and validity analyses were underlined as psychometric properties by Mellinger and Hanson (2020). Comprehensive instructions came from Fabrigar et al. (1999) and Williams et al. (2010) for exploratory factor analysis (EFA) and (Brown, 2015) for confirmatory factor analysis (CFA).
7. **Prepare usage documentation:** Preparation of guidelines for the use of the scale is important, especially for its use in different contexts and cultures (Gudmundsson, 2009).

### Sample

This study was conducted with two different sample groups. The first sample was a group of 30 participants who were used in the preliminary study (plot study) phase to evaluate the comprehensibility of the scale. The second sample was used to examine the validity and reliability (psychometric properties) of the scale and consisted of 651 participants. Before data analysis, a data cleaning process was applied; in this context, participants who marked all items as "1" or "5" were excluded from the sample, and it was assumed that these participants answered the questions without reading them. After this cleaning process, the sample size was reduced to 580 participants.

74.31% of the participants were female and 25.69% were male. In terms of age groups, 13.62% were younger than 18 years, 37.07% were between 18-19 years, 24.66% were between 20-21 years, 15% were between 22-23 years and 9.66% were 23 years and older. 76.55% of the participants were undergraduate students and 23.45% were graduate students. During the evaluation of the psychometric properties of the scale, in order to avoid both EFA and CFA on the same sample, the sample of 580 participants was randomly divided into two groups and data analysis was conducted in this way.

### Data Analysis

This study measured students' opinions on academic communication supplemented by AI by means of a scale development process. Content validity, pilot studies, exploratory and confirmatory factor analyses, reliability analysis, and demographic variable analysis comprised the data analysis approach.

In the content validity stage, item-content validity index (I-CVI), CVI/Ave and content validity index for universal agreement (CVI/UA) were calculated in line with the opinions of 9 experts (Yusoff, 2019). In EFA, KMO value, Bartlett's test of sphericity results and factor loading were analyzed. In the CFA process, $\chi^2/df$, CFI, TLI, SRMR, RMSEA indices were examined. For reliability analysis, Cronbach's alpha (α) and McDonald's omega (ω) values were examined (Brown, 2015; Williams et al., 2010).

When descriptive statistics were analyzed, mean, standard deviation, Skewness and Kurtosis tests were examined. When the effect of demographic variables was examined, Bayesian t-test and Bayesian ANOVA results showed that there was no significant difference between age groups (BF10 = 0.019). These results showed that students' perceptions of AI-supported academic communication did not vary according to gender and age.

## FINDINGS

### Define the Construct and Literature Review

The purpose of this research is to understand the effects of AI-assisted academic communication tools on students.

The construct "student perceptions of AI-assisted academic communication" is a multidimensional conceptual construct that aims to measure students' perceptions, attitudes, and intention to use AI-assisted

academic communication tools. This construct assesses students' perceptions of the usefulness of AI tools in academic communication, ease of use, reliability, ethical concerns, and their impact on learning processes.

## Literature Review and Scale Dimensions

1. **Perceived usefulness and effectiveness:** The literature underlines that AI technologies could raise academic performance and enhance learning procedures (Kim et al., 2020; Palasundram et al., 2019; Sayed et al., 2023). Students are of the opinion that the capability of these technologies to provide prompt feedback and individualized assistance is beneficial (Seo et al., 2021). This criterion evaluates the extent to which students perceive that AI tools contribute to their academic performance.
2. **Ease of use and accessibility:** According to the technology acceptance model, students' acceptance of AI products primarily relies on their apparent simplicity of use (Ma & Lei, 2024). This dimension measures how easily students might apply and combine AI tools.
3. **Trust and reliability:** Students have faith in educational AI systems, according to Choi et al. (2024), because they can personalize their support and have their learning experience improved. The majority of students have faith in AI systems that personalize their learning materials and respond to their specific demands. They also help them. More likely to wow pupils are interactive courses or adaptive tests derived from AI technologies. These elements influence how reliable and successful students find AI technologies, so they are important. Students are more likely to rely on and trust an AI system that offers relevant, correct data together with insightful comments catered to their educational route. Students' belief in AI-generated data and feedback in their academic work so depends on how quality and dependability they view it. According to Tossell et al. (2024), students do not completely trust ChatGPT, but they find it valuable as a learning tool.
4. **Ethical concerns and academic integrity:** Concerns about privacy and the possibility of biased results coming from AI systems are two ethical issues that come up when these systems are used. These technologies can also lead to unethical behavior like plagiarism or hurting students' ability to think of their own ideas, which raises concerns about academic ethics (Currie, 2023; Mijwil et al., 2023; Utami et al., 2023). The literature often addresses ethical questions with the application of AI techniques and academic integrity as well as students worry that the usage of AI can result in ethical transgressions including plagiarism or compromise of originality of their work (Utami et al., 2023). This dimension gauges students' opinions on the moral sides of AI application.
5. **Learning experience and engagement:** AI tools have the potential to make the learning experience more engaging and increase student engagement (Wang et al., 2024). This dimension evaluates the impact of AI-supported communication on students' learning.
6. **Privacy and data security:** The use of AI tools raises privacy and data security issues related to the collection and analysis of student data. In this context, including information on possible regulations and best practices to ensure data privacy can be useful to alleviate privacy concerns. The use of AI tools raises privacy and data security issues related to the collection and analysis of student data (Selwyn, 2019; Williamson et al., 2020). This dimension assesses students' concerns about the data use and privacy of AI tools.
7. **Cultural and disciplinary context:** Perceptions of the acceptance and reliability of AI tools may differ across cultural backgrounds and academic disciplines (Chugai & Havrylenko, 2024; Ma et al., 2024). This dimension assesses how students' cultural and disciplinary contexts influence their perceptions of AI tools.

The "student perceptions of AI-assisted academic communication" survey seeks to evaluate the spectrum of views held by students on the instruments intended to promote AI. This study intends to give legislators and educators strategic and pragmatic knowledge thus optimizing the integration of AI technology in educational contexts and solving any problems. Within the parameters of this study, many aspects of students' interaction with AI technology are examined, with a special eye toward important trends. By means of this multifarious approach, teachers and legislators will be able to acquire insightful analysis that would enable them to maximize AI integration in educational environments and manage possible challenges.

