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# Exploring physics students' attitudes toward ChatGPT using the ABC model

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**Abstract**

The integration of artificial intelligence tools such as ChatGPT into educational settings has sparked a paradigm shift in higher education, necessitating a deeper understanding of students' attitudes toward these technologies. The ABC model, which delineates attitudes into affective, behavioral, and cognitive components, provides a robust framework for such investigations. Prior studies have applied this model broadly across multiple disciplines. However, little is known about its applicability in physics education, where a strong emphasis on analytical reasoning and quantitative problem-solving might influence attitudes uniquely. Addressing this gap, we conducted a cross-sectional survey study using an online questionnaire administered to N = 1,189 physics students enrolled at German universities. We developed an instrument, adapted from prior research, to assess students' attitudes toward ChatGPT in the context of physics learning. The validity of the instrument's hypothesized three-factor structure was then evaluated via confirmatory factor analysis. The results paint a clear picture: The three-factor solution demonstrated satisfactory global fit (CFI = 0.95, RMSEA = 0.05, SRMR = 0.04) and significantly outperformed alternative two- and one-factor models based on likelihood ratio tests and information criteria. The results thus affirm the empirical validity of this instrument in capturing physics students' attitudes toward ChatGPT according to the ABC model, contributing to a nuanced understanding of learner perspectives on ChatGPT in discipline-specific educational contexts. Additionally, an overview is provided of physics students' attitudes toward learning with ChatGPT by analyzing their responses on the item level. Implications for educational practice and future research are discussed.

**Keywords:** physics education, ChatGPT, attitudes, ABC model

## INTRODUCTION

The emergence of generative artificial intelligence (GenAI) like ChatGPT presents a paradigm shift for higher education, as educators, students, and academic institutions are increasingly engaging with ChatGPT and integrating it into teaching, learning, and research activities (Ahadi et al., 2023; Al-Jahwari & Yousif, 2024). As institutions grapple with adapting curricula and academic integrity policies (Hasanein & Sobaih, 2023; Mbwambo & Kaaya, 2024; Neumann et al., 2023; Sallam et al., 2023; Schön et al., 2023) to shifting skill requirements (Köhler & Hartig, 2024; Schön et al., 2023) and ethical concerns (Anwar et al., 2024; Bukar et al., 2024; Fajt & Schiller, 2025; Mbwambo & Kaaya, 2024), understanding the student perspective on GenAI-tools has become critical for the physics education community. To understand this perspective, however, one must first consider the capabilities and limitations of such tools within the physics domain: While ChatGPT can be proficient with text-based concepts and achieve high success on well-defined textbook problems (Horchani, 2025; Tong et al., 2024; Wang et al., 2024), its accuracy plummets on under-specified problems that require physical modeling and real-world assumptions (Wang et al., 2024). This limitation appears to stem not from a lack of physics knowledge, but from an inability to construct physical models and reason spatially with diagrams (Polverini et al., 2025; Wang et al., 2024). Given


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**Contribution to the literature**

- This study provides a large-scale, discipline specific examination of physics students' attitudes toward ChatGPT.
- This study empirically validates an adapted ABC-model-based instrument for measuring affective, behavioral and cognitive attitudes toward ChatGPT in the context of physics learning.
- This study offers a detailed descriptive profile of how physics students perceive and use ChatGPT when learning physics.

