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PAPER

Generative AI in Teaching Technical Report Writing to Engineering Students: A Case Study on Technology Acceptance and Writing Self-Efficacy

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ABSTRACT

The growing incorporation of generative artificial intelligence (GAI) in educational settings is transforming the teaching of technical writing in engineering education. However, there is little evidence on how students adopt these technologies in the development of technical reports, a key transversal skill in their future professional practice. This case study analyzes the relationship between GAI acceptance and self-efficacy in technical report writing among 158 engineering students at a national university in Peru. A quantitative, correlational approach and a non-experimental design were used. The results indicate that most students show moderate to high levels of technological acceptance and self-efficacy in writing technical reports, with a clear predominance of positive attitudes towards the use of GAI. Significant positive correlations were found between the dimensions of perceived use, ease of use, and intention to use GAI with the key stages of planning, drafting, and reviewing technical reports. It is concluded that the effective integration of GAI improves academic and professional engineering education by strengthening students' confidence and skills in specialized writing. Finally, it is recommended that future research incorporate variables such as intrinsic motivation and critical thinking, considering their application in different branches of engineering.

KEYWORDS

generative artificial intelligence (GAI), technical report, engineering students, technology acceptance, writing self-efficacy

1 INTRODUCTION

The integration of artificial intelligence (AI) into higher education has facilitated the development of personalized learning environments, automated feedback systems, and data analysis tools that support academic performance improvement and

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individualized learning [1], [2]. The technologies contribute to autonomous learning, enhance student engagement, and encourage pedagogical innovation, although ethical and methodological challenges remain and require careful consideration during implementation [3], [4]. Within this context, generative artificial intelligence (GAI), represented by tools such as ChatGPT and large language models, has emerged as a valuable resource for delivering interactive, accessible, and tailored educational experiences for both students and instructors [5], [6]. These models enable the automated generation of educational content, provide immediate feedback, and support the development of digital skills across diverse learning settings [7], [8]. In addition, AI-based educational chatbots expand opportunities for academic guidance and independent learning through personalized recommendations and flexible access to educational resources [9], [10]. However, recent literature highlights the need for institutional policies to regulate aspects such as academic integrity, authorship, and ethical use, given the ongoing debates regarding their alignment with traditional pedagogical practices [11].

University students generally perceive tools such as ChatGPT as useful and accessible learning resources, expressing favorable attitudes toward their integration while also emphasizing the importance of appropriate guidance to prevent excessive reliance and ensure ethical use [12]. Recent studies indicate that the use of GAI can enhance student engagement, personalized learning, and the development of skills such as creativity and critical thinking, provided that responsible implementation strategies are in place [13]. Similarly, factors such as academic self-discipline influence the acceptance of these technologies by strengthening self-regulation, learning management, and awareness of their educational impact, thereby foresting more positive attitudes toward their adoption [14]. Likewise, prospective teachers who integrated GAI tools into their instructional design reported higher levels of technological acceptance and motivation, highlighting perceived usefulness (PU) and intention to use as key determinants in educational adoption [15]. The ability of GAI to assist with complex tasks, such as academic writing, becomes particularly relevant when linked to the development of transversal competencies, defined as the combination of knowledge, skills, and attitudes that enable students to perform effectively across diverse academic and professional contexts beyond their disciplinary specialization [16].

Therefore, written communication, as an essential component of transversal skills, plays a fundamental role in university education, since it allows knowledge to be mobilized and ideas to be expressed clearly in academic and professional settings [17]. Academic writing proficiency directly affects the comprehension of specialized texts, the organization of ideas, and the production of rigorous academic work, whereas insufficient levels may limit academic performance and critical analysis skills [18], [19]. Recent research shows that first-year students often perceive academic writing as challenging; however, exposure to expressive genres and formative processes involving structured feedback and peer collaboration supports the development of self-efficacy and academic belonging [20], [21]. Similarly, authentic research experiences that combine synchronous and asynchronous support with autonomy in written production foster intrinsic motivation and confidence to produce high-quality academic texts [22], [23]. Finally, performance expectations and trust in the information source emerge as critical factors influencing students' willingness to integrate generative technologies such as ChatGPT into academic writing activities, thereby strengthening the development of these transversal competencies [24].