**Table 1.** CVI

| No | Item | I-CVI | S-CVI | S-CVI/UA |
|---|---|---|---|---|
| 1 | I am confident that AI tools can improve my academic performance. | 0.889 | 0.889 | |
| 2 | I believe that AI-assisted communication is beneficial for my studies. | 1.000 | 1.000 | 1 |
| 3 | AI-assisted communication helps me address my weaknesses in academic communication. | 1.000 | 1.000 | 1 |
| 4 | I am familiar with AI tools that can assist with academic writing. | 1.000 | 1.000 | 1 |
| 5 | I will use AI-assisted communication tools whenever possible. | 1.000 | 1.000 | 1 |
| 6 | I would recommend the use of AI-assisted academic communication tools to my peers. | 1.000 | 1.000 | 1 |
| 7 | I feel comfortable using AI tools that are integrated with my learning management system. | 1.000 | 1.000 | 1 |
| 8 | I am concerned about the privacy of my data when using AI-assisted communication tools. | 1.000 | 1.000 | |
| 9 | AI diminish the quality of my academic discussions. | 1.000 | 1.000 | 1 |
| 10 | I am likely to explore new AI tools for academic communication. | 1.000 | 1.000 | 1 |
| 11 | I find AI-assisted communication tools helpful for my academic work. | 1.000 | 1.000 | 1 |
| 12 | I am not good at using AI for academic communication. | 1.000 | 1.000 | 1 |
| 13 | AI-assisted writing tools help me improve my grammar and style. | 0.889 | 0.889 | |
| 14 | I feel that AI tools respect my privacy and handle my data securely. | 1.000 | 1.000 | 1 |
| 15 | I have a positive attitude towards integrating AI into academic settings. | 1.000 | 1.000 | 1 |
| 16 | AI-assisted communication helps me complete academic tasks more efficiently. | 1.000 | 1.000 | 1 |
| 17 | I plan to use AI tools regularly for academic purposes. | 1.000 | 1.000 | 1 |
| 18 | AI tools is helpful for improving my academic communication skills. | 1.000 | 1.000 | 1 |
| 19 | Using AI for academic communication makes learning more engaging. | 1.000 | 1.000 | 1 |
| 20 | AI tools help me better understand complex academic concepts. | 1.000 | 1.000 | 1 |
| 21 | I would like to learn more about how to effectively use AI tools for academic communication. | 1.000 | 1.000 | 1 |
| 22 | I feel comfortable using AI tools for brainstorming ideas for my assignments. | 1.000 | 1.000 | 1 |
| 23 | I find it challenging to properly cite or acknowledge the use of AI tools in my academic work. | 1.000 | 1.000 | 1 |
| 24 | Learning to use AI tools for academic communication is straightforward. | 1.000 | 1.000 | 1 |
| 25 | I worry that relying on AI tools might hinder my own learning and skill development. | 1.000 | 1.000 | 1 |
| 26 | I trust the accuracy of information and feedback provided by AI tools. | 1.000 | 1.000 | 1 |
| 27 | I trust the reliability of information provided by AI tools. | 1.000 | 1.000 | 1 |
| 28 | I feel that using AI tools gives me an unfair advantage over students who don't use them. | 0.444 | | |
| 29 | I believe AI-assisted communication can be a fair and unbiased learning tool. | 1.000 | 1.000 | 1 |
| 30 | Using AI tools for academic communication saves me time. | 1.000 | 1.000 | 1 |
| 31 | AI-assisted communication tools have improved the quality of my academic work. | 1.000 | 1.000 | 1 |
| 32 | Using AI-assisted communication tools is challenging. | 1.000 | 1.000 | 1 |
| 33 | I intend to use AI-assisted communication tools in my future academic work. | 1.000 | 1.000 | 1 |
| 34 | I enjoy using AI tools for academic communication. | 1.000 | 1.000 | 1 |
| 35 | I'm concerned about potential plagiarism issues when using AI tools for academic writing. | 0.667 | | |
| 36 | I can quickly become proficient in using AI-assisted communication tools. | 1.000 | 1.000 | 1 |
| 37 | AI-assisted communication feels impersonal compared to traditional methods. | 0.889 | 0.889 | |
| 38 | Using AI in academic communication enhances my learning experience. | 1.000 | 1.000 | 1 |
| 39 | Using AI tools for academic tasks makes me feel less authentic in my work. | 1.000 | 1.000 | 1 |
| 40 | I believe using AI tools for academic writing is ethical. | 0.444 | | |

## Generate Initial Item Pool

The items for the scale were created considering the studies reviewed and considering the dimensions mentioned above. 40 items were written, and 9 of them were expressed in a negative way. The wording of the items is shown in **Table 1**.

## Content Validation by Expert Judgement

In the first stage, a form consisting of 40 items was created and submitted to expert opinion. The expert group consisted of 5 experts working in the field of communication and linguistics, 4 experts working in the field of educational technologies and experienced in AI, and 1 measurement and evaluation expert. In total, the opinions of 9 experts were received.

The experts were asked to evaluate each item one by one. The evaluation criteria are as follows:

- "1": The item serves the purpose of the scale.
- "0": The item does not serve the purpose of the scale.

As a result of the experts' evaluations, I-CVI was calculated for each item. I-CVI values vary between 0.444 and 1. According to Yousuf (2010), the minimum I-CVI value for 9 experts should be 0.78.