these technical capabilities, the literature outlines a wide range of pedagogical implementations that leverage the tool's strengths. For instance, ChatGPT shows potential as a personalized physics tutor that can offer step-by-step guidance (Liang et al., 2023), support authentic scientific practices such as hypothesis design (Kotsis, 2024, 2025), and act as a conversational partner to foster critical thinking and reflection (Gregorcic & Pendrill, 2023; Bitzenbauer, 2023). Empirical evidence highlights ChatGPT's potential to enhance student learning, with a major meta-analysis finding large positive effects on performance and medium effects on higher-order thinking (Wang et al., 2024). This is supported by studies showing that structured artificial intelligence (AI) integration can produce significant learning gains by addressing misconceptions (El Fathi et al., 2025), improve science knowledge and motivation while reducing anxiety (Ng et al., 2024), and improve outcomes in game-based environments (Chen & Chang, 2024). However, these opportunities are accompanied by significant risks, such as factual hallucinations, which can introduce and reinforce stubborn physics misconceptions (Gregorcic & Pendrill, 2023; Bitzenbauer, 2023). This risk is compounded by students' high trust in AI's output, leading to an uncritical acceptance of incorrect information (Ding et al., 2023; Krupp et al., 2023). This exemplifies the concern that such passive dependency reduces independent problem-solving and critical thinking skills (Forero & Herrera-Suárez, 2023) and diminishes peer collaboration, as students may turn to the AI for strategic guidance instead of engaging in problem-solving dialogue with their human partner (Groothuijsen et al., 2024). A deeper insight into this dynamic is offered by analyzing the student's perspectives. However, recent studies reveal glaring disparities in students' educational use of ChatGPT. Specifically, male students (Elhassan et al., 2025; Stöhr et al., 2024), those enrolled in science-related disciplines (Fontao et al., 2024; Ravšelj et al., 2025; Stöhr et al., 2024; Sublime & Renna, 2024), older or more experienced learners (Abdaljaleel et al., 2024; Köhler & Hartig, 2024; Sublime & Renna, 2024), and students from wealthier countries (Ravšelj et al., 2025) tend to report higher usage rates and more positive attitudes toward GenAI tools such as ChatGPT. Students report using such tools for summarizing texts, generating ideas, drafting essays, explaining complex concepts (Ravšelj et al., 2025), as well as for supporting exam preparation (Ahmed, 2024; Almulla & Ali, 2024; İpek et al., 2023). These applications highlight its potential to enhance individualized learning and reduce barriers to academic support (Ahmed, 2024; Naznin et al., 2025). However, the unequal adoption patterns emphasize the need for inclusive strategies to ensure that all students can benefit from AI-assisted learning opportunities, regardless of their background or field of study (Daepp & Counts, 2025; Kacperski et al., 2025; Thong et al., 2023). Ultimately, these patterns of adoption and use are heavily influenced by students' underlying attitudes toward technologies such as ChatGPT (Kim et al., 2009; Or, 2023; Svenningsson et al., 2022). Given that students' attitudes toward ChatGPT in education are among the strongest predictors of their intention to use it (cf. Ahadzadeh et al., 2024; Mariñas et al., 2025; Paudel & Acharya, 2024; Wang et al., 2025), they warrant deeper exploration to inform interventions that can foster equitable and meaningful integration of AI in education.

## RESEARCH BACKGROUND

### Attitudes

Eagly and Chaiken (1993) define an attitude as "a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor" (Eagly & Chaiken, 1993, p. 1). This definition has three essential features: attitudes as tendencies, attitudes as evaluative, and attitudes that are developed toward an attitude object. Since attitudes can be short-termed as well as long-termed, Eagly and Chaiken (2007) chose the term tendency specifically for its neutrality regarding the temporal stability of attitudes, allowing for both enduring and transient attitudes. These tendencies are always directed toward attitude objects–discrete and mentally represented entities that elicit evaluative responses. Attitude objects can be abstract or concrete, individual or collective, and their definitional role distinguishes attitudes from more diffuse constructs like moods. In this study, the attitude object is ChatGPT. Crucially, attitudes are inherently evaluative. They manifest in cognitive, affective, and behavioral responses, yet are distinct from these expressions. Instead, attitudes are the latent internal predispositions that underline such responses, providing a theoretical foundation for understanding variability in evaluative