In this context, this study aims to analyze the relationship between GAI acceptance and self-efficacy in technical report writing, focusing the analysis on engineering students developing technical communication skills in engineering. A quantitative methodology, with a correlational scope and a non-experimental cross-sectional design, is applied to a sample of 158 students belonging to the schools of mechanical and electrical engineering, electronics, and systems engineering at a public university in Peru. The relevance of the study lies in its specific focus on the impact of emerging technologies such as GAI on a critical competency for professional practice in engineering: technical report writing, which integrates planning, writing, and specialized review skills. From this perspective, the following research questions are posed:

- RQ1: How does the perception of usefulness of GAI relate to self-efficacy in planning technical reports among engineering students?
- RQ2: How does perceived ease of use of GAI relate to self-efficacy in writing technical reports among engineering students?
- RQ3: How does the intention to use GAI relate to self-efficacy in reviewing technical reports among engineering students?

2 CONCEPTUAL FRAMEWORK

2.1 Technology acceptance model

Several theoretical models have been developed to understand technology acceptance, with the technology acceptance model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) being the most widely used in educational contexts to evaluate the adoption of digital tools [25]. These models provide a solid framework for analyzing the integration of GAI in higher education. The TAM model, recognized for its simplicity and robustness, focuses on two fundamental constructs: PU, which reflects users' belief about how a technology will improve their performance, and perceived ease of use (PEU), which indicates the degree to which the technology is perceived as intuitive and easy to use [26]. These elements are crucial for evaluating emerging technologies such as GAI, where the accessibility of the interface and the practical value of the results are determining factors for its acceptance. Empirical evidence confirms that both PU and PEU significantly impact the intention to use, which in turn drives the effective adoption of technologies in educational settings [27], [28]. This suggests that understanding the acceptance of GAI tools in higher education requires analyzing how students perceive their functionality and usability in academic activities such as writing technical reports. Recent research highlights that PU and PEU are key factors that shape users' attitudes toward technology adoption, directly influencing their intention to use and actual usage behavior [28], [29]. This relationship connects the TAM with the way students incorporate GAI tools into their learning processes. Thus, it is necessary to adapt and validate this model in scenarios where GAI-assisted technical writing becomes an emerging practice with both pedagogical and technological implications. The basic structure of the TAM model is presented in Figure 1 [31].

