Prisma Sains: Jurnal Pengkajian Ilmu dan Pembelajaran Matematika dan IPA IKIP Mataram
https://e-journal.undikma.ac.id/index.php/prismasains/index
e-mail: prismasains.pkpsm@gmail.com

October 2026. Vol. 14, No. 4
p-ISSN: 2338-4530
e-ISSN: 2540-7899
pp. 2577-2591

GenAI Reliance in Physics Learning: Its Relationship with Physics Anxiety and Students' Physics Learning Outcomes

[1]Tasya Febriana Feodika, [1]*Habibi, [2]Ririn Yuniawan, [2]Mokhammad Yusuf, [2]Faridatul Amiroh, [2]Jelita Puspita Ningrum Khoirunnisa

[1]Physics Education Department, Universitas Negeri Surabaya, Surabaya, Indonesia
[2]SMA Negeri 1 Babat, Lamongan, Indonesia

*Corresponding author e-mail: habibi@unesa.ac.id

Received: September 2026; Revised: October 2026; Published: October 2026

Abstract

The increasing use of Generative Artificial Intelligence (GenAI) in education has raised questions about its relationship with students' learning experiences and academic outcomes. This study aimed to examine the relationships among students' GenAI reliance, physics anxiety, and physics learning outcomes. A quantitative correlational design was employed involving 100 tenth-grade students from one senior high school in Lamongan, Indonesia, recruited through convenience sampling. Data were collected using questionnaires measuring GenAI reliance and physics anxiety, while students' physics learning outcomes were obtained from teacher records. The data were analyzed using descriptive statistics and Spearman's rank-order correlation. The findings indicated a positive correlation between GenAI reliance and physics anxiety ($\rho = 0.456$, $p < 0.001$), as well as a positive correlation between GenAI reliance and physics learning outcomes ($\rho = 0.347$, $p < 0.001$). Meanwhile, the relationship between physics anxiety and physics learning outcomes was positive but not statistically significant ($\rho = 0.171$, $p = 0.089$). Responses to the open-ended questions suggested that students used GenAI primarily to understand physics concepts, obtain explanations, and identify steps for solving problems. Some students also reported using GenAI because they lacked confidence in their own answers or feared making mistakes. These findings indicate that GenAI reliance is associated with physics anxiety and students' physics learning outcomes. However, the correlational design of this study does not establish causal relationships, and students' learning outcomes may also be associated with other factors beyond their reliance on GenAI.

Keywords: GenAI; Gen AI reliance; Physics anxiety; Physics learning outcomes

How to Cite: Feodika, T. F., Habibi, H., Yuniawan, R., Yusuf, M., Amiroh, F., & Khoirunnisa, J. P. N. (2026). GenAI Reliance in Physics Learning: Its Relationship with Physics Anxiety and Students' Physics Learning Outcomes. *Prisma Sains: Jurnal Pengkajian Ilmu Dan Pembelajaran Matematika Dan IPA IKIP Mataram*, *14*(4), 2577–2591. https://doi.org/10.33394/j-ps.v14i4.22775

https://doi.org/10.33394/j-ps.v14i4.22775

Copyright© 2026, Feodika et al.
This is an open-access article under the CC-BY License

INTRODUCTION

Physics examines various natural phenomena through physical concepts, principles, and laws. Learning physics requires mastering concepts and the ability to solve problems accurately. Students must connect concepts to phenomena and employ mathematical reasoning during their studies (Weber and Wilhelm, 2024; Musengimana et al., 2025). These requirements align with the Merdeka Curriculum, which encourages active student engagement in the learning process (Dewi et al., 2025). However, difficulties in understanding concepts and solving problems remain challenges in physics education (Weber and Wilhelm, 2024; Musengimana et al., 2025). Therefore, the role of technology should be considered in the evolution of physics instruction.

Generative AI (GenAI) can generate information based on user-provided instructions. This technology can serve as a supporting tool in physics education. Students can utilize it to grasp concepts, access examples, and assist in solving physics problems (Dahlkemper et al., 2023; Podlasov and Matviichuk, 2023). GenAI also enables students to quickly obtain

explanations tailored to their specific learning needs in terms of format and depth. Its use can foster a more flexible and interactive learning experience while supporting student autonomy (Baek et al., 2024). Such ease of access and versatility have led to the increasing adoption of GenAI as a tool to support learning.

The use of GenAI in learning is becoming PISA 2025 data indicate increasingly prevalent among students. PISA 2025 data indicate that 53% of Indonesian students use AI chatbots at least once a week to assist with their studies (OECD, 2026). However, the use of GenAI as a learning aid should be distinguished from students' reliance on the technology. Ordinary GenAI use refers to utilizing AI-generated information to support learning, whereas GenAI reliance reflects students' tendency to depend on AI assistance when understanding concepts or completing academic tasks (Stojanov et al., 2024). Previous studies have identified various patterns of students' reliance, ranging from reflective and collaborative use to thoughtless adoption of AI-generated responses (Hou et al., 2025a, 2025b). Although reliance does not necessarily indicate problematic dependence, concerns may arise when students increasingly depend on AI-generated assistance at the expense of their independent reasoning, effort, and self-regulation (An et al., 2026). In physics learning, students' tendency to rely on GenAI may also be related to their psychological experiences when facing challenging concepts and problem-solving tasks, particularly physics anxiety.

Students' physics learning experiences involve both cognitive and affective aspects, including physics anxiety, which refers to feelings of worry or tension when understanding concepts, solving problems, or taking physics tests (Mihardi & Supahar, 2026). Unlike general academic anxiety, physics anxiety is specifically associated with physics learning, while research on science anxiety has distinguished it from general anxiety and test anxiety (Megreya et al., 2021). These experiences may also involve a lack of self-confidence and fear of failure when facing physics tasks (Bande & Bellen, 2025). Rosiyanah and Astra (2025) reported that 56% of students experienced very high physics anxiety and 36% experienced high anxiety before the intervention. Similarly, Al Sultan (2023) reported initial physics anxiety scores of 47.14 and 45.82 in the experimental and control groups, respectively. In contrast, Izzati et al. (2026) found that most of the 232 senior high school students experienced low physics test anxiety. These findings suggest that physics anxiety may vary across student populations and learning contexts, warranting further investigation into its relationship with students' experiences in physics learning.