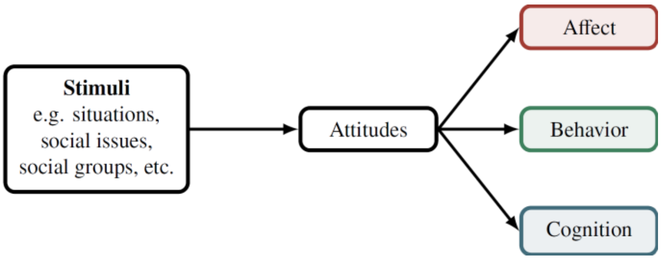


**Figure 1.** Adapted schematic conception of attitudes according to Rosenberg et al. (1960, p. 3)

behavior across contexts (Eagly & Chaiken, 2007). Empirical evidence suggests that attitudes are, in part, genetically determined (cf. Eaves & Eysenck, 1974; Kandler et al., 2014; Olson et al., 2001; Stößel et al., 2006). However, genetic factors alone are insufficient to fully account for the development of attitudes. Empirical findings also indicate that attitudes are acquired through learning processes (cf. Abrahamson et al., 2002; Eaves & Eysenck, 1974; Hatemi, 2013). To summarize, attitudes are latent constructs, more specifically they are a result of an evaluation with a degree of favor or disfavor followed by observable responses such as judgments, emotions, or behaviors. Distinguishing attitudes from their expressions is essential to avoid conflating situational variability in responses with changes in the underlying attitude. This separation enhances theoretical precision and measurement validity by acknowledging that expressions may be context-dependent, while the latent attitude can remain stable (Eagly & Chaiken, 1993, 2007). The ABC model, which distinguishes between affective, behavioral, and cognitive components, constitutes a central theoretical framework in the study of attitudes in social psychology and was first formulated by Rosenberg et al. (1960) (cf. Ajzen & Fishbein, 1975; Breckler, 1984; Eagly & Chaiken, 1993; Rosenberg et al., 1960). Also known as the Tripartite Model of Attitudes (Eagly & Chaiken, 1993; Ostrom, 1969) or the multicomponent view of attitudes (Ajzen & Fishbein, 1975), it conceptualizes attitudes as internal psychological states comprising three distinct yet interconnected components (Breckler, 1984). Although attitudes themselves are not directly observable, they are inferred from stimuli associated with the attitude object and can be empirically examined through the responses they generate (Eagly & Chaiken, 1993). These responses–cognitive, affective, and behavioral (cf. **Figure 1**)–can each vary along a continuum from extremely positive to extremely negative, thereby allowing attitudes to be located within three evaluative dimensions (Eagly & Chaiken, 1993).

The affective component refers to emotional reactions, moods, and feelings, as well as physiological responses mediated by the sympathetic nervous system in relation to the attitude object (Eagly & Chaiken, 1993). In contrast, the behavioral component–sometimes termed the conative component (Ajzen & Fishbein, 1975)–encompasses both overt behaviors and behavioral intentions directed toward the attitude object (Eagly & Chaiken, 1993). Complementing these, the cognitive component refers to thoughts and ideas about the attitude object, which are conceptualized as beliefs. These beliefs associate the object with specific attributes, and these attributes themselves convey evaluative meaning–either positive or negative (Eagly & Chaiken, 1993).

### Attitudes Toward ChatGPT

Even though a positive attitude has been shown to positively influence the frequency of use (Köhler & Hartig, 2024), few studies have applied the ABC model to the role and use of ChatGPT in educational contexts (Acosta-Enriquez et al., 2024b). Therefore, we provide a concise overview of the limited research on students' attitudes toward the use of ChatGPT in learning environments. Ajlouni et al. (2023) surveyed 623 undergraduate students in Jordan and reported an overall positive attitude toward the use of ChatGPT in learning contexts, characterized by highly positive behavioral and cognitive components and moderately positive affective responses. In contrast, Estrada-Araoz et al. (2024) found medium-level attitudes among 269 Peruvian students, with each component of the ABC model also receiving moderate evaluations. This suggests a perceived balance between the benefits and drawbacks of using ChatGPT as a learning tool. Furthermore, Estrada-Araoz et al. (2024) observed that students at more advanced stages of their academic studies exhibited more favorable attitudes toward ChatGPT. Similarly, Ahmad et al. (2024) reported moderately positive attitudes in a sample of 42 Malaysian students. Lastly, Acosta-Enriquez et al. (2024b) demonstrated that the cognitive and affective components exert a significant influence on the behavioral component, thereby shaping students' intentions to use ChatGPT. Moreover, the study found that the cognitive component strongly drives the affective component, indicating a hierarchical structure in which students' beliefs about ChatGPT shape their emotional responses. Notably, age and gender did not moderate these relationships.

## RESEARCH RATIONALE

While prior research has applied the ABC model to investigate students' attitudes toward ChatGPT, these studies have typically relied on heterogeneous samples drawn from a broad range of academic disciplines. Such general approaches, while useful for identifying overarching trends, may obscure discipline-specific nuances. Our study focuses exclusively on physics students, a group whose academic context presents unique characteristics that may meaningfully shape their attitudes toward AI tools like ChatGPT. Physics, as a

**Table 1.** Overview of the instrument and its three components including example items and Cronbach's alpha for each component

| Component (# items) | Example item | Cronbach's alpha |
|---|---|---|
| Affective (6) | A2: I enjoy using ChatGPT when learning physics. | 0.77 |
| Behavioral (5) | B2: I use ChatGPT in physics as an educational re- source. | 0.83 |
| Cognitive (9) | C1: Learners should be able to use ChatGPT when learning physics. | 0.85 |