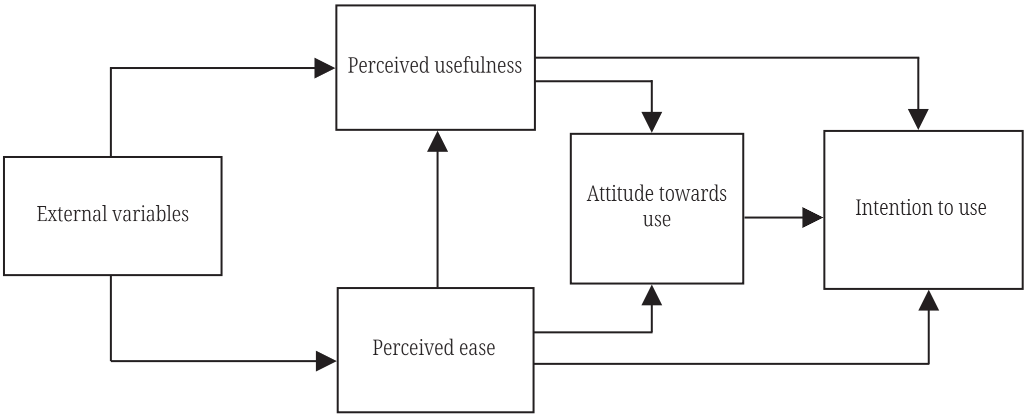

Fig. 1. Base diagram of the TAM model

2.2 Self-efficacy in writing

Among the four language skills that comprise the teaching-learning process, writing stands out as a complex cognitive endeavor that requires meticulous reflection, textual organization, and the capacity for constant self-assessment [32]. In this context, self-efficacy within social learning theory is understood as an individual's belief in their ability to successfully execute a specific task in a particular domain. This perception, rather than a general assessment of skills, focuses on anticipatory judgments about figure actions and varies according to the type of activity, as is the case with academic writing [33]. In higher education, writing texts such as technical reports, theses, or scientific articles constitutes an essential competency, where accurately communicating technical procedures and results is a constant requirement [34], especially in engineering programs. In this context, the use of technologies such as GAI has begun to transform the way students approach these tasks, raising new questions about their impact on confidence in technical writing. Written production in educational settings is closely linked to reading comprehension and critical thinking, skills that are in turn influenced by reading self-efficacy, a relevant predictor of academic writing performance [35]. From a socio-cognitive perspective, writing self-regulation is understood as the ability to plan, monitor, and revise one's own writing process. These processes are fundamental not only for improving textual quality but also for strengthening the writer's autonomy. These dimensions of planning, writing, and revising have been rigorously addressed in specific instruments such as the Self-Efficacy for Writing Scale, widely used to measure perceived self-efficacy in university educational contexts. This approach is particularly useful when analyzing how engineering students approach specialized writing tasks, such as the preparation of technical reports supported by technologies such as GAI. Research has shown that the perception of self-efficacy directly influences decision-making, effort, perseverance, and emotional management when faced with writing tasks, while previous experiences of failure or negative comments can diminish a student's confidence and written performance [36]. This phenomenon manifests itself in difficulties in planning the text, identifying the appropriate discourse type, revising effectively, and overcoming the fear of public exposure of the writing. Even the effective link established with the prepared text can make its critical review difficult, especially when it comes to long documents such as technical reports or research projects [37].

3 RESEARCH METHODOLOGY

3.1 Research approach, scope, and design

This study adopts a quantitative approach, seeking to empirically analyze the relationship between engineering students' acceptance of GAI and self-efficacy in writing technical reports. This approach provides objective evidence on how generative technologies influence self-perceptions of technical writing skills through the selection and analysis of numerical data. The quantitative approach also allows for the formulation and testing of hypotheses and the establishment of statistically significant patterns that support or refute theoretical assumptions [38]. Regarding the scope of the study, it is defined as correlational, since its purpose is to identify significant associations between the two main variables without manipulating conditions or experimental intervention. The correlational approach in studies with a quantitative approach uses inferential statistical procedures to generalize the findings obtained from the sample to the study population, thus favoring the projection of the results to a broader level [39]. Furthermore, a non-experimental transactional or cross-sectional design was used, with data collected at a single point in time and under natural conditions, without alterations to the educational environment. It should be noted that, as part of a specific chapter on technological tools for writing technical reports, students initially interacted with the application of GAI through guided in-class activities. Following this instructional phase, a questionnaire was administered to all students enrolled in the third cycle of three engineering programs: Mechanical and Electrical Engineering, Electronic Engineering, and Systems Engineering. Since the course is mandatory and was taught in a single academic semester, all 158 students present in class participated, thus eliminating the need to apply inclusion or exclusion criteria for sample selection. Data collection took place during regular class hours after obtaining the students' informed consent. The study was conducted during the last week of April 2025, during which ChatGPT-4.1 was used as the GAI tool.

3.2 Validity of the data collection instrument

The measurement instrument was designed using validated scales adapted to the specific context of technical report writing in engineering, integrating theoretical dimensions from the TAM model proposed by Davis, as outlined in [40], and the self-efficacy construct, validated in the study conducted by [41]. First, the variable "acceptance of the GAI" was structured into three dimensions: perceived usefulness, ease of use, and intention to use. Second, the variable "self-efficacy in technical report writing" was operationalized in three dimensions applied to technical report writing: planning, technical writing, and report review. Both sections of the instrument underwent content validation through expert judgment. In addition, an internal consistency analysis was performed using Cronbach's alpha coefficient, obtaining values above 0.85 for all dimensions, indicating high reliability of the instrument [42]. The structure of the data collection instrument is presented below, organized by variable, dimension, item, and measurement scale. Each statement was rated by participants using a 5-point Likert-type scale, where 1 represents "Strongly Disagree" and 5 "Strongly agree." Table 1 shows the data collection instrument and the reliability if any item was not considered.