Beyond affective aspects such as physics anxiety, students' learning experiences are also shaped by the cognitive and practical demands of the material. Physical quantities and measurement provide a relevant context for examining these demands because students are expected to understand physical quantities, use measuring instruments, interpret measurement results, and perform calculations. Based on observations and an interview with the physics teacher at the research school, the availability of measuring instruments is limited, meaning that not all students have the opportunity to use the instruments independently. This condition may restrict students' opportunities to gain direct experience with measurement and connect theoretical concepts with practical activities. Difficulties in understanding measurement concepts have also been reported among senior high school students. An analysis of 141 tenth-grade students found that 34.45% experienced misconceptions in measurement, with the highest proportion occurring in the subtopic of significant figures (39.57%), followed by measurement uncertainty (33.07%) and physical quantities and units (30.71%) (Putri & Sugianto, 2025). These challenges can be illustrated through mathematical relationships commonly used in physical quantities and measurement, particularly density and its maximum relative uncertainty. Density is expressed as:

$$\rho = \frac{m}{V} \qquad (1)$$

The maximum relative uncertainty in density can be expressed as:

$$\frac{\Delta\rho}{\rho} = \frac{\Delta m}{m} + \frac{\Delta V}{V} \quad (2)$$

Applying these relationships requires students to understand the connections among physical quantities, interpret measurement data, and perform calculations accurately. When facing such tasks, students may use GenAI to obtain explanations or assistance with calculations. Previous research has identified different patterns of student reliance on GenAI during problem-solving, including reflective, cautious, thoughtless, and collaborative patterns (Hou et al., 2025). Meanwhile, physics learning anxiety has been examined as a specific construct in senior high school students, highlighting the relevance of considering students' affective experiences alongside their cognitive demands (Mihardi & Supahar, 2026). Therefore, physical quantities and measurement offer a relevant learning context for examining the relationships among GenAI reliance, physics anxiety, and students' physics learning outcomes.

Previous studies have reported different findings regarding the relationship between GenAI use and students' learning outcomes. On the positive side, ChatGPT-assisted instruction has been found to improve students' physics outcomes, potentially by supporting concept understanding and problem-solving (Alarbi et al., 2024). A meta-analysis of experimental studies also reported an overall positive effect of ChatGPT on academic outcomes (Deng et al., 2025). However, these benefits may not necessarily extend to independent learning. Students who used standard ChatGPT assistance performed worse on subsequent assessments without AI support, suggesting that reliance on AI-generated assistance may limit the development of independent problem-solving skills (Bastani et al., 2025). Similarly, stronger reliance on GenAI was negatively associated with academic outcomes (Lintner et al., 2026). These contrasting findings may reflect differences in how students use GenAI, their level of reliance on AI-generated responses, their characteristics, and the learning contexts in which the technology is used. In addition, using GenAI to obtain explanations and feedback may offer different learning benefits from relying on generated answers without engaging in independent reasoning. Therefore, the relationship between GenAI reliance and learning outcomes cannot be assumed to be consistently positive or negative and warrants further investigation in the context of physics learning.

Given this phenomenon, the relationship between GenAI reliance and students' learning experiences warrants attention. This relationship encompasses physics anxiety and students' learning outcomes regarding the topics of physical quantities, units, and measurement. However, research linking GenAI reliance to these two aspects remains limited.

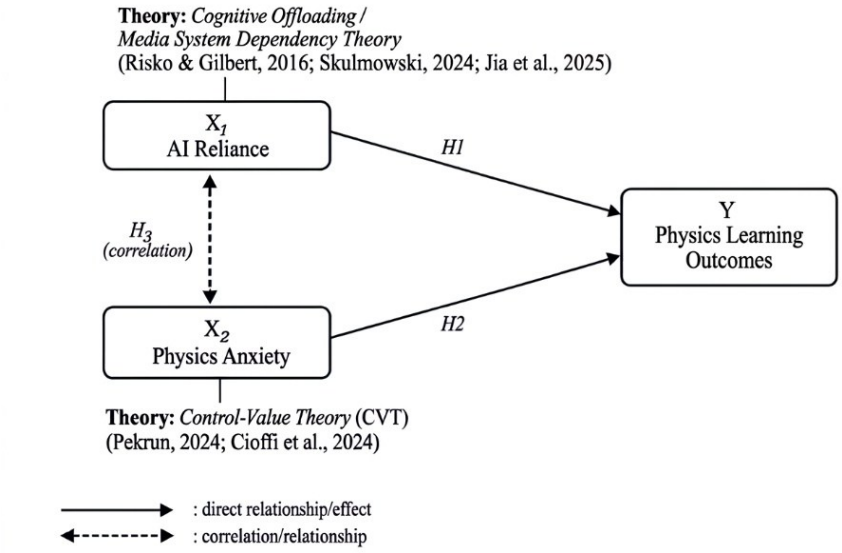


Figure 1. Conceptual Framework of the Relationships Among GenAI Reliance, Physics Anxiety, and Physics Learning Outcomes

Figure 1 illustrates the study's conceptual framework, depicting the relationships between GenAI reliance, physics anxiety, and physics learning outcomes. H_1 posits that higher levels of GenAI reliance are associated with lower physics learning outcomes. This prediction draws on the cognitive offloading perspective, which suggests that excessive reliance on external tools may reduce students' engagement in independent cognitive processes (Risko & Gilbert, 2016; Skulmowski, 2024). However, GenAI may also support learning by providing explanations, examples, and feedback that facilitate understanding. This possibility is supported by findings showing a positive relationship between students' interaction with generative AI and learning outcomes, with self-efficacy and cognitive engagement playing mediating roles (Liang et al., 2023). Thus, the relationship may depend on how students use AI assistance. H_2 indicates that higher physics anxiety is linked to lower learning outcomes. This aligns with Control-Value Theory (CVT), which explains that academic emotions are influenced by students' perceptions of control over and the value of a task; high anxiety can impede engagement and cognitive processes during learning (Pekrun, 2024; Cioffi et al., 2024). H_3 suggests a relationship between GenAI reliance and physics anxiety, as heavy reliance on external assistance may be linked to students' beliefs regarding their own ability to comprehend and complete physics tasks.

Previous studies have reported both positive contributions of GenAI supported learning to academic outcomes and potential drawbacks of excessive reliance on AI-generated assistance (Deng et al., 2025; Bastani et al., 2025; Lintner et al., 2026). These contrasting findings suggest that general GenAI use and students' reliance on the technology may have different implications for learning outcomes. However, how GenAI reliance relates to students' subject specific anxiety, particularly physics anxiety, remains insufficiently understood. This relationship also warrants examination alongside learning outcomes in physics, where students face conceptual and mathematical challenges. Physical quantities and measurement provide a relevant context because the topic requires conceptual understanding, measurement skills, data interpretation, and mathematical reasoning (Putri & Sugianto, 2025). To address these gaps, this study examines the relationships of GenAI reliance with physics anxiety and learning outcomes in this specific content area. It provides context specific empirical evidence on the cognitive and affective dimensions associated with students' reliance on GenAI in physics learning.