Note. An overview of all items is provided in **Appendix A**

discipline, places a strong emphasis on analytical reasoning, quantitative problem-solving, and precision–skills (cf. Kieser et al., 2023). As outlined before, these are requirements where the quality of answers generated by ChatGPT is highly volatile. Furthermore, physics students often work with symbolic representations and complex conceptual frameworks that go beyond the purely textual explanations that ChatGPT provides, further compromising the tool's perceived effectiveness and potentially leading to greater skepticism or more cautious adoption within this academic community. As a result, their affective (e.g., trust and confidence), behavioral (e.g., frequency of use and reliance), and cognitive (e.g., perceived usefulness or limitations) attitudes toward ChatGPT may differ markedly from those presented in prior research (cf. Ahmad et al., 2024; Ajlouni et al., 2023; Estrada-Araoz et al., 2024). Investigating this specific context allows us to capture these discipline-specific attitudes and contributes a more granular understanding to the broader discourse on educational AI adoption. Lastly, due to these expected volatilities, it is a priori not clear whether attitudes of physics students toward ChatGPT can be separated empirically into three distinct components that are in line with the ABC model. Thus, the first and primary goal of this research is to adapt existing measures of attitudes using the ABC model and create a novel instrument that allows them to capture these constructs in the context of learning physics with ChatGPT. In light of this, the following research questions (RQs) are investigated:

**RQ1.** To what extent can physics students' attitudes toward ChatGPT be described through the lens of the ABC model?

**RQ2.** What are the affective, behavioral and cognitive attitudes that learners hold toward the use of ChatGPT when learning physics?

## METHODS

### Study Design and Sample

A cross-sectional survey study was conducted to explore students' attitudes toward the use of ChatGPT for learning physics. A questionnaire was administered digitally via LimeSurvey to N = 1189 students ($N_1$ = 800 male, $N_2$ = 356 female, $N_3$ = 33 diverse) from German universities. It was configured to automatically terminate if respondents indicated that they were unfamiliar with ChatGPT as such individuals would neither have prior experience with ChatGPT nor be able to form an informed attitude toward it. It is important to note that the German higher education context may shape students' attitudes toward AI tools such as ChatGPT. While many universities explicitly encourage the responsible use of GenAI, institutional guidelines typically emphasize transparency and restrict AI-generated content in graded assignments or theses. Data collection was conducted during the winter term 2024/2025. All participants were either enrolled in physics or closely related study programs (e.g., physics teacher training). On average, the participants were aged 22.0 ± 4.4. Only fully completed responses were further analyzed.

### Instrument

The questionnaire was based on the instrument developed by Ajlouni et al. (2023), who similarly investigated attitudes toward ChatGPT according to the ABC model. Since their original questionnaire focused on students' attitudes toward learning with ChatGPT in general, modifications were necessary to tailor it to the context of physics learning, resulting in a version specifically designed for physics contexts. The format of equipping the statements with a 5-point rating scale was retained. It was translated into German to prevent distortions in the results due to limited English proficiency within the German-speaking target group. The questionnaire was subsequently reviewed by two experts in physics education for linguistic clarity and content validity before being distributed to the participants. **Table 1** provides a concise overview of the final instrument in terms of scale length, example items and Cronbach's alpha. A detailed overview of all items is provided in **Table A1** in the **Appendix A**.

### Data Analysis

Confirmatory factor analysis (CFA) was used to assess the extent to which the hypothesized framework of the ABC model can be applied to the data. To this end, we followed the procedure outlined by Bitzenbauer and Ubben (2025). In a first step, we checked whether the data satisfy the precondition of multivariate normal distribution using Mardia's test from the MVN R-package (cf. Jackson et al., 2009). Given that the assumption of multivariate normality was violated, we proceeded using robust maximum likelihood estimation using the Yuan-Bentler mean-adjusted estimator, as implemented in the lavaan R-package (Yuan & Bentler, 1998). Items with negative polarity have been inverted prior to the analysis.

### *Global model fit*

To assess global fit of the model, we used several metrics: The $\chi 2$ goodness-of-fit test, the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean residual (SRMR). Model fit was evaluated against the commonly recommended thresholds proposed by Schermelleh et al. (2003), namely CFI ≥ 0.95, RMSEA ≤ 0.05, and SRMR ≤ 0.05. Additionally, to account for model complexity, different models were compared using Akaike information criterion (AIC) and Bayesian information Criterion (BIC). Both criteria balance goodness-of-fit with parsimony by penalizing models with more estimated parameters, helping to avoid overfitting (Vrieze, 2012). AIC favors models with better predictive accuracy, while BIC imposes a stricter penalty on complexity, especially with larger samples. For both criteria, lower values indicate a better-fitting model (Chakrabarti & Ghosh, 2011). Lastly, likelihood ratio tests (LRTs) were used to complement AIC and BIC comparisons because they provide a formal statistical test for comparing nested models–where one model is a constrained version of another. While AIC and BIC offer information-based criteria that balance fit and complexity, LRTs directly test whether the more complex model provides a significantly better fit to the data than the simpler one. This approach strengthens model selection by combining statistical significance testing with information criteria, offering a more comprehensive evaluation of competing models (cf. Buzick, 2010).