Table 1. Data collection instrument and reliability results

Variable	Dimension	Item (Question)	Cronbach's Alpha Without Considering Item
Acceptance of GAI	Perception of usefulness	**1.** I believe that the GAI improves the quality of the technical reports I write.	0.901
		2. Using GAI allows me to write complex sections such as the introduction or technical conclusions more quickly.	0.896
		3. GAI's suggestions help me improve the clarity and precision of my technical reports.	0.900
	Ease of use	**4.** I find it easy to learn how to use GAI to write parts of a technical report.	0.873
		5. I easily integrate the responses generated by GAI into the structure of my report.	0.906
		6. I feel comfortable using GAI to support the preparation of technical reports.	0.907
	Intention of use	**7.** I plan to continue using GAI to write technical reports in my upcoming courses or projects.	0.882
		8. I would recommend responsible use of GAI to other engineering students to support their technical writing.	0.889
		9. If allowed, I would use GAI more frequently as a complementary tool in the preparation of technical reports.	0.874
Self-efficacy in writing technical reports	Planning the technical report	**10.** I feel capable of identifying key technical objectives before starting to write a report.	0.882
		11. I can organize the sections of a technical report in a logical and structured manner.	0.896
	Technical writing	**12.** I can write the results of a technical practice or experiment clearly and precisely.	0.876
		13. I am able to describe complex technical procedures using understandable language, without compromising technical accuracy.	0.896
		14. I find it easy to integrate explanatory graphs, tables, or formulas coherently within the body of the report.	0.883
	Review of the technical report	**15.** I review my reports carefully to improve their writing, presentation, and organization.	0.881
		16. Identify technical or conceptual errors, and I am able to correct them based on feedback or specialized sources.	0.854
		17. I can assess the overall coherence of the report before its final delivery.	0.882

3.3 Data processing and analysis

The collected data were processed and analyzed using SPSS v26 statistical software, following the guidelines for quantitative studies with a non-experimental design and correlational scope. First, descriptive analyses (mean frequencies, standard deviation) were applied to characterize the levels of acceptance of GAI through its dimensions: perceived usefulness, ease of use, and intention to use and self-efficacy in preparing technical reports, measured according to the dimensions of planning, writing, and technical review. Additionally, Python-based tools were employed to generate the box plots, as this approach gives greater control over the visualization parameters, customization of Likert-scale categories, and integration of descriptive statistics directly into the figures. It is important to note that, since the data collected were ordinal categorical in nature, the mean values of each dimension and variable were used to obtain a clearer and more representative depiction within the box plots.

In order to verify the assumptions for the inferential analysis, the data normality test was performed using the Kolmogorov-Smirnov statistic due to the sample size under study, considering a significance level of 0.05. Table 2 shows the result of the Kolmogorov-Smirnov normality test for study variables, in which the p-value was less than 0.05, which leads to establishing that the data collected do not present a normal distribution. Therefore, Spearman's rank correlation was employed as a non-parametric method to analyze the strength and direction of associations between the variables, providing a more appropriate statistical approach for the study.

Table 2. Result of the Kolmogorov-Smirnov Normality Test for study variables

Study Variables	Kolmogorov-Smirnov		
	Statistical	gl	Sig.
Acceptance of GAI	0.266	158	0.000
Self-efficacy in writing technical reports	0.318	158	0.000

3.4 Study hypothesis

Based on the proposed variables, acceptance of GAI and self-efficacy in writing technical reports, and in accordance with the dimensions defined in the theoretical model, the following hypotheses are formulated to guide the correlational analysis for the present study. These hypotheses seek to establish statistically significant links between the perception and use of emerging technologies and the self-perception of technical communicative competence in engineering students.