METHOD

This study employs a quantitative approach with a correlational design. A correlational design is used to identify the existence, direction, and strength of the relationship between two or more variables without manipulating the research variables (Dessie et al., 2024). This design was selected to align with the study's objective of examining the interrelationships among GenAI reliance, physics anxiety, and students' physics learning outcomes. Accordingly, the study examines statistical associations among these variables rather than causal relationships, and does not aim to determine whether one variable causes changes in another. The research variables consist of GenAI reliance (X_1), physics anxiety (X_2), and physics learning outcomes (Y).

Table 1. Relationships Between Variables

Variables	**X_1**	**X_2**
Y	X_1 - Y	X_2 – Y
X_1	X_1	X_2 – X_1
X_2	X_1 – X_2	X_2

Note: X_1 : GenAI Reliance; X_2: Physics Anxiety; Y : Student Physics Learning Outcomes

The three variables were measured based on conditions occurring naturally during instruction, without administering any special treatment to the students. Therefore, a correlational design was selected because the study aimed to determine the relationships between variables, rather than to test for effects or cause and effect relationships.

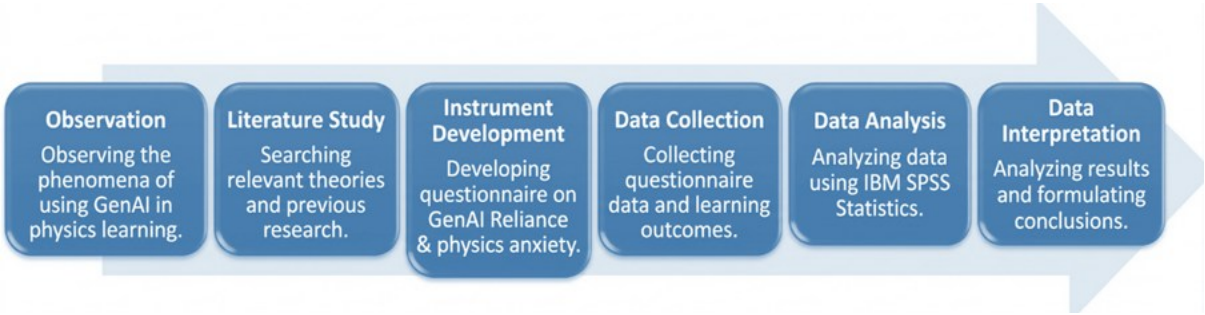


Figure 2. Research Flow (Jabnabillah and Astiati, 2024)

Research Subjects

The study population comprised Grade X students enrolled in physics classes at one high school in Lamongan Regency, Indonesia. Data were collected from 100 students selected through convenience sampling. Students' physics learning outcome data were obtained from their teachers' records after the questionnaire survey. Participants were recruited based on their accessibility, willingness to participate, and fulfillment of the research criteria. To be included in the study, students had to be enrolled in Grade X physics classes, complete the questionnaire, and have available physics assignment scores on physical quantities and measurement. Convenience sampling was considered appropriate because the students were accessible to the researchers. Furthermore, the school did not require students to store their mobile phones during lessons, allowing them to access GenAI during physics learning, although internet connectivity may have varied.

Research Instruments

Data were collected through questionnaires and documentation of students' physics learning outcomes. The questionnaire was developed by the researchers based on relevant literature concerning GenAI reliance and physics anxiety. It consisted of 10 closed-ended statements and two open-ended questions. Five items measured GenAI reliance (Items 1–5), while the other five measured physics anxiety (Items 6–10).

The GenAI reliance items assessed students' efforts to solve physics problems independently before using GenAI, their tendency to seek AI assistance when facing difficulties, their reliance on AI-generated solutions, their perceived difficulty in learning without AI assistance, and their preference for AI assistance over their own abilities. The physics anxiety items assessed students' ability to remain calm when solving problems independently, concerns about misunderstanding concepts, nervousness when explaining solutions in class, anxiety when facing physics examinations, and feelings of being overwhelmed by multistep problems. A four point Likert scale was employed for measurement.

Table 2. Student Response Scale

Scale	Point
Strongly Agree (SA)	4
Agree (A)	3
Disagree (D)	2
Strongly Disagree (SD)	1

(Source: Jabnabillah and Astiati, 2024)

Items 1 and 6 were negatively worded and reverse-scored before calculating the construct scores, ensuring that higher scores consistently represented greater GenAI reliance and physics anxiety. Item validity was evaluated using the corrected item-total correlation, with values greater than 0.30 considered acceptable. All five GenAI reliance items met this criterion, with coefficients ranging from 0.376 to 0.596, while the five physics anxiety items ranged from 0.340 to 0.719. Internal consistency was assessed separately for each construct using

Cronbach's alpha (Rasyid et al., 2026). The coefficients were 0.722 for GenAI reliance and 0.754 for physics anxiety, indicating acceptable internal consistency.

Students' physics learning outcomes were obtained from the physics teacher's records of assignment scores on physical quantities and measurement. These scores were matched with questionnaire responses using respondent codes. In addition, two open-ended questions explored students' reasons for using GenAI when experiencing difficulties in physics learning and their reasons for feeling uncertain when solving physics problems independently. The responses served as supplementary information to contextualize the quantitative findings and were not included in the calculation of the main variable scores.

Data were analyzed using descriptive statistics and Spearman's rank-order correlation. Spearman's correlation was selected to examine the direction and strength of associations among the three variables using ranked data. The analysis examined the relationships among GenAI reliance, physics anxiety, and physics learning outcomes, with statistical significance set at $p < 0.05$.

The study was conducted with permission from the participating school and voluntary student participation. Respondents' identities were protected using identification codes, and all data were handled confidentially. Consent procedures for underage participants followed applicable school and research requirements.

Data Analysis

The collected data were analyzed using IBM SPSS Statistics. Data analysis was conducted using descriptive statistics and correlational analysis. Descriptive statistics were employed to characterize GenAI reliance, physics anxiety, and students' physics learning outcomes based on mean values, standard deviations, and minimum and maximum scores. Data regarding GenAI usage frequency were analyzed using frequency distributions and percentages to illustrate usage patterns based on students' responses. All 100 respondents provided complete data for the three study variables, therefore no missing data were identified, and all 100 observations were included in each correlation analysis. Open-ended responses were analyzed using inductive thematic coding. Responses were grouped into categories based on recurring patterns and similar meanings. The coding was conducted by one researcher, and the frequency of each category was calculated.