### *Local model fit*

Local fit on the indicator level was assessed by examining the factor loadings λ of all indicators, corresponding error variances $1\text{-}\lambda^2$ (no cross-loadings were permitted in the model specification), and indicator reliabilities $\lambda^2$. Consistent with the recommendation by Kline (1998), items with standardized factor loadings below 0.30 were excluded from the model. Local fit on the factor level was assessed by computing

(a) factor reliability using McDonald's ω, which is appropriate in the case of non-equivalent factor loadings across indicators, with values above 0.70 indicating acceptable reliability (cf. McDonald, 1999) and

(b) the average extracted variance (AEV) per factor. According to the Fornell-Larcker criterion, AEV values are suggested to exceed the squared inter-factor correlations to demonstrate sufficient discriminant validity (Fornell & Larcker, 1981).

**Table 2.** Results of the CFA on the model level for all models under investigation

| Criterion | Cutoff-value | A+B+C | A+(BC) | (AB)+C | (AC)+B | ABC |
|---|---|---|---|---|---|---|
| $\chi^2$ | – | 467 | 6885 | 824 | 1051 | 1158 |
| df | - | 160 | 190 | 169 | 169 | 170 |
| p | - | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| CFI | ≥0.95 | 0.95 | 0.90 | 0.90 | 0.87 | 0.84 |
| SRMR | ≤0.05 | 0.04 | 0.05 | 0.05 | 0.06 | 0.07 |
| RMSEA | ≤0.05 | 0.05 | 0.07 | 0.07 | 0.09 | 0.09 |
| AIC | - | 45,357 | 45,764 | 45,764 | 46,035 | 46,156 |
| BIC | - | 45,592 | 45,957 | 45,957 | 46,229 | 46,217 |

Note. The abbreviation A+B+C relates to the three-factor model, while A+(BC) relates to the two-factor model where B and C have been merged into one factor, and so on

### Descriptive Statistics

To complement the CFA and provide a more holistic picture of the data, we further report general descriptive statistics, including response distribution, mean values, standard deviation (SD) as well as median values for all indicators.

The data analysis was conducted using R 4.4.2 and its packages lavaan, MVN, semTools and semPlot.

## RESULTS

### Confirmatory Factor Analysis Results

### *Results regarding global model fit*

An overview of all models under investigation and their corresponding fit indices is provided in **Table 2**. Here, A + B + C denotes the three-factor model, A + (BC) denotes the two-factor model where behavioral and cognitive items have been merged into a single factor (and analogous for (AB) + C as well as (AC) + B and ABC is the one-factor model consisting of all items. We did not analyze two-factor models that combine items from different attitude components, as such models, regardless of empirical considerations, lack theoretical plausibility. The CFI is decreasing from left to right in **Table 2**, indicating a better model fit as additional constraints are imposed. This trend is reflected further in increasing SRMR and RMSEA statistics. Not only does the three-factor model have the lowest $\chi 2$ statistic, but it is also the only model that meets all requirements with regard to the cutoff-values.

In addition, LRTs, conducted via the lavtestLRT function provided by the lavaan package, reveal highly significant statistical differences between the three-factor model and all two-factor models, as well as between the three-factor model and the one-factor model (cf. **Table 3**). However, with a CFI of 0.95, SRMR of 0.04 and RMSEA of 0.05, the three-factor model meets all usual requirements presented above and thus has a satisfactory global fit to the data. Lastly, the three-factor

**Table 3.** Results of direct model comparison LRTs, including the differences in the $\chi 2$ statistic as well as the degrees of freedom

| Model | $\chi^2$ difference | df difference | Significance level |
|---|---|---|---|
| A+B+C | - | - | - |
| A+(BC) | 6,418 | 30 | *** |
| (AB)+C | 357 | 9 | *** |
| (AC)+B | 584 | 9 | *** |
| ABC | 691 | 10 | *** |

Note. Significance codes: 0 '***', 0.001 '**', 0.01 '*', & 0.05 '.' & All rows refer to the first one, comparing the respective model with the three-factor model A+B+C