- H1: There is a positive and significant relationship between the perception of usefulness of GAI and self-efficacy in planning technical reports in engineering students.
- H2: There is a positive and significant relationship between the perception of ease of use of GAI and self-efficacy in writing technical reports in engineering students.
- H3: There is a positive and significant relationship between the intention to use GAI and self-efficacy in reviewing technical reports in engineering students.

4 RESULTS

4.1 Descriptive analysis

Regarding the descriptive analysis of the data collected from students at the three professional engineering schools, it was identified that the majority of students fell into the "Agree" and "Strongly Agree" categories in the dimensions assessed for both acceptance of GAI and Self-efficacy in writing technical reports. In the case of the variable "Acceptance of GAI," it was observed that approximately 41.4% of students selected the "Agree" category, while 17.7% opted for "Strongly Agree." Similarly, in the Self-efficacy in writing technical reports dimension, 25.3% of students chose the "Strongly Agree" category, while 24.1% selected "Agree." These results reflect a predominantly positive perception toward the integration of the GAI in the planning, writing, and review of technical reports. Likewise, intermediate categories, such as "Neutral" and "Disagree," presented considerably lower frequencies. These findings show a clear trend toward acceptance and favorable perception of GAI and serve as a basis for exploring the relationships posed in the research questions.

Furthermore, a box plot analysis revealed that the mean values for the dimensions of the GAI Acceptance variable "Perception of usefulness, Ease of use, and Intention of use" were located between the "Agree" and "Strongly Agree" categories, with medians ranging from 4 to 5, and with minimum values that rarely fell below the "Neutral" category. Thus, for example, the PEU dimension showed a mean of 4.72, evidencing the highest score among the three acceptance dimensions. This result indicates that students perceive the GAI as a useful, easy-to-use tool and that they are willing to integrate it into their technical report writing activities. Some dispersion was also observed in the perception of ease of use, with some students reporting scores close to "neutral"; however, the majority of the data was concentrated in the upper part of the scale, confirming a general tendency toward positive opinions. Figure 2 presents the box plot for the dimensions of the variable "Acceptance of the GAI."