Before to the correlation analysis, normality and linearity tests were conducted to determine the appropriate correlation technique. The normality test was performed using the Kolmogorov-Smirnov test at a 5% significance level. Data were considered normally distributed if the significance value exceeded 0.05, whereas a value below 0.05 indicated a non-normal distribution. The linearity test was based on the "Deviation from Linearity" value, a relationship was deemed linear if the significance value for Deviation from Linearity was greater than 0.05. The test results indicated that not all variables met the normality assumption and not all variable pairs exhibited a linear relationship.

Before conducting the correlation analysis, scatterplots with LOESS smoothing curves were examined to assess the monotonicity of the relationships between the variables. This visual inspection was performed for the three variable pairs GenAI reliance and physics anxiety, GenAI reliance and physics learning outcomes, and physics anxiety and physics learning outcomes. Spearman's rank-order correlation was then used to examine the associations between the variables.

The relationships between research components were analyzed using Spearman's correlation (Spearman's rho) at a 5% significance level (Zakaria et al., 2026). Spearman's correlation was used to examine the associations between GenAI reliance and physics anxiety, GenAI reliance and physics learning outcomes, and physics anxiety and physics learning outcomes. Accordingly, the initial significance level ($\alpha = 0.05$) was divided by the number of tests ($k = 3$), yielding an adjusted significance threshold of $\alpha = 0.0167$. The 95% confidence intervals for the correlation coefficients were estimated using the percentile bootstrap method

with 1,000 resamples. The correlation coefficient value was used to determine the direction and strength of the relationship, while the significance value was used to determine the statistical significance of the relationship. A relationship was considered statistically significant if the significance value was less than 0.05. The analysis results were interpreted based on the direction, strength, and significance of the relationships, without drawing conclusions regarding cause-and-effect relationships.

Table 3. Guidelines for the Degrees of Association/Correlation

Coefficient Interval	Level of Relationship
0.00 – 0.199	Very weak
0.20 – 0.399	Weak
0.40 – 0.599	Moderate
0.60 – 0.799	Strong
0.80 – 1.000	Very strong

(Source: Jabnabillah and Astiati, 2024)

RESULTS AND DISCUSSION

Data analysis begins by outlining patterns of Generative AI usage in physics learning. Data on usage frequency serve as supporting information to observe trends in students' utilization of Generative AI. This data is not included in the calculation of the GenAI reliance score, as the level of reliance is determined based on five statements within the research instrument.

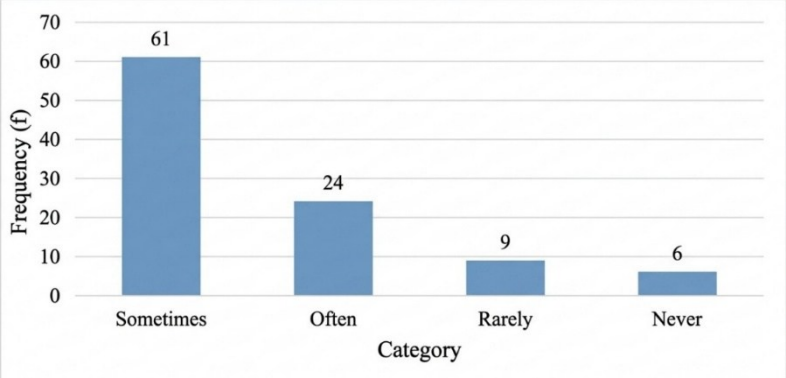


Figure 3. Frequency of Generative AI Use in Physics Learning

Figure 3, the most common frequency of GenAI usage falls into the "sometimes" category (61%), followed by the "often" category (24%). Meanwhile, usage in the "rarely" and "never" categories stands at only 9% and 6%, respectively. This pattern indicates that the majority of students have used GenAI in physics learning, although high frequency usage is not yet the dominant trend. This pattern serves as a preliminary basis for identifying students' tendencies to rely on GenAI, using reliance scores derived from the research instrument.

The tendency for GenAI reliance was further identified through the total scores of five statements included in the instrument. A similar analysis was conducted for the physics anxiety variable, while student learning outcome was assessed using documentation scores obtained from teachers. Descriptive statistics for all three variables included the mean and the standard deviation.

Table 4. Normality Test and Descriptive Statistics Results

Variable	Normality		Descriptive Statistic	
	Score	Criteria	Mean	Std. Deviation
X_1	0.001	Abnormal	10.50	2.49
X_2	0.000	Abnormal	13.21	2.48
Y	0.200	Normal	77.31	9.31

Table 4, GenAI reliance shows a mean score of 10.50 with a standard deviation of 2.49; the scores fall within a range of 5–18 against a theoretical range of 5–20. Meanwhile, physics

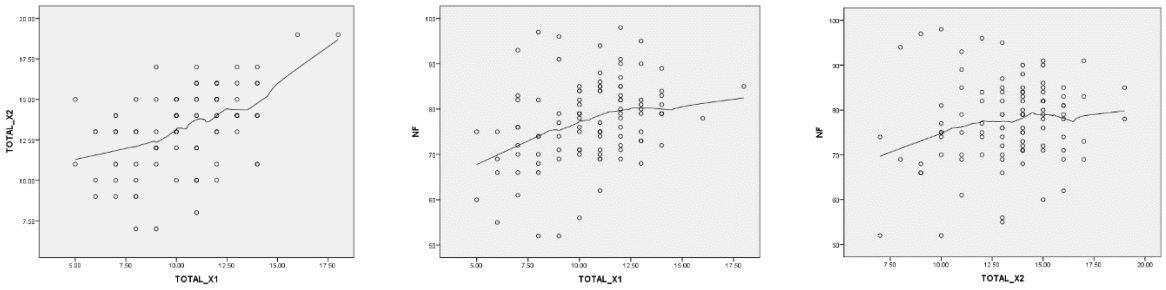
anxiety has a mean of 13.21 with a standard deviation of 2.48 and a score range of 7–19 (theoretical range: 5–20). Students' physics learning outcomes shows a mean of 77.31 with a standard deviation of 9.31 and a score range of 52–98. These differences in score ranges and variations indicate diversity in the characteristics of the three research variables. However, this descriptive overview does not yet reveal the interrelationships between the variables. Therefore, the analysis proceeded with normality and linearity tests to determine the appropriate correlation technique.