**Table 4.** Results of the CFA for the three-factor ABC model including item estimates (i.e., factor loadings, standard error, and error variance) as well as reliability calculations (i.e., indicator reliability, factor reliability and AEV)

| Indicator | | FL (SD) | EV | IR | ω | AEV |
|---|---|---|---|---|---|---|
| Affective | A1 | 0.527 (0.042) | 0.722 | 0.278 | 0.76 | 0.45 |
| | A2 | 0.911 (0.027) | 0.170 | 0.830 | | |
| | A3 | 0.783 (0.034) | 0.387 | 0.613 | | |
| | A4 | 0.666 (0.038) | 0.556 | 0.444 | | |
| | A5 | 0.294 (0.041) | 0.914 | 0.086 | | |
| | A6 | 0.391 (0.034) | 0.847 | 0.153 | | |
| Behavioral | B1 | 0.675 (0.036) | 0.544 | 0.456 | 0.84 | 0.52 |
| | B2 | 0.803 (0.031) | 0.354 | 0.646 | | |
| | B3 | 0.776 (0.033) | 0.397 | 0.603 | | |
| | B4 | 0.518 (0.044) | 0.732 | 0.268 | | |
| | B5 | 0.830 (0.029) | 0.312 | 0.688 | | |
| Cognitive | C1 | 0.637 (0.038) | 0.594 | 0.406 | 0.78 | 0.36 |
| | C2 | 0.816 (0.031) | 0.335 | 0.665 | | |
| | C3 | 0.827 (0.030) | 0.317 | 0.683 | | |
| | C4 | 0.595 (0.037) | 0.646 | 0.354 | | |
| | C5 | 0.517 (0.040) | 0.733 | 0.267 | | |
| | C6 | 0.602 (0.036) | 0.637 | 0.363 | | |
| | C7 | 0.517 (0.036) | 0.733 | 0.267 | | |
| | C8 | 0.359 (0.046) | 0.871 | 0.129 | | |
| | C9 | 0.380 (0.037) | 0.856 | 0.144 | | |

Note. FL: Factor loading; EV: Error variance; IR: Indicator reliability; & ω: Factor reliability

model exhibits the lowest values for both AIC and BIC and thus is preferred based on model fit and parsimony criteria. Therefore, the local fit statistics of the three-factor model are reported in the following subsection.

### *Results regarding local model fit*

**Table 4** summarizes all employed metrics on indicator and construct level, including item estimates as well as reliability calculations. Here, factor variances were fixed to 1 in order to identify the model by standardizing the latent variables. This approach allows all factor loadings to be freely estimated, facilitating direct interpretation of the strength of the relationship between each item and its underlying factor (Bitzenbauer & Ubben, 2025). All but one item have factor loadings above 0.30, with only $A_5$ failing to meet this threshold.

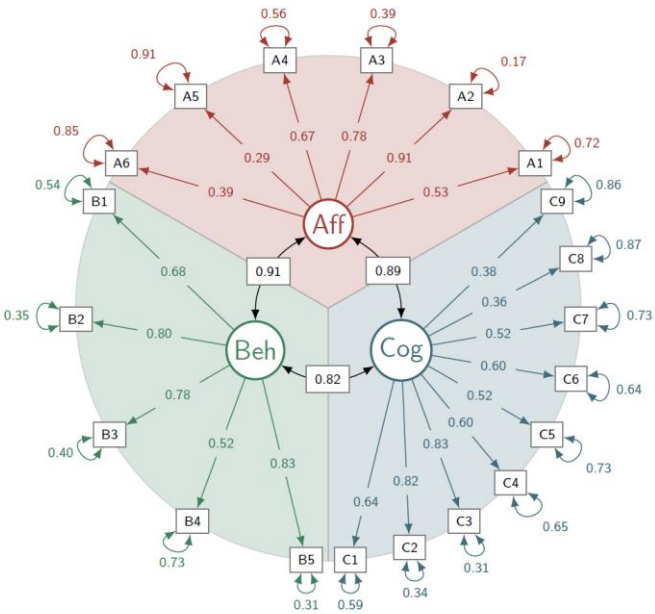


**Figure 2.** Path diagram of the three-factor ABC model (numbers on the single-sided arrows indicate factor loadings, while numbers on the double-sided arrows indicate error variances of the respective item & numbers on arrows between factors indicate the respective correlations) (Source: Author's own illustration)

However, with a loading of 0.29 it does not fall far outside the usually accepted range and can thus be retained. On the construct level, all three factors have high reliability, with $\omega_A = 0.76$ for the affective component, $\omega_B = 0.84$ for the behavioral component and $\omega_C = 0.78$ for the cognitive component.