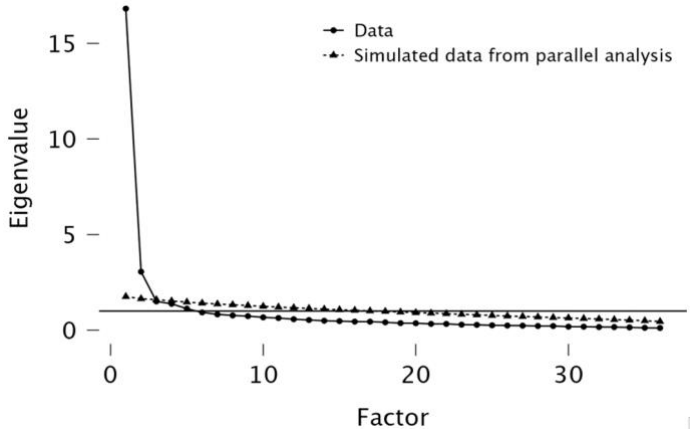


**Figure 2.** Scree plot based on parallel analysis (Source: Created by the authors)

Three items that did not meet this criterion were removed from the scale:

- "I feel that using AI tools gives me an unfair advantage over students who don't use them."
- "I'm concerned about potential plagiarism issues when using AI tools for academic writing."
- "I believe using AI tools for academic writing is ethical."

The CVI/Ave value calculated for the first form of the scale is 0.956. After the items were removed, the CVI/Ave value was calculated as 0.991. The CVI/UA value was found to be 0.892. As a result of the analysis, it was seen that the content validity of the new scale form consisting of 37 items was achieved (**Appendix A**).

## Pilot Study

A small pilot group used the revised scale to see whether the target group comprehended it. One questioned against every item, "Is this item understandable to you?" Every item was rated by the participants as either "0," (not completely understood) or "1," (totally understood). According to the data obtained from the pilot study, averages were calculated for each item based on the "0" and "1" scores given by the participants. The means of the items ranged between 0.90 and 1. Six items had a mean score below 1. These items are as follows:

- "I find AI-assisted communication tools helpful for my academic work."
- "AI-assisted writing tools help me improve my grammar and style."
- "I find it challenging to properly cite or acknowledge the use of AI tools in my academic work."
- "I trust the accuracy of information and feedback provided by AI tools."
- "Using AI tools for academic tasks makes me feel less authentic in my work."

The experts looked over these low average items one more. The assessments led to the decision to maintain the objects in their present shape. An important first step in determining the comprehensibility of the scale by the target group and in making required changes is this pilot research. The scale became more logical and helpful in line with the comments received.

## EFA Results

Kaiser-Meyer-Olkin (KMO) and Bartlett's tests were applied to assess the suitability of the data set for factor analysis. While the KMO test measures the adequacy of the sample, Bartlett's test of sphericity evaluates whether the correlation between variables is sufficient. As a result of the KMO test, the overall KMO value was found to be 0.956. This value indicates that the data set is quite suitable for factor analysis. Moreover, individual KMO values ranged from 0.708 to 0.978, confirming that all variables were suitable for factor analysis. The results of Bartlett's test of sphericity are $\chi^2 = 1786.464$, $df = 559$ and $p < .001$. The significant p-value indicates that the data set is suitable for factor analysis (Gie Yong & Pearce, 2013). Parallel analysis method was used to determine the number of factors (Williams et al., 2010). When the scree plot graph in **Figure 2** is analyzed, it is seen that a two-factor structure was obtained. The item-33 with factor loadings below 0.4 were removed from the scale and the analyses were repeated.

**Table 2.** Factor loading and explained variance

| Items | Factor 1 | Factor 2 | Uniqueness |
|---|---|---|---|
| IT_16 | 0.868 | | 0.245 |
| IT_11 | 0.838 | | 0.301 |
| IT_18 | 0.837 | | 0.292 |
| IT_15 | 0.835 | | 0.298 |
| IT_17 | 0.820 | | 0.307 |
| IT_20 | 0.814 | | 0.347 |
| IT_30 | 0.793 | | 0.354 |
| IT_34 | 0.792 | | 0.332 |
| IT_37 | 0.789 | | 0.335 |
| IT_19 | 0.786 | | 0.386 |
| IT_06 | 0.779 | | 0.367 |
| IT_07 | 0.774 | | 0.393 |
| IT_02 | 0.774 | | 0.398 |
| IT_21 | 0.769 | | 0.421 |
| IT_05 | 0.765 | | 0.393 |
| IT_22 | 0.760 | | 0.408 |
| IT_32 | 0.754 | | 0.411 |
| IT_10 | 0.742 | | 0.461 |
| IT_03 | 0.731 | | 0.458 |
| IT_28 | 0.722 | | 0.485 |
| IT_01 | 0.700 | | 0.516 |
| IT_29 | 0.699 | | 0.522 |
| IT_13 | 0.692 | | 0.525 |
| IT_35 | 0.675 | | 0.544 |
| IT_24 | 0.640 | | 0.583 |
| IT_14 | 0.636 | | 0.594 |
| IT_26 | 0.613 | | 0.631 |
| IT_27 | 0.596 | | 0.645 |
| IT_04 | 0.559 | | 0.694 |
| IT_25 | | 0.711 | 0.492 |
| IT_09 | | 0.700 | 0.423 |
| IT_23 | | 0.619 | 0.621 |
| IT_36 | | 0.571 | 0.677 |
| IT_12 | | 0.515 | 0.736 |
| IT_08 | | 0.472 | 0.779 |
| IT_31 | | 0.439 | 0.812 |
| Eigenvalues | 16.274 | 2.540 | |
| Proportion variance | 0.452 | 0.071 | |

In the two-factor structure obtained, the first factor consists of 29 items (**Table 2**). The factor loadings of the items in this factor vary between 0.559 and 0.868. When the items collected in the first factor were analyzed, it was seen that they contained positive statements about the use of AI in academic communication. Therefore, the first factor was named as “positive dimension”. This factor explains 45.2% of the total variance in the scale. The second factor consists of 7 items with factor loadings between 0.439 and 0.711. Since the items in this factor contain negative expressions, it is named as “negative dimension”. The second factor explains 7.1% of the total variance in the scale. Although the second factor explained a relatively modest proportion of variance, this pattern is not unusual in attitudinal scales developed in the social sciences, where a dominant first factor is often accompanied by smaller but still meaningful secondary dimensions. Factor retention was therefore not based solely on the percentage of explained variance, but also on the convergence of parallel analysis and scree plot results, the interpretability of the factor content, and the subsequent CFA evidence supporting the two-factor solution (Costello & Osborne, 2005).