The normality test and descriptive statistics for the three study variables. The normality test was conducted using the Kolmogorov Smirnov test with Lilliefors correction. At the 0.05 significance level, GenAI reliance (X_1) obtained a significance value of 0.001, while physics anxiety (X_2) obtained a value of less than 0.001. Both values were below 0.05, indicating significant deviations from a normal distribution. In contrast, physics learning outcomes (Y) had a significance value of at least 0.200, indicating no statistically significant deviation from normality. These findings show that not all variables met the normality assumption. Therefore, Spearman's rank order correlation was considered for the subsequent analysis, subject to the examination of monotonic relationships.

Table 5. Linearity Test Results

Relationship Between Variables	Sig. Deviation from Linearity	Information
$X_1 – X_2$	0.019	Non-linear
$X_1 – Y$	0.394	Linear
$X_2 – Y$	0.005	Non-Linear

Table 5, The linearity test results presented show that the relationships between X_1 and X_2 ($p = 0.019$), X_2 and Y ($p = 0.005$) significantly deviated from linearity, as their significance values were below 0.05. In contrast, the relationship between X_1 and Y ($p = 0.394$) did not show a significant deviation from linearity. These findings indicate that the relationships among the study variables do not uniformly follow a linear pattern. However, a deviation from linearity does not necessarily indicate a non-monotonic relationship. Therefore, additional visual examinations using scatterplots with LOESS smoothing curves were conducted to assess the monotonic patterns of the relationships.



(a) (b) (c)

Figure 4. (a) Scatterplot of GenAI Reliance and Physics Anxiety (X_1–X_2). (b) Scatterplot of GenAI Reliance and Physics Learning Outcomes (X_1–Y). (c) Scatterplot of Physics Anxiety and Physics Learning Outcomes (X_2–Y)

Figure 4, the LOESS smoothing curves generally indicate increasing patterns across the three variable pairs. In Figure (a), the curve shows an overall upward trend, suggesting that higher GenAI reliance tends to be associated with higher physics anxiety, although the rate of increase varies across the range of scores. Similarly, Figure (b) shows an increasing pattern between GenAI reliance and physics learning outcomes, followed by a tendency to level off at higher scores. Figure (c) also indicates a generally increasing pattern between physics anxiety and learning outcomes, despite some fluctuations and a slight decline in the middle-to-upper score range. Overall, none of the three plots displays a clear U-shaped or inverted U-shaped

pattern. These visual observations suggest that the relationships are approximately monotonic, although their patterns are not necessarily linear. Therefore, the visual assessment provides support for using Spearman's rank-order correlation in examining the associations among the study variables.

Table 6. Spearman Correlation Results

Variables	Spearman's ρ	N	ρ −value	95% CI	Level of Relationship
$X_1 – X_2$	0.456	100	<0.001	0.301 – 0.613	Moderate
$X_1 – Y$	0.347	100	<0.001	0.158 – 0.508	Weak
$X_2 – Y$	0.171	100	0.089	-0.053 – 0.377	Very weak and not significant

Table 6, presents the Spearman's rank-order correlation results for the three pairs of variables. GenAI reliance (X_1) showed a moderate positive association with physics anxiety (X_2) ($\rho = 0.456$, $p < 0.001$, 95% CI [0.301, 0.613]). A positive association was also found between GenAI reliance (X_1) and physics learning outcomes (Y) ($\rho = 0.347$, $p < 0.001$, 95% CI [0.158, 0.508]). In contrast, the association between physics anxiety (X_2) and physics learning outcomes (Y) was weak and not statistically significant ($\rho = 0.171$, $p = 0.089$, 95% CI [−0.053, 0.377]). After applying the Bonferroni adjusted significance threshold of 0.0167, the first two associations remained statistically significant, whereas the association between physics anxiety and learning outcomes remained nonsignificant. These findings indicate that GenAI reliance was associated with both physics anxiety and physics learning outcomes, but they do not establish causal relationships.

The Relationship Between GenAI Reliance, Physics Anxiety, and Learning Outcomes

The results revealed a moderate positive association between X_1 and X_2 ($\rho = 0.456$, $p < 0.001$). This indicates that students with higher levels of GenAI reliance tended to report higher levels of physics anxiety. One possible explanation is that students who experience anxiety or uncertainty when learning physics may seek additional explanations and assistance through GenAI. Thus, the observed association may reflect students' tendency to seek external learning support when facing difficulties, rather than indicating that GenAI reliance increases physics anxiety. This interpretation is consistent with Jia et al. (2025), who identified academic anxiety as a factor associated with students' reliance on GenAI. However, the correlational design of this study does not establish the direction of this relationship or determine whether either variable influences the other.

The results also showed a weak positive association between X_1 and Y ($\rho = 0.347$, $p < 0.001$). This indicates that greater GenAI reliance tended to be associated with higher learning outcomes, although the relationship was relatively weak. Several possible explanations may help interpret this finding. Students with stronger academic performance may be more inclined to explore GenAI as an additional learning resource. Students with stronger prior knowledge may also be better able to evaluate and use AI-generated explanations to support their understanding of physics concepts. However, prior academic outcomes was not examined in this study, so this possibility remains an interpretation rather than an established explanation. GenAI-generated explanations and assistance may also provide opportunities for students to engage with challenging physics concepts. This possibility is supported by Han et al. (2025), whose meta-analysis reported positive effects of GenAI-supported learning on learning outcomes, although these effects varied across learning contexts. Nevertheless, this finding should also be considered alongside Jia et al. (2025), who reported a negative association between GenAI reliance and academic outcomes. These contrasting findings suggest that the relationship between GenAI use and learning outcomes may vary according to students' patterns of AI use and their learning contexts. Furthermore, differences in access to technology and study habits may also be associated with variations in students' learning outcomes. Therefore, the positive association found in this study should not be interpreted as evidence that greater reliance on GenAI directly improves students' learning outcomes.

The association between X_2 and Y was positive but very weak and not statistically significant ($\rho = 0.171$, $p = 0.089$). This indicates that although higher physics anxiety tended to be associated with higher learning outcomes, the relationship was very weak and did not reach statistical significance. This finding differs from previous studies reporting significant associations between anxiety and physics outcomes (Achor et al., 2023; Ocheni et al., 2024). Nevertheless, the nonsignificant result does not establish that physics anxiety is unrelated to learning outcomes. Rather, it indicates that this study did not provide sufficient statistical evidence to confirm an association between these variables. The confidence interval for this correlation (95% CI [−0.053, 0.377]) also indicates uncertainty in the estimated relationship. Therefore, the possibility of an association between physics anxiety and learning outcomes cannot be ruled out. Differences in students' prior academic outcomes, motivation, self-efficacy, and study habits may also be associated with variations in learning outcomes. In addition, differences in the physics topics examined, anxiety measurement instruments, and indicators of academic performance may help explain why findings differ across studies. Therefore, the relationship between physics anxiety and physics learning outcomes warrants further investigation in different educational contexts.