The respective path diagram for the three-factor model is provided in **Figure 2**. It is noteworthy, however, that all correlations between the factors are very high, with $\rho_{AB} = 0.91$, $\rho_{AC} = 0.89$, and $\rho_{BC} = 0.82$, indicating a strong relationship between the factors. Thus, in each case, the average extracted variance per factor is smaller than its squared correlations with the other two factors, suggesting that the constructs are not sufficiently distinct according to the Fornell-Larcker criterion (Fornell & Larcker, 1981). Despite this, the AVE values–ranging from 0.36 to 0.52–indicate that the constructs account for a substantial proportion of the variance in their respective indicators. While this limitation regarding insufficient discriminant validity will be revisited in the Limitations section, we will refrain from delving into it more deeply at this point since all other findings consistently support the three-factor model as the best-fitting solution and standard CFA indices justify the model's adequacy.

In summary, the CFA results at all levels support the empirical distinction of physics students' attitudes toward learning with ChatGPT into three interrelated yet distinct constructs, consistent with the hypothesized ABC model: An affective, a behavioral, and a cognitive component.

**Table 5.** Descriptive statistics including mean (M), SD, median (MD), percentage of student's agreements (+, rating: 4 = rather agree, 5 = agree), disagreements (-, rating: 2 = rather disagree, 1 = disagree) for all items, and percentage of undecided votes (°, rating: 3 = undecided)

| I | M ± SD | M | SD | MD | + | ° | - |
|---|---|---|---|---|---|---|---|
| A1 | 1 5 | 3.40 | 1.16 | 3 | 49.5 | 29.0 | 21.5 |
| A2 | 1 5 | 3.26 | 1.41 | 4 | 50.8 | 15.8 | 33.4 |
| A3 | 1 5 | 2.92 | 1.30 | 3 | 37.3 | 15.8 | 46.9 |
| A4 | 1 5 | 3.25 | 1.27 | 3 | 48.6 | 22.4 | 29.0 |
| A5 | 1 5 | 3.85 | 1.18 | 4 | 68.2 | 15.5 | 16.3 |
| A6 | 1 5 | 1.73 | 1.07 | 1 | 10.5 | 10.8 | 78.7 |
| B1 | 1 5 | 2.86 | 1.43 | 3 | 42.9 | 14.6 | 42.5 |
| B2 | 1 5 | 3.06 | 1.37 | 3 | 45.6 | 16.9 | 37.5 |
| B3 | 1 5 | 2.80 | 1.42 | 3 | 39.5 | 16.9 | 43.6 |
| B4 | 1 5 | 2.54 | 1.46 | 2 | 33.1 | 10.2 | 56.7 |
| B5 | 1 5 | 2.65 | 1.31 | 3 | 26.5 | 28.5 | 45.0 |
| C1 | 1 5 | 3.62 | 1.17 | 4 | 57.8 | 26.5 | 15.7 |
| C2 | 1 5 | 3.53 | 1.13 | 4 | 53.6 | 28.5 | 17.9 |
| C3 | 1 5 | 3.28 | 1.16 | 3 | 43.9 | 32.6 | 23.5 |
| C4 | 1 5 | 2.57 | 1.16 | 2 | 21.0 | 27.9 | 51.1 |
| C5 | 1 5 | 2.98 | 1.18 | 3 | 35.3 | 29.6 | 35.1 |
| C6 | 1 5 | 2.95 | 1.19 | 3 | 34.3 | 32.8 | 32.9 |
| C7 | 1 5 | 2.30 | 1.10 | 2 | 14.4 | 26.0 | 59.6 |
| C8 | 1 5 | 3.11 | 1.22 | 3 | 43.1 | 26.0 | 30.9 |
| C9 | 1 5 | 2.23 | 1.07 | 2 | 12.2 | 26.8 | 61.0 |

Note. I: Indicator

### Descriptives

To gain a more comprehensive understanding of the data we complement the CFA by additionally providing an overview of all descriptive statistics regarding the students' responses in **Table 5**, including means, medians, SDs as well as response distributions for each item. For the indicators of factor A, mean values range from 1.73 ($A_6$; "I feel nervous if I can't access ChatGPT when learning physics") to 3.85 ($A_5$; "I feel concerned about using ChatGPT when learning physics, because it may generate inaccurate results"), with SDs between 1.07 and 1.41. Medians span a broad range from 1 ($A_6$) to 4 ($A_2$; "I enjoy using ChatGPT"). Agreement percentages (+) vary accordingly from 10.5% ($A_6$) to 68.2% ($A_5$), while disagreement rates (-) range from 16.3% ($A_5$) to 78.7% ($A_6$). Among the indicators of factor B, mean values fall between 2.54 ($B_4$; "I use ChatGPT to summarize and analyze educational material in physics") and 3.06 ($B_2$; "I use ChatGPT in physics as an education resource"), with SDs ranging from 1.31 to 1.46. Medians are either 3 with one exception ($B_4$). Agreement levels range from 26.5% ($B_5$; "I use ChatGPT to achieve my learning goals in physics") to 45.6% ($B_2$), and disagreement rates from 37.5% ($B_2$) to 56.7% ($B_4$). Lastly, for the indicators of the cognitive component, mean values extend from 2.23 ($C_9$; "The use of ChatGPT promotes the development of creativity") to 3.62 ($C_1$; "Learners should be able to use ChatGPT when learning physics"), with SDs ranging from 1.07 to 1.22. Medians vary between 2 and 4. Agreement percentages range from 12.2% ($C_9$) to 57.8% ($C_1$), while disagreement levels range from 15.7% in the case of $C_1$ and to 61.0% in the case of $C_9$.

## DISCUSSION AND CONCLUSION

As Ostrom (1969) found over 50 years ago, the three components of the ABC model also exhibit a strong correlation also with regards to students' attitudes toward ChatGPT use for learning physics. This indicates that the components may be part of, or subcomponents within, a single psychological construct. Nonetheless, the three factors can be distinguished (Breckler, 1984). Furthermore, the CFA demonstrates that the attitudinal structure is best described by the ABC model, in comparison to other models, an outcome that has also been found in mathematics by Walker et al. (2020) in recent times. An examination of the subscales reveals that students' attitudes are generally moderate across all components. While individual items occasionally elicited stronger agreement or disagreement, the overall response pattern remains relatively balanced. The affective component showed a mean of 2.76 (SD = 0.84), the behavioral component 2.74 (SD = 1.08), and the cognitive component 2.89 (SD = 0.77), with all medians at 3 on a 5-point rating scale ranging from 1 ("disagree") to 5 ("agree").

More than two-thirds of students expressed agreement with the statement "I feel concerned about using ChatGPT when learning physics, because it may generate inaccurate results." Zhao et al. (2024) found that students' worries–especially feelings of discomfort and technological insecurity–significantly reduce their likelihood of accepting and using ChatGPT in educational contexts. In general, students in applied sciences tend to express significantly more concerns about inaccuracy than those in humanities (Ravšelj et al., 2025). This pattern reflects a broader relationship: Lower usage of AI is often associated with skepticism (Stöhr et al., 2024), while increased usage is often associated with higher levels of AI literacy (Abdulayeva et al., 2025). Therefore, it can be concluded that students need to be taught how to use ChatGPT responsibly, learn to identify potential errors it produces, and develop critical thinking skills in the process. In other words, students should be taught how to prompt, how to identify artifacts and hallucinations, as well as ChatGPT's sensitivity to contexts.

### Physics Students in Comparison: ABC-Based Insights Across Fields

As outlined in the research background, only few studies about students' attitudes toward ChatGPT have been conducted within the framework of the ABC model. In contrast to the initial findings by Ajlouni et al. (2023), we did not observe consistently positive attitudes toward ChatGPT. Our findings reveal a more balanced picture, with no uniformly positive evaluations–neither in overall assessments nor across the individual components of the ABC model. Instead, our descriptive results are more consistent with those of Estrada-Araoz et al. (2024), who observed a central tendency in participants' responses. Ajlouni et al. (2023), Ahmad et al. (2024), and Estrada-Araoz et al. (2024) all investigated higher education students' attitudes in the ABC model with students from diverse academic backgrounds. Notably, the sample in Ajlouni et al. (2023) was relatively balanced between students majoring in sciences and humanities, making it the most comparable to our sample. In contrast, Estrada-Araoz et al. (2024) focused on students from administration, accounting, and law, while Ahmad et al. (2024) surveyed students from the faculty of language and management and reported moderately positive attitudes. Among these, Ajlouni et al. (2023) is particularly noteworthy for sharing the most similar disciplinary composition with our sample yet yielding the most divergent results. Further insight is provided by Kubullek et al. (2024), who conducted their research in the context of higher education in Germany. Although their study did not employ the ABC model, they found that STEM students expressed more positive attitudes toward ChatGPT in educational settings than their peers in business-related fields, despite both groups reporting generally favorable views. The STEM students also showed a higher frequency of ChatGPT usage. Fontao et al. (2024) explored attitudes toward ChatGPT among students enrolled in secondary education teacher training programs–specifically including prospective physics teachers, who were also represented in our sample. Their results showed that future science teachers had significantly more experience with ChatGPT than their peers in the humanities. Science students were also more impressed by the potential of ChatGPT and found it to be more accessible. In contrast, students from the humanities expressed more concerns about the implications of ChatGPT for their future teaching roles, perceiving it as a greater threat to job security. Science students, by comparison, were more confident in their potential to generate high-quality instructional content. Similar findings were found by Sublime and Renna (