## CFA Results

CFA was conducted in the second half of the randomly split sample to verify the two-factor structure identified in EFA. The diagonally weighted least squares estimator was employed given the ordinal nature of Likert-type data, and robust standard errors were used (Li, 2016).

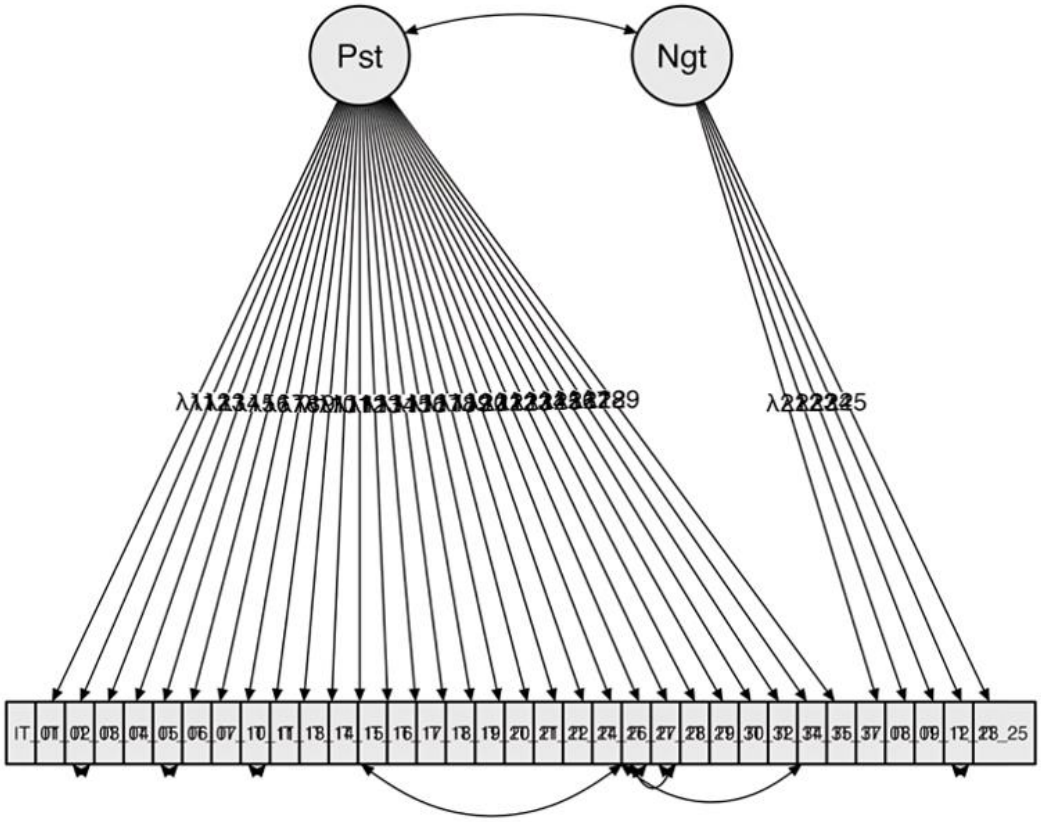


**Figure 3.** Final model based on CFA (Source: Created by the authors)

The initial model included all 36 items (29 positive and 7 negative). The fit indices of this model indicated inadequate fit with the data: $\chi^2$ (593) = 3,936.205, $p < .001$, $\chi^2/df = 6.64$, CFI = 0.879, TLI = 0.871, NFI = 0.860, SRMR = 0.091, RMSEA = 0.120 (90% confidence interval [CI] [0.117, 0.124]). All fit indices fell below the acceptable thresholds recommended in the literature (Hu & Bentler, 1999; Kline, 2016). These results indicated that the initial model required improvement.

Upon inspection of the factor loadings, two items in the negative dimension (IT_31 and IT_36) exhibited unacceptably low standardized loadings of 0.288 and 0.344, respectively. These items were removed from the model. Additionally, examination of modification indices (as shown in **Figure 3**) and item content revealed nine pairs of items that shared residual covariance due to overlapping semantic content or shared method characteristics. Specifically, IT_26 and IT_27 both addressed trust in AI tools (accuracy versus reliability), IT_05 and IT_06 reflected behavioral intention (personal use versus peer recommendation), IT_02 and IT_03 captured perceived benefit of AI for academic work, IT_26 and IT_28 as well as IT_27 and IT_28 belonged to a common trust and fairness cluster, IT_12 and IT_23 both expressed perceived difficulty in using or citing AI, IT_10 and IT_11 related to exploratory interest and perceived helpfulness, IT_14 and IT_27 shared a general trust in AI systems, and IT_24 and IT_35 both pertained to ease of use and practical engagement with AI tools. Correlated residuals were added between these pairs to account for their shared variance beyond the latent factor (Brown, 2015).

The final model, consisting of 34 items (29 positive and 5 negative) with nine correlated residual pairs, demonstrated acceptable fit with the data: $\chi^2$ (517) = 1,883.891, $p < .001$, $\chi^2/df = 3.64$, CFI = 0.949, TLI = 0.945, NFI = 0.932, SRMR = 0.056, RMSEA = 0.082 (90% CI [0.078, 0.086]). The CFI and TLI values approached or exceeded the commonly recommended threshold of 0.95 (Hu & Bentler, 1999), and the SRMR value was well below the 0.08 criterion. The RMSEA value fell within the marginally acceptable range, and considering the model complexity with 34 indicators, this value can be regarded as reasonable (Browne & Cudeck, 1992). **Table 3** presents the fit indices for both the initial and final models.