To account for the three pairwise correlation tests, the Bonferroni correction was applied to control the risk of Type I error. The adjusted significance threshold was calculated using the following equation:

$$\alpha_{adjusted} = \frac{\alpha}{k} = \frac{0.05}{3} = 0.0167 \quad (3)$$

Accordingly, correlations were considered statistically significant when their p-values were below 0.0167. Based on this adjusted threshold, the positive associations between GenAI reliance and physics anxiety, as well as between GenAI reliance and physics learning outcomes, remained statistically significant (both $p < 0.001$). In contrast, the association between physics anxiety and learning outcomes was not statistically significant ($p = 0.089$), as its p-value exceeded the adjusted threshold. Thus, applying the Bonferroni correction did not change the interpretation of the three correlation results. However, these findings should be interpreted cautiously because the correlational design does not establish causality, factors such as prior academic outcomes, motivation, self-efficacy, access to technology, and study habits were not examined, and the study was limited to one school and one physics topic.

Analysis of Student Responses to the Use of GenAI

These results are reinforced by a descriptive analysis of students' essay responses regarding their reasons for using GenAI. This analysis provides insight into how students utilize GenAI when encountering difficulties in learning physics. The students' answers were subsequently categorized based on common themes emerging from the responses

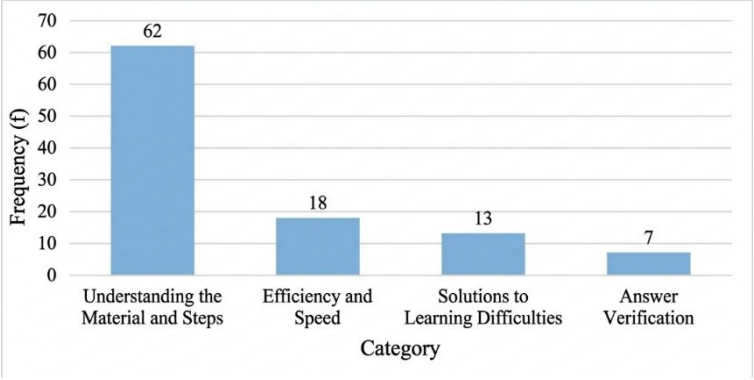


Figure 5. Frequency Distribution of Reasons for Using Generative AI

Figure 5, presents students' responses to the open-ended question*: "When experiencing difficulties in learning physics, why do you use GenAI to help you solve them?"* The most

frequently reported reason was to understand the material and solution steps (62.0%). Efficiency and speed ranked next (18.0%), followed by addressing learning difficulties (13.0%). Using GenAI to verify answers accounted for the lowest percentage (7.0%). These findings indicate that students primarily use GenAI to support their understanding of physics material, particularly when they encounter difficulties in grasping concepts or solving problems. This finding is consistent with Valeri et al. (2025), who reported that secondary school students used ChatGPT to support their understanding of STEM concepts. Similarly, Fadillah et al. (2024) found that ChatGPT can help secondary school students understand physics concepts and overcome learning difficulties. Beyond the reasons for using GenAI, students' responses also provide insight into their confidence when solving physics problems independently.

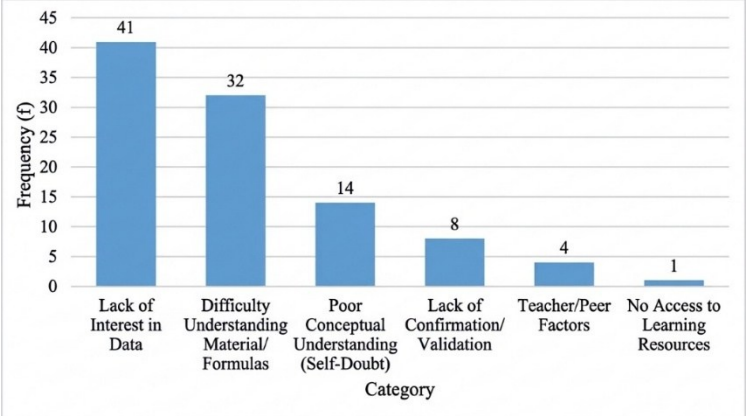


Figure 6. Frequency Distribution of Reasons for Lack of Self-Confidence

Figure 6, presents students' responses to the following open-ended question: *"Why do you feel uncertain when you have to complete physics assignments or solve problems using your own abilities?"* The most frequently reported reason was the fear of making mistakes and receiving poor grades (41%), followed by difficulty understanding the material or formulas (32%). Self-doubt regarding their own abilities accounted for 14% of responses. Meanwhile, 8% of students reported seeking confirmation or validation from GenAI, while 4% mentioned other factors and 1% provided no response. These findings indicate that fear of making mistakes and difficulties in understanding physics material are among the main reasons students seek assistance from GenAI. Fear of making mistakes and self-doubt also reflect affective aspects of students' physics learning experiences and may be related to physics anxiety, particularly when students encounter difficulties and lack confidence in solving problems independently. Some students also reported seeking confirmation or validation from GenAI when working on physics problems. However, these responses do not establish that GenAI reduces students' physics anxiety or directly improves their confidence.

These responses provide supplementary context for interpreting the quantitative findings but do not establish causal relationships between GenAI reliance, physics anxiety, and learning outcomes. Teachers may consider students' learning difficulties when integrating GenAI as an additional source of explanation and support, while encouraging students to evaluate AI-generated information and engage independently in problem-solving. However, this study did not directly examine the effects of GenAI use on students' anxiety, self-confidence, or critical thinking.

The practical implications of these findings are that GenAI may serve as an additional source of explanations and learning support when students encounter difficulties with physical quantities and measurement. However, the positive association between GenAI reliance and physics anxiety highlights the need for appropriate teacher guidance, digital ethics, and attention to students' emotional experiences. Such guidance is important to encourage students to evaluate AI-generated information and maintain independent critical thinking. Future

research could employ structural equation modeling (SEM) or experimental designs incorporating potential mediating or moderating variables, such as self-efficacy, digital literacy, and critical thinking, to further investigate these relationships and develop AI-supported pedagogical strategies that support students' affective and cognitive development.