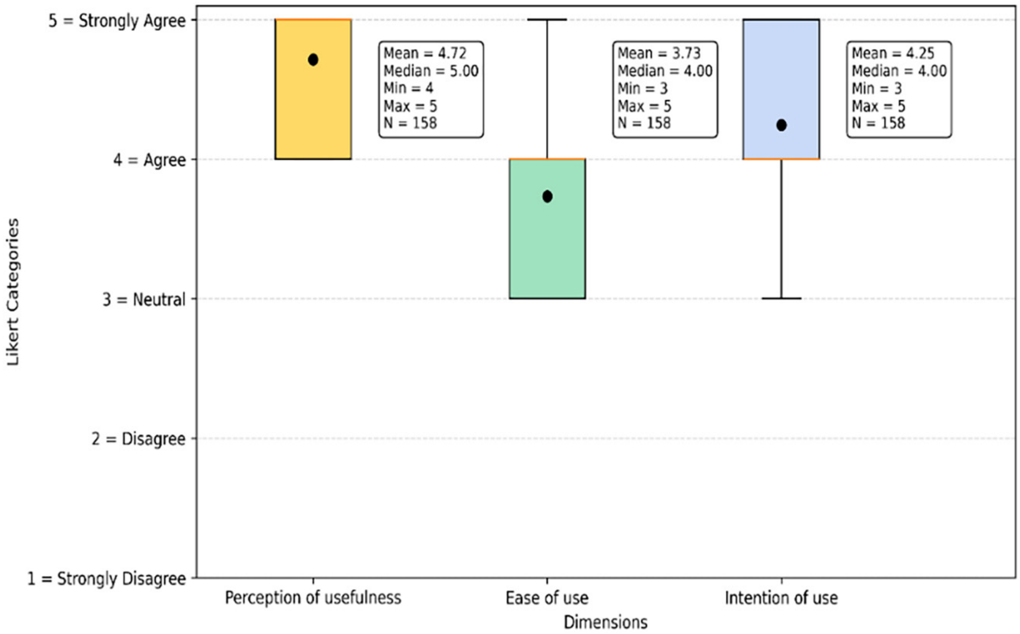

Fig. 2. Box plot for the dimensions of the variable Acceptance of the GAI

On the other hand, Figure 3 displays the box plot corresponding to the study's two main variables: Acceptance of GAI and Self-efficacy in writing technical reports. The results show that the mean for acceptance of GAI was 4.19, while for self-efficacy in writing technical reports it was slightly higher, at 4.5. In both cases, the median remained close to "Agree" and "Strongly Agree," with minimum values that did not fall below the "Neutral" level. These findings suggest that students not only accept the use of the GAI but also perceive themselves to have a high level of self-efficacy in writing technical reports. The fact that both variables concentrated in the upper categories of the Likert scale indicates consistency in the positive perceptions of the technology tool and of the students' own academic writing skills. This behavior is essential for explaining the correlations that link acceptance of GAI with Self-efficacy in planning, writing, and reviewing technical reports.

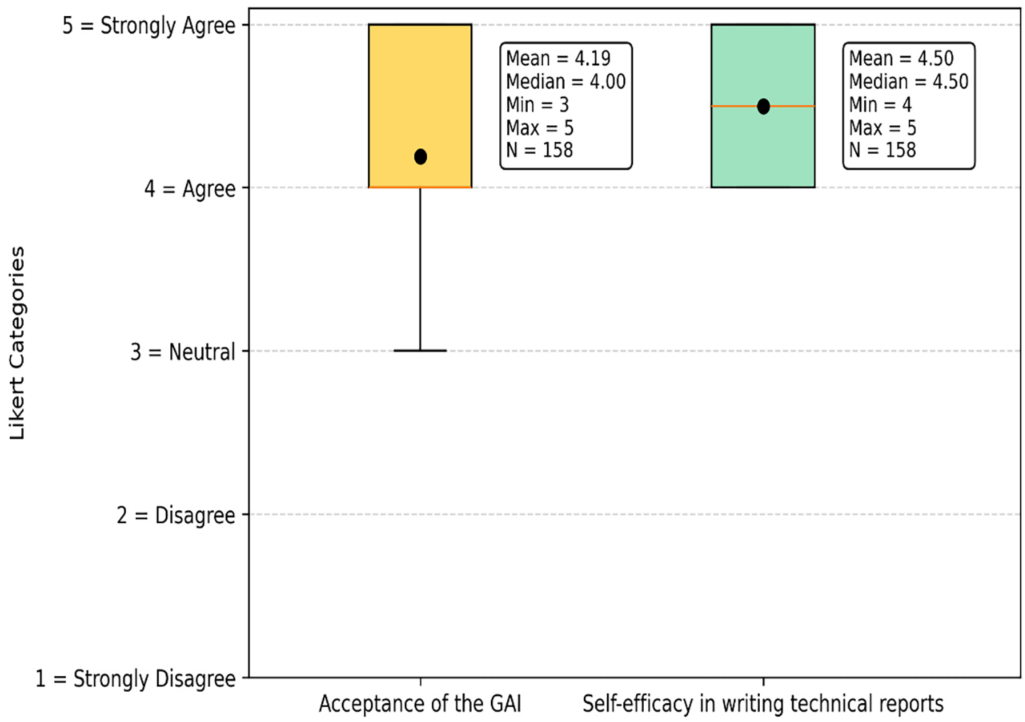

Fig. 3. Box plot of the study variables: Acceptance of GAI and Self-efficacy in writing technical reports