In the final model, the standardized factor loadings for the positive dimension ranged from 0.591 (IT_04) to 0.889 (IT_34), all statistically significant at $p < .001$. For the negative dimension, factor loadings ranged from

**Table 3.** CFA criteria for each model

| Index | Initial model | Final model | Acceptable | Good |
|---|---|---|---|---|
| $\chi^2/df$ | 6.64 | 3.64 | < 5 | < 3 |
| CFI | 0.879 | 0.949 | > 0.90 | > 0.95 |
| TLI | 0.871 | 0.945 | > 0.90 | > 0.95 |
| NFI | 0.860 | 0.932 | > 0.90 | > 0.95 |
| SRMR | 0.091 | 0.056 | < 0.08 | < 0.05 |
| RMSEA | 0.120 | 0.082 | < 0.10 | < 0.08 |
| RMSEA 90% CI | [0.117, 0.124] | [0.078, 0.086] | | |

**Table 4.** Factor loading, z-values based on CFA

| Factor | Item | Loading | Standard error | z-value | p | 95% CI |
|---|---|---|---|---|---|---|
| Positive dimension | | | | | | |
| | IT_01 | 0.778 | 0.021 | 37.20 | < .001 | [0.737, 0.819] |
| | IT_02 | 0.746 | 0.023 | 32.18 | < .001 | [0.701, 0.792] |
| | IT_03 | 0.669 | 0.028 | 23.80 | < .001 | [0.613, 0.724] |
| | IT_04 | 0.591 | 0.032 | 18.71 | < .001 | [0.529, 0.653] |
| | IT_05 | 0.747 | 0.021 | 35.02 | < .001 | [0.705, 0.789] |
| | IT_06 | 0.813 | 0.017 | 47.74 | < .001 | [0.780, 0.847] |
| | IT_07 | 0.829 | 0.016 | 53.32 | < .001 | [0.799, 0.860] |
| | IT_10 | 0.737 | 0.022 | 33.58 | < .001 | [0.694, 0.780] |
| | IT_11 | 0.821 | 0.016 | 50.59 | < .001 | [0.789, 0.853] |
| | IT_13 | 0.702 | 0.024 | 29.29 | < .001 | [0.655, 0.749] |
| | IT_14 | 0.668 | 0.026 | 25.45 | < .001 | [0.616, 0.719] |
| | IT_15 | 0.852 | 0.014 | 60.46 | < .001 | [0.825, 0.880] |
| | IT_16 | 0.884 | 0.012 | 76.51 | < .001 | [0.861, 0.906] |
| | IT_17 | 0.859 | 0.013 | 66.76 | < .001 | [0.833, 0.884] |
| | IT_18 | 0.842 | 0.015 | 55.49 | < .001 | [0.812, 0.871] |
| | IT_19 | 0.790 | 0.018 | 43.01 | < .001 | [0.754, 0.826] |
| | IT_20 | 0.814 | 0.017 | 48.19 | < .001 | [0.781, 0.847] |
| | IT_21 | 0.741 | 0.021 | 34.63 | < .001 | [0.700, 0.783] |
| | IT_22 | 0.818 | 0.016 | 49.71 | < .001 | [0.785, 0.850] |
| | IT_24 | 0.618 | 0.030 | 20.67 | < .001 | [0.560, 0.677] |
| | IT_26 | 0.633 | 0.029 | 22.03 | < .001 | [0.577, 0.689] |
| | IT_27 | 0.621 | 0.029 | 21.19 | < .001 | [0.564, 0.679] |
| | IT_28 | 0.732 | 0.022 | 32.90 | < .001 | [0.688, 0.775] |
| | IT_29 | 0.712 | 0.025 | 29.07 | < .001 | [0.664, 0.760] |
| | IT_30 | 0.829 | 0.016 | 50.59 | < .001 | [0.797, 0.861] |
| | IT_32 | 0.823 | 0.017 | 48.73 | < .001 | [0.790, 0.856] |
| | IT_34 | 0.889 | 0.012 | 76.82 | < .001 | [0.866, 0.911] |
| | IT_35 | 0.692 | 0.023 | 30.13 | < .001 | [0.647, 0.737] |
| | IT_37 | 0.851 | 0.016 | 54.31 | < .001 | [0.821, 0.882] |
| Negative dimension | | | | | | |
| | IT_08 | 0.445 | 0.062 | 7.195 | < .001 | [0.324, 0.567] |
| | IT_09 | 0.836 | 0.051 | 16.56 | < .001 | [0.737, 0.935] |
| | IT_12 | 0.585 | 0.054 | 10.88 | < .001 | [0.479, 0.690] |
| | IT_23 | 0.523 | 0.059 | 8.830 | < .001 | [0.407, 0.640] |
| | IT_25 | 0.586 | 0.047 | 12.59 | < .001 | [0.494, 0.677] |

Note. All factor loadings are statistically significant at $p < .001$

0.445 (IT_08) to 0.836 (IT_09), all statistically significant at $p < .001$. The correlation between the positive and negative factors was 0.441 ($p < .001$), indicating a moderate positive association between the two dimensions. **Table 4** presents the factor loadings, standard errors, z-values, p-values, and 95% CIs for each item.

## Reliability and Validity

The internal consistency reliability of the scale was assessed through multiple indicators, including Cronbach's α, McDonald's ω, and composite reliability (CR). For the positive dimension, both Cronbach's α and McDonald's ω values were 0.969, with a CR of 0.976. The average variance extracted (AVE) for this dimension was 0.588, exceeding the recommended threshold of 0.50 (Fornell & Larcker, 1981). These values indicate excellent internal consistency and convergent validity for the positive dimension.

**Table 5.** Reliability coefficient and convergent validity

| Factor | Cronbach's α | McDonald's ω | CR | AVE | HTMT |
|---|---|---|---|---|---|
| Positive | 0.969 | 0.969 | 0.976 | 0.588 | |
| Negative | 0.696 | 0.705 | 0.738 | 0.371 | 0.311 |
| Overall | 0.958 | 0.958 | | | |

**Table 6.** Descriptive statistics on perception

| Group | Median | Mean | SD | Skewness | SE of Skewness | Kurtosis | SE of Kurtosis |
|---|---|---|---|---|---|---|---|
| Positive dimension | 3.41 | 3.392 | 0.815 | -0.38 | 0.101 | 0.327 | 0.203 |
| Negative dimension | 3.00 | 2.859 | 0.820 | -0.059 | 0.101 | 0.011 | 0.203 |

Note. SD: Standard deviation & SE: Standard error

For the negative dimension, Cronbach's α was 0.696, and McDonald's ω was 0.705, with a CR of 0.738. Although the AVE for this dimension (0.371) fell below the conventional 0.50 threshold, Fornell and Larcker (1981) noted that convergent validity can still be considered adequate when the CR exceeds 0.60, even if the AVE is below 0.50. The relatively lower reliability of the negative dimension compared to the positive dimension is not uncommon in attitudinal scales where negatively worded items tend to exhibit greater measurement variability (DiStefano & Motl, 2006). Nevertheless, all reliability coefficients for this dimension remained within acceptable bounds.

For the overall scale, both Cronbach's α and McDonald's ω values were 0.958, indicating a high level of internal consistency across all 34 items. These findings confirm that the scale consistently measures the intended construct.

Discriminant validity was assessed using the heterotrait-monotrait (HTMT) ratio of correlations (Henseler et al., 2015). The HTMT value between the positive and negative dimensions was 0.311, well below the conservative threshold of 0.85. This result provides strong evidence that the two factors represent conceptually distinct dimensions. **Table 5** presents the reliability and validity indicators for each dimension.

## Prepare Usage Documentation

The scale developed in the study aims at student perceptions of AI-assisted academic communication. The scale consists of 36 items in total and includes two sub-dimensions. These sub-dimensions represent positive and negative attitudes towards the use of AI.

The positive sub-dimension of the scale consists of items numbered 1, 2, 3, 4, 4, 5, 6, 7, 10, 11, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 24, 26, 27, 28, 29, 30, 32, 33, 34, 35, and 37. These items are evaluated using a 5-point Likert scale. The options on the Likert scale are as follows: 1–strongly disagree, 2–disagree, 3–undecided, 4–agree, 5–strongly agree. By averaging the items in the positive subdimension, a comment can be made about the positive perceptions of the participants. An increase in the mean value indicates that the participants have more positive thoughts about the use of AI.

The negative sub-dimension of the scale consists of items numbered 8, 9, 12, 23, and 25. These items should be reverse coded and scored. The reverse coding is as follows: 5–strongly disagree, 4–disagree, 3–undecided, 2–agree, 1–strongly agree. The increase in the mean of the items in the negative sub-dimension shows that the participants have positive attitudes towards the use of AI.

### *Students' perceptions AI-assisted academic communication*

When we analyze **Table 6**, some important differences between the positive and negative dimensions stand out. The positive dimension has a higher mean and median value and its data is spread over a wider range. This dimension also shows a more pronounced left-skewed distribution. By contrast, the negative dimension shows a smaller distribution and somewhat lower mean and median value. Although both dimensions deviate somewhat from the usual distribution, the positive dimension's distribution is rather more pointed. These variations imply a qualitative difference between the two aspects of the measured phenomena, with the positive dimension centered around higher values.

**Table 7.** Bayesian t-test based on gender

| Group | N | Mean | Standard deviation | $BF_{10}$ | error % |
|---|---|---|---|---|---|
| Positive dimension | Female | 431 | 3.399 | 0.111 | 0.148 |
| | Male | 149 | 3.373 | | |
| Negative dimension | Female | 431 | 2.865 | 0.110 | 0.150 |
| | Male | 149 | 2.842 | | |

**Table 8.** Average based on age

| Group | Age | N | Mean | Standard deviation |
|---|---|---|---|---|
| Positive dimension | <18 | 79 | 3.404 | 0.824 |
| | 18-19 | 215 | 3.412 | 0.863 |
| | 20-21 | 143 | 3.365 | 0.737 |
| | 22-23 | 87 | 3.361 | 0.856 |
| | >23 | 56 | 3.422 | 0.764 |
| Negative dimension | <18 | 79 | 2.785 | 0.829 |
| | 18-19 | 215 | 2.887 | 0.843 |
| | 20-21 | 143 | 2.828 | 0.717 |
| | 22-23 | 87 | 2.811 | 0.895 |
| | >23 | 56 | 3.007 | 0.848 |

**Table 9.** Bayesian ANOVA based on age variable

| Group | Models | P (M) | P (M \| data) | $BF_M$ | $BF_{10}$ | Error % |
|---|---|---|---|---|---|---|
| Positive dimension | Null model | 0.500 | 0.996 | 240.4 | 1.000 | |
| | Age | 0.500 | 0.004 | 0.004 | 0.004 | 0.071 |
| Negative dimension | Null model | 0.500 | 0.988 | 80.10 | 1.000 | |
| | Age | 0.500 | 0.012 | 0.012 | 0.012 | 0.028 |

### *Gender's effect on perception*

The Bayesian analysis's findings indicate that students' opinions of academic communication supported by AI are not significantly different between genders (**Table 7**). Positive and negative aspects alike, the mean values of male and female participants are rather near to one another. In the positive dimension, the mean of female is 3.399, while the mean of men is 3.373; in the negative dimension, the mean of women is 2.865, while the mean of men is 2.842. Despite these small differences, Bayes factors ($BF_{10}$) are below 1 for both dimensions (0.148 and 0.150, respectively). These values strongly support the null hypothesis that there is no difference between genders. Although there is a significant difference in sample size in favor of women (N = 431 for women, N = 149 for men), this does not seem to have significantly affected the results. Finally, this study reveals that the view and application of AI-supported academic communication tools do not differ depending on gender. These results can be regarded as a favorable sign for gender equality in the application of AI in the educational setting.

### *Participants age's effect on perceptions*

Regarding PD, for all age groups, the mean values are rather close (**Table 8**). The group above 23 years of age (3.422) has the greatest mean; the group 22-23 years old shows the lowest mean (3.361). These numbers varied very little; the averages of every group ranged from 3.3 to 3.5. This indicates that a positive view of academic communication facilitated by AI does not differ much between age groups. Analyzing the ND reveals somewhat more variation between age groups. The lowest mean was observed in the group below the age of 18 (2.785), and the highest mean was observed in the group above the age of 23 (3.007). Generally speaking, one may say that when age rises, the mean of the negative dimension usually somewhat increases. This could imply that older pupils approach AI use somewhat more caution. Nonetheless, the favorable and negative dimension indicates that students generally have a neutral or somewhat favorable view toward AI-supported academic communication since the value for all age groups is about 3. The consistency of the answers is indicated by the fact that the standard deviation values similarly show no significant variations between the groups. For the statistical relevance of the differentiation, a Bayesian ANOVA test was carried out.

The Bayesian ANOVA results presented in **Table 9** provide strong evidence that students' perceptions of AI-assisted academic communication do not differ significantly across age groups. For the positive dimension,

the null model received overwhelming support from the data, with P(M|data) = 0.996 and $BF_{10}$ = 0.004. This $BF_{10}$ value indicates that the data support the null hypothesis (no difference between age groups) approximately 250 times more than the alternative hypothesis. For the negative dimension, a similar pattern was observed, with P(M|data) = 0.988 and $BF_{10}$ = 0.012, suggesting that the data favor the null hypothesis approximately 83 times more than the alternative. According to Jeffreys' (1998) BF interpretation guidelines, $BF_{10}$ values below 0.01 represent decisive evidence, and values between 0.01 and 0.033 represent very strong evidence in favor of the null hypothesis. The low error percentages (0.071% and 0.028%) further confirm the reliability of these estimations. Taken together, these findings indicate that students across all age groups hold comparable views regarding AI-assisted academic communication, and the adoption and perception of such tools appear to be independent of age.

## DISCUSSION

The purpose of this work was to create a legitimate and reliable scale to evaluate students' opinions of academic communication driven by AI. The created scale showed a two-factor structure and these elements were labeled as "positive dimension" and "negative dimension." These two categories were decided to methodically handle the good and negative elements required to grasp the consequences of AI technologies in the sphere of education. While the positive dimension evaluates the advantages of AI technologies such as efficiency, ease of access and contribution to the learning process, the negative dimension addresses potential risks such as data privacy, ethical concerns and technological dependency. This difference lets one evaluate both good and negative impressions in a fair manner. This framework conforms to earlier research exposing both favorable and unfavorable opinions on the application of AI technology in education (Holmes et al., 2019; Selwyn, 2019).

The positive dimension includes students' perceptions of the potential benefits of AI-supported academic communication, such as increased productivity, faster access to information and facilitating the learning process, while the negative dimension includes perceptions of the negative effects of using AI, such as ethical and privacy concerns. These two aspects offer a whole picture for appreciating the complicated effects of AI technology in the field of education.

The scale's validity and dependability studies turned out that the created instrument is psychometrically good. High internal consistency coefficients (Cronbach's α and McDonald's ω > 0.90) show that the scale's dependability is strong and consistent with like investigations (Chugai & Havrylenko, 2024; Liu et al., 2024). This finding indicates that the scale measures students' perceptions of AI-supported academic communication in a stable and consistent way to its high reliability coefficients. The high Cronbach's α and McDonald's ω values indicate that the scale provides consistency in measurements and the changes in students' perceptions are not random. Furthermore, exploratory and confirmatory factor analyses confirmed that the two-factor structure of the scale was statistically significant and appropriate. This strengthens the content validity and construct validity of the scale, thus indicating that the use of the scale can be valid in different settings.

A positive score of 3.392 shows that students like using AI in education. This is similar to what Shalevska and Kostadinovska-Stojchevska (2024) found in 2024. Students see the benefits of AI and think it is useful for their studies. They say AI helps them learn faster and access information that is relevant to them. This optimistic viewpoint aligns with research findings regarding the potential of AI to enhance academic performance. According to García-Martínez et al. (2023), AI has positive effect on student academic performance. The meta-analysis study found that AI has a small effect size of 0.351 on elementary students' mathematics achievement (Hwang, 2022). These findings clearly demonstrate the extent to which

AI technology enhances academic performance. The mean of the negative dimension (2.871) is close to the neutral value, indicating concerns among students regarding the application of AI. The questions may pertain to ethical issues, data privacy, and security, topics frequently addressed in the literature (Avsheniuk et al., 2024; Williamson et al., 2020). Students express concerns regarding the potential utilization of personal data and the risks that AI applications may pose to privacy. Stringent regulations and transparency standards are essential to protect data privacy and address these concerns. The design of AI systems can benefit from strategies that prioritize privacy and methods that minimize data usage. These responses help students feel

more confident about AI. However, there is a risk that AI could make students too dependent on it, which would harm their critical thinking skills. This shows that we need to think about the ethical and safety issues of using AI in education. Education policies should address these issues.

The study shows that students' views on AI in education are similar regardless of gender or age. This challenges previous research. The study shows that students' views on AI in education are similar regardless of gender or age. This challenges a previous study that found that men and women have different views on AI. This may be because of differences in the people who took part or because of how the studies were done in different cultures. More research is needed to understand how social and cultural factors affect people's acceptance of AI.

The scale was developed using a variety of methods, including content validity, pilot research, and factor analysis. This process made sure the scale had strong psychometric properties and followed DeVellis (2016) scale development principles. An expert review was used to assess whether the scale covered the right topics. The pilot study tested how easy the scale was to understand and if it could be used in the real world. One of the strengths of the study is that the analyses were conducted based on a large sample group (N = 580). This raises the overall result generalizability. Furthermore, Bayesian statistical techniques gave more consistent findings than conventional frequency-based techniques (Wagenmakers et al., 2018). By lowering sensitivity to sample size and offering a more complete view of the dataset, Bayesian studies allegedly improve the accuracy of parameter estimations. Thus, the choice of Bayesian techniques in this work enabled a stronger interpretation of the results.

The study has certain restrictions, though as well. The fact that the sample came from one nation and during a particular timeframe could restrict the generalizing of the findings across many cultural settings and times. Moreover, the cross-sectional approach of the study made it impossible to investigate changes in students' impressions across time. The cross-sectional methodology provides insufficient information on determining causal correlations; so, longitudinal studies are required to find more about how students' opinions of AI-supported academic communication evolve and alter.

Finally, this study provides a valid and accurate instrument to measure how well students regard academic communication supplemented by AI. The findings show that although students have specific concerns, they regard things generally quite well. These findings should drive politicians and educators to act especially to ensure that AI technologies are used more morally and practically in the classroom. Teachers should be able to teach students about AI. Laws should be made to make sure people behave well and keep data safe. This helps students trust AI tools and fit in at school. These results can help policymakers and educators know how to use AI in education the right way. AI-supported technologies in education help students learn, but they also raise ethical questions. Educators and students must understand these technologies to ensure they are used fairly and effectively. They should be trained in how to use AI tools responsibly.

## CONCLUSION

The purpose of this work was to create a legitimate and dependable scale to gauge how students felt of academic communication helped by AI. Showing a two-factor structure, the created scale comprises two sub-dimensions known as "positive dimension" and "negative dimension". The scale is psychometrically sound, according to extensive validity and dependability studies.

The investigation produced mostly the following conclusions:

1. Students thought of academic communication supported by AI generally favorably.
2. Students did, however, also show some worries over the application of AI.
3. It was discovered that age and gender had no appreciable effect on how students felt.

Though there are certain problems, these findings show that most students are in favor of using AI technologies in the sphere of education. This situation emphasizes the need of educators and legislators in order to mix AI technologies into learning environments with a purposeful and intelligent attitude.

## RECOMMENDATIONS

The following suggestions apply in view of the results of this research:

1. Training and support for students on the application of AI-supported academic communication tools should come from educational institutions. This could enable students to securely and more wisely apply these technologies.
2. Policy makers should draft codes of ethics and data security guidelines for the application of AI technology in the sphere of education. This promotes sensible technological use and helps students' concerns be reduced.
3. Future research could track students across time to examine how their views of academic communication are supported by AI change.
4. Similar studies conducted on many educational levels and in several cultural environments could help to evaluate the generalizability of the outcomes.
5. Research can be carried out to investigate the link between students' impressions and their actions of applying AI technology in actual academic environments.
6. Experimental research might be planned to evaluate student performance under the influence of academic communication technologies backed by AI.

### Limitations of the Study

This study has various limitations:

1. The study was conducted with data taken during a certain period in one country. This can limit the generalizability of the results to many historical periods and cultural environments.
2. The cross-sectional nature of the study made it hard to analyze over time variations in students' impressions. With a longitudinal study, one would have been more suited to grasp the changes in perspective over time.
3. Self-report was used to compile the data. This method brings many possible biases, including social desirability bias.
4. The study excluded any fluctuations in students' degree of AI technology use. These variances could influence impressions.
5. The study mostly focused on academic communication facilitated by AI in general but omitted to look at specific apps (such as Grammarly and ChatGPT).

Despite these limitations, the study significantly clarifies how students see academic communication enabled by AI. Future research could aim to acquire more comprehensive and broadly applicable conclusions by addressing these limitations.

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**Ethics declaration:** This study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki. The research protocol was reviewed and formally approved by the Ethics Committee of Kazan State Power Engineering University. All participants were fully informed about the nature, purpose, and potential risks of the research. Voluntary informed consent was obtained from all individual participants included in the study prior to data collection. Participants were notified of their right to withdraw from the study at any time without penalty.

**AI statement:** In order to improve the language, we, the authors of this work, used the AI technology Claude Sonnet 4.6. We evaluated and verified the finished product of our work after applying these AI technologies. We take full responsibility for the content of our published work as authors.

**Declaration of interest:** The authors declared no competing interests.

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

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# APPENDIX A

**Table A1.** Items

| No | Items |
|---|---|
| 1 | I am confident that AI tools can improve my academic performance. |
| 2 | I believe that AI-assisted communication is beneficial for my studies. |
| 3 | AI-assisted communication helps me address my weaknesses in academic communication. |
| 4 | I am familiar with AI tools that can assist with academic writing. |
| 5 | I will use AI-assisted communication tools whenever possible. |
| 6 | I would recommend the use of AI-assisted academic communication tools to my peers. |
| 7 | I feel comfortable using AI tools that are integrated with my learning management system. |
| 8 | I am concerned about the privacy of my data when using AI-assisted communication tools. |
| 9 | AI diminish the quality of my academic discussions. |
| 10 | I am likely to explore new AI tools for academic communication. |
| 11 | I find AI-assisted communication tools helpful for my academic work. |
| 12 | I am not good at using AI for academic communication. |
| 13 | AI-assisted writing tools help me improve my grammar and style. |
| 14 | I feel that AI tools respect my privacy and handle my data securely. |
| 15 | I have a positive attitude towards integrating AI into academic settings. |
| 16 | AI-assisted communication helps me complete academic tasks more efficiently. |
| 17 | I plan to use AI tools regularly for academic purposes. |
| 18 | AI tools is helpful for improving my academic communication skills. |
| 19 | Using AI for academic communication makes learning more engaging. |
| 20 | AI tools help me better understand complex academic concepts. |
| 21 | I would like to learn more about how to effectively use AI tools for academic communication. |
| 22 | I feel comfortable using AI tools for brainstorming ideas for my assignments. |
| 23 | I find it challenging to properly cite or acknowledge the use of AI tools in my academic work. |
| 24 | Learning to use AI tools for academic communication is straightforward. |
| 25 | I worry that relying on AI tools might hinder my own learning and skill development. |
| 26 | I trust the accuracy of information and feedback provided by AI tools. |
| 27 | I trust the reliability of information provided by AI tools. |
| 28 | I believe AI-assisted communication can be a fair and unbiased learning tool. |
| 29 | Using AI tools for academic communication saves me time. |
| 30 | AI-assisted communication tools have improved the quality of my academic work. |
| 31 | Using AI-assisted communication tools is challenging |
| 32 | I intend to use AI-assisted communication tools in my future academic work. |
| 33 | I enjoy using AI tools for academic communication. |
| 34 | I can quickly become proficient in using AI-assisted communication tools. |
| 35 | AI-assisted communication feels impersonal compared to traditional methods. |
| 36 | Using AI in academic communication enhances my learning experience. |