CONCLUSION

This study found that students' reliance on GenAI was positively associated with both physics anxiety and physics learning outcomes. However, no statistically significant association was found between physics anxiety and learning outcomes. These findings suggest that GenAI reliance is related to both affective and cognitive aspects of physics learning, although the direction and nature of these relationships remain unclear. Given the correlational and cross-sectional design, the findings do not establish causal effects. Further research using validated measures and longitudinal or experimental designs is needed to clarify these relationships.

RECOMMENDATION

The study's results differ from previous research regarding the relationships between GenAI reliance, physics anxiety, and physics learning outcomes. The positive relationship found here between GenAI reliance and learning outcome contrasts with findings indicating the opposite trend. Furthermore, physics anxiety showed no significant relationship with learning outcomes, differing from the results of several earlier studies. Consequently, future research should examine the interrelationships among these three variables across different student characteristics, physics topics, and learning contexts to obtain more consistent findings.

ACKNOWLEDGMENTS

The author wishes to thank themselves for the effort and commitment shown in completing this research. Gratitude is also extended to the academic supervisor, the school, the physics teacher, and all the students who participated in the study. Appreciation is further expressed to everyone who provided support throughout the research process and the preparation of this article.

FUNDING INFORMATION

This research received no external funding

AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Tasya Febriana Feodika	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	✓
Habibi		✓			✓	✓		✓	✓		✓	✓		
Ririn Yuniawan	✓			✓		✓	✓	✓		✓		✓	✓	
Mokhammad Yusuf				✓		✓	✓		✓					
Faridatul Amiroh		✓		✓		✓	✓			✓			✓	
Jelita Puspita N. Khoirunnisa				✓		✓	✓				✓			

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the research, data analysis, interpretation of the findings, or preparation of this manuscript. The authors confirm that the research was conducted independently and that no competing interests influenced the results or conclusions. Authors state no conflict of interest.

ETHICAL APPROVAL

This research involved human participants, specifically tenth-grade high school students, and was conducted with permission from the participating school. Before data collection, informed consent was obtained from the students and their parents or legal guardians. Appropriate measures were taken to maintain the confidentiality and privacy of participants' information and responses. The collected data were used solely for research purposes and were handled responsibly to protect participants' identities.

DATA AVAILABILITY

The data supporting the findings of this study consist of questionnaire responses and students' physics learning outcome records collected during the research. These data are not publicly available because they contain information obtained from student participants. However, the data may be made available by the corresponding author upon reasonable request, subject to applicable privacy and confidentiality considerations.

REFERENCES

Achor, E. E., Kyado, J. J., Ejeh, E. E., & Eba, K. I. (2023). Perceived influence of test anxiety on the academic performance of secondary school students in physics. *Journal of Research in Science and Mathematics Education, 2*(2), 102–116. https://doi.org/10.56855/jrsme.v2i2.495

Alarbi, K., Halaweh, M., Tairab, H., Alsalhi, N. R., Annamalai, N., & Aldarmaki, F. (2024). Making a revolution in physics learning in high schools with ChatGPT: A case study in UAE. *Eurasia Journal of Mathematics, Science and Technology Education, 20*(9). https://doi.org/10.29333/ejmste/14983

Al Sultan, A. A. (2023). Effects of the POSSE strategy on reading comprehension of physics texts and physics anxiety among high school students. *International Journal of Learning, Teaching and Educational Research, 22*(5), 243–261. https://doi.org/10.26803/ijlter.22.5.12

An, C., Lu, K., & Yang, J. (2026). The dependency trap: A systematic review of the contributing factors and consequences of student over-reliance on generative AI in higher education. *Humanities and Social Sciences Communications, 13*, Article 1604. https://doi.org/10.1057/s41599-026-08959-2

Baek, C., Tate, T., & Warschauer, M. (2024). "ChatGPT seems too good to be true": College students' use and perceptions of generative AI. *Computers and Education: Artificial Intelligence, 7*, 100294. https://doi.org/10.1016/j.caeai.2024.100294

Bande, R. J., & Bellen, J. (2025). Understanding the Lived Experiences of Students Struggling with Physics Anxiety: A Descriptive Phenomenological Study. International Journal of Multidisciplinary Educational Research and Innovation. 3(4), 564-581. https://doi.org/10.64637/660816

Bastani, H., Bastani, O., Sungu, A., Ge, H., Kabakcı, Ö., & Mariman, R. (2025). Generative AI without guardrails can harm learning: Evidence from high school mathematics. *Proceedings of the National Academy of Sciences, 122*(26). https://doi.org/10.1073/pnas.2422633122

Cioffi, A., Galano, S., Passeggia, R., & Testa, I. (2024). Validation of two test anxiety scales for physics undergraduate courses through confirmatory factor analysis and Rasch analysis. *Physical Review Physics Education Research, 20*(1), 010126. https://doi.org/10.1103/PhysRevPhysEducRes.20.010126

Dahlkemper, M., Lahme, S. Z., & Klein, P. (2023). How do physics students evaluate artificial intelligence responses on comprehension questions? A study on the perceived scientific accuracy and linguistic quality of ChatGPT. *Physical Review Physics Education Research, 19*, 010142. https://doi.org/10.1103/PhysRevPhysEducRes.19.010142

Deng, R., Jiang, M., Yu, X., Lu, Y., & Liu, S. (2025). Does ChatGPT enhance student learning? A systematic review and meta-analysis of experimental studies. Computers & Education, 227. https://doi.org/10.1016/j.compedu.2024.105224

Dessie, E., Gebeyehu, D., & Eshetu, F. (2024). Motivation, conceptual understanding, and critical thinking as correlates and predictors of metacognition in introductory physics. *Cogent Education, 11*(1), 2290114. https://doi.org/10.1080/2331186X.2023.2290114

Fadillah, M. A., Usmeldi, U., Lufri, L., Mawardi, M., & Festiyed, F. (2024). Exploring user perceptions: The impact of ChatGPT on high school students' physics understanding and learning. *Advances in Mobile Learning Educational Research, 4*(2), 1197–1207. https://doi.org/10.25082/AMLER.2024.02.013

Han, X., Peng, H., & Liu, M. (2025). The impact of GenAI on learning outcomes: A systematic review and meta-analysis of experimental studies. *Educational Research Review, 48*, Article 100714. https://doi.org/10.1016/j.edurev.2025.100714

Hou, C., Zhu, G., & Sudarshan, V. (2025a). The role of critical thinking on undergraduates' reliance behaviours on generative AI in problem-solving. *British Journal of Educational*