4.2 Inferential analysis

To test the research hypotheses, the results of the Spearman's Rho correlation tests between the dimensions corresponding to the variable Acceptance of GAI and Self-efficacy in the technical report writing area are presented below. Table 3 shows the results for the dimension PU of GAI and Self-efficacy in Technical Report Planning. The analysis indicates a significant positive correlation, with a Spearman's Rho coefficient of 0.686 and a significance level of $p < 0.01$. This finding supports hypothesis H1. It shows that students who perceive greater usefulness in GAI tools tend to feel more competent in the initial stages of organizing, structuring, and designing technical reports in engineering education contexts. The strength of this association, classified as moderate to high, suggests that the perception of usefulness may directly influence the confidence with which students approach complex technical tasks. Considering that planning is a key component of technical writing, this result highlights the importance of technological acceptance as a factor that facilitates academic performance.

Table 3. Results of the hypothesis test between the perception of the usefulness of the GAI and self-efficacy in planning technical reports

			Perception of the Usefulness of GAI	Self-Efficacy in Planning Technical Reports
Spearman's Rho (ρ)	Perception of the usefulness of GAI	Correlation coefficient	1	0.686
		Sig. (bilateral)	–	0.000
		N	158	158
	Self-efficacy in planning technical reports	Correlation coefficient	0.686	1
		Sig. (bilateral)	0.000	–
		N	158	158

Table 4 presents the results for the dimensions PEU of the GAI and self-efficacy in writing technical reports. The analysis revealed a significant and positive correlation with a Spearman's Rho coefficient of 0.743 and p-value < 0.01. These results provide empirical support for hypothesis H2. Students who perceive the GAI as easier to use tend to show greater confidence in developing written technical content. The strength of this correlation, classified as high, suggests that reducing the perceived complexity of interacting with GAI tools may directly enhance students' ability to write technical reports with clarity, coherence, and terminological precision. Furthermore, this association underscores the importance of usability and accessibility in technological tools within engineering education. Greater ease greater of use can lead to more effective integration of GAI into academic practices and strengthen students' technical writing and digital skills.

Table 4. Results of the hypothesis test between the perception of ease of use of the GAI and self-efficacy in writing technical reports

			Perception of Ease of Use of the GAI	Self-Efficacy in Writing Technical Reports
Spearman's Rho (ρ)	Perception of ease of use of the GAI	Correlation coefficient	1	0.743
		Sig. (bilateral)	–	0.000
		N	158	158
	Self-efficacy in writing technical reports	Correlation coefficient	0.743	1
		Sig. (bilateral)	0.000	–
		N	158	158

In Table 5, the results for the dimension Intention to use the GAI and Self-Efficacy in reviewing technical reports show a statistically significant positive correlation, with a Spearman's Rho coefficient of 0.703 and a significance level of p < 0.01. This finding supports hypothesis H3, indicating that students who reported a stronger intention to use GAI tools also tended to perceive themselves as more competent in reviewing technical reports. The magnitude of the correlation, classified as high, suggests that students' willingness to incorporate GAI may be linked to greater confidence when identifying errors, refining content, and improving report quality. However, the results do not imply causality. Instead, they show an association between the intention to use GAI and perceived self-efficacy in review tasks. This may reflect students' recognition of the benefits of GAI in supporting key stages of technical report preparation, including evaluation and iterative improvement.

Table 5. Results of the hypothesis test between the intention to use the GAI and self-efficacy in reviewing technical reports

			Intention to Use the GAI	Self-Efficacy in Reviewing Technical Reports
Spearman's Rho (ρ)	Intention to use the GAI	Correlation coefficient	1	0.703
		Sig. (bilateral)	–	0.000
		N	158	158
	Self-efficacy in reviewing technical reports	Correlation coefficient	0.703	1
		Sig. (bilateral)	0.000	–
		N	158	158

5 DISCUSSION

Regarding RQ1, the results show that the PU of GAI is positively related to Self-efficacy in planning technical reports. Specifically, when students perceive these tools as useful resources for their learning, they gain greater confidence in organizing and structuring academic documents. This result coincides with the findings of [43], who emphasize that the integration of GAI technologies in education can improve learning effectiveness and optimize teaching processes, provided a balance use is encouraged to avoid overreliance and to promote critical thinking and self-regulation. Likewise, the study by [44] indicates that the adaptive feedback provided by tools such as GAI can strengthen self-regulated learning, which reinforces the relationship observed in this study between PU and confidence in planning academic tasks. Similarly, [45], reports that favorable perceptions about the usefulness and ease of use of technologies such as ChatGPT are linked to improvements in the quality and effectiveness of academic writing, which coincides with the relationship identified in this study.