Technology, 56(5), 1919–1941. https://doi.org/10.1111/bjet.13613

Hou, C., Zhu, G., Sudarshan, V., Lim, F. S., & Ong, Y. S. (2025b). Measuring undergraduate students' reliance on generative AI during problem-solving: Scale development and validation. *Computers & Education, 234*, Article 105329. https://doi.org/10.1016/j.compedu.2025.105329

Izzati, E. N., Sukarelawan, M. I., Base, M., Ubao, R. I., & Fayanto, S. (2026). Comparing physics test anxiety between religious-based and public senior high school students using Rasch measurement and differential item functioning (DIF). *Edusainstika: Jurnal Pembelajaran MIPA, 6*(1), 1–18. https://doi.org/10.31958/je.v6i1.17379

Jabnabillah, F., & Astiati, S. D. (2024). Pearson correlation analysis to determine the relationship between student responses and satisfaction using the Quizizz application. *Pi: Mathematics Education Journal, 7* (2), 57-63. https://doi.org/10.21067/pmej.v7i2.10109

Jia, Z., Li, Y., & Wang, X. (2025). The impact of generative AI dependency on academic achievement: The role of false self-efficacy and learning engagement. *Behavioral Sciences, 15*(10), 1348. https://doi.org/10.3390/bs15101348

Liang, J., Wang, L., Luo, J., Yan, Y., & Fan, C. (2023). The relationship between student interaction with generative artificial intelligence and learning achievement: Serial mediating roles of self-efficacy and cognitive engagement. Frontiers in Psychology, 14. https://doi.org/10.3389/fpsyg.2023.1285392

Lintner, T., Juhaňák, L., Žáková, M., Plch, L., & Ropovik, I. (2026). Generative AI use and academic achievement: A cross-sectional study of Czech seventh-grade students. *Education and Information Technologies, 31*, 4829–4848. https://doi.org/10.1007/s10639-026-14002-3

Megreya, A. M., Szűcs, D., & Moustafa, A. A. (2021). The abbreviated science anxiety scale: Psychometric properties, gender differences and associations with test anxiety, general anxiety and science achievement. *Plos One, 16*(2), Article e0245200. https://doi.org/10.1371/journal.pone.0245200

Mihardi, S., & Supahar. (2026). Development of a physics learning anxiety instrument for high school students. *JIPFRI (Jurnal Inovasi Pendidikan Fisika dan Riset Ilmiah), 10*(1), 96–107. https://doi.org/10.30599/jipfri.v10i1.4960

Musengimana, T., Yadav, L. L., Uwamahoro, J., & Nizeyimana, G. (2025). Instructional strategies for enhancing students' problem-solving skills in physics: A systematic review. *Discover Education, 4*, 380. https://doi.org/10.1007/s44217-025-00733-x

Mutia Dewi, N., Sutarto, S., Ernasari, E., & Alif Faresta, R. (2025). How do physics teachers implement the Merdeka Curriculum in learning activities? Journal of Education and Teaching (JET), 6(1), 230-245. https://doi.org/10.51454/jet.v6i1.530

Ocheni, C. A., Okeke, A. O., Agah, J. J., Oguguo, B. C. E., Ene, C. U., Ezugwu, I. J., & Asongo, S. T. (2024). Moderation of gender and school location on the prediction of test anxiety on physics students' academic achievement in waves motion. *Physics Education Research Journal, 6*(1), 11–20. https://doi.org/10.21580/perj.2024.6.1.20668

OECD. (2026). PISA 2025 results (Volume I): Indonesia. https://www.oecd.org/en/publications/pisa-2025-results-volume-i-country-notes_2d4ff9ea-en/indonesia_9c880f8a-en.html

Pekrun, R. (2024). Control-value theory: From achievement emotion to a general theory of human emotions. Educational Psychology Review, 36. https://doi.org/10.1007/s10648-024-09909-7

Podlasov, S. O., & Matviichuk, O. V. (2023). Application of ChatGPT in the teaching of physics to bachelor's students at a technical university. *Information Technologies and Learning Tools, 97*(5), 149–166. https://doi.org/10.33407/itlt.v97i5.5374

Putri, R. O., & Sugianto Putri. (2025). Analysis of misconceptions regarding measurement concepts among 10th-grade high school students using a Google Forms-assisted four-tier

diagnostic test. *Unnes Physics Education Journal, 14*(1), 93–100. https://doi.org/10.15294/upej.v14i1.24629

Rasyid, J., Masri, M. J., Sulfianty, & Aris, N. A. (2026). Pengaruh penggunaan AI generatif terhadap physics learning anxiety dan motivasi belajar peserta didik. *Charm Sains: Jurnal Pendidikan Fisika, 7*(2), 136-143. https://doi.org/10.67006/charmsains.v7i2.612

Risko, E. F., & Gilbert, S. J. (2016). Cognitive offloading. *Trends in Cognitive Sciences, 20*(9), 676–688. https://doi.org/10.1016/j.tics.2016.07.002

Rosiyanah, R., & Astra, I. M. (2025). Penerapan Metode Think Pair Share Berbasis Emotion Regulation untuk Menurunkan Physics Anxiety dan Meningkatkan Pemahaman Konsep Murid. *Jurnal Terapan Pendidikan Dasar Dan Menengah, 5*(4), 292–300. https://doi.org/10.28926/jtpdm.v5i4.2286

Skulmowski, A. (2024). Placebo or assistant? Generative AI between externalization and anthropomorphization. Educational Psychology Review, 36. https://doi.org/10.1007/s10648-024-09894-x

Stojanov, A., Liu, Q., & Koh, J. H. L. (2024). University students' self-reported reliance on ChatGPT for learning: A latent profile analysis. *Computers and Education: Artificial Intelligence, 6*, Article 100243. https://doi.org/10.1016/j.caeai.2024.100243

Valeri, F., Nilsson, P., & Cederqvist, A.-M. (2025). Exploring students' experience of ChatGPT in STEM education. *Computers and Education: Artificial Intelligence, 8*, 100360. https://doi.org/10.1016/j.caeai.2024.100360

Weber, J., & Wilhelm, T. (2024). Contributing factors to the improvement of conceptual understanding in a computer-based intervention in Newtonian dynamics. *Physical Review Physics Education Research, 20*(2), 020130. https://doi.org/10.1103/PhysRevPhysEducRes.20.020130

Zakaria, A., Jatmiko, B., Prahani, B. K., & Wijaksono, C. F. (2026). Identification of generative AI usage profiles and implications for critical thinking skills in physics learning. *JPPS (Jurnal Penelitian Pendidikan Sains), 15*(2), 83–93. https://doi.org/10.26740/jpps.v15n2.p83-93