Regarding RQ2, the results show that the perceived ease of use of GAI is significantly related to Self-efficacy in writing technical reports. An accessible and user-friendly technological environment not only facilitates interaction with the tool but also enhances students' confidence to produce coherent and academically rigorous texts. According to [46], the incorporation of these technologies in higher education must be accompanied by the development of technological and critical thinking skills, as well as ethical and responsible use. Likewise, the work of [47] shows that strategic and continuation with GAI leads to better academic writing outcomes compared to limited or poorly planned use. However, the study by [48] highlights that ease of use is a key factor in the adoption of GAI tools, especially in educational contexts with different levels of technological experience, emphasizing the need for pedagogical environments that support accessible and autonomous learning interactions.

For RQ3, the results reveal that the intention to use GAI is positively related to Self-efficacy in reviewing technical reports. Students intending to use these tools tend to feel more confident in evaluating and improving the quality of their technical reports. This finding is consistent with [49], who note that GAI-assisted instruction can foster critical thinking through constructive feedback and exploration of multiple perspectives in academic writing. Furthermore, the study by [50], they highlight that preparation, especially in terms of ethical skills and values, influences the intention to adopt these tools, highlighting the need to integrate technical and ethical training in higher education. However, the study by [51] warns that the widespread use of these technologies could limit critical thinking and academic reflection if not accompanied by pedagogical strategies that strengthen autonomy and self-regulation, reinforcing the importance of a balanced and pedagogically oriented use.

Finally, this study's cross-sectional correlational design limits causal inferences between GAI acceptance and self-efficacy in technical writing; nevertheless, focusing on engineering students from a single educational institution offers a detailed description of this academic context. Research with much larger samples and experimental methodologies, such as the work of [52], has shown that a larger sample size facilitates a more precise analysis of the variability of perceptions toward the adoption of AI in higher education. Likewise, the study by [53] points out that many studies on AI in academic writing face similar methodological limitations, such as small samples or non-experimental designs. Therefore, future studies should expand sample coverage and adopt experimental or longitudinal approaches that involve educational interventions.

6 CONCLUSION

The results of this study show that the majority of engineering students present favorable attitudes toward the adoption of GAI and a high perceived self-efficacy in technical writing, with a significant concentration of responses in the "Agree" and "Strongly Agree" categories for both variables analyzed. The inferential analysis confirmed positive relationships between the perception of usefulness of GAI and self-efficacy in planning technical reports ($\rho = 0.686$), suggesting that students who value the usefulness of these tools develop greater confidence in organizing and structuring their academic documents. Similarly, a positive correlation was found between perceived ease of use and self-efficacy in writing technical reports ($\rho = 0.743$), indicating that simple and accessible interaction with GAI can favor both the student experience and the production of technically coherent and accurate texts. Likewise, it was identified that the intention to use AI is positively correlated with self-efficacy in reviewing technical reports ($\rho = 0.703$), evidencing that students with a greater willingness to integrate these tools feel more capable of evaluating and improving the quality of their technical reports. These findings demonstrate that technological acceptance positively impacts students' perceived self-efficacy, improving their ability to address tasks or activities in specialized engineering academic contexts. Consequently, it is concluded that the pedagogically oriented integration of AI in technical report writing courses has the potential to strengthen students' confidence and competencies in specialized academic writing. Therefore, it is recommended to expand the scope of the research to include additional variables such as intrinsic motivation, critical thinking, and self-regulated learning in order to analyze in greater depth how these factors interact with the use of AI-based tools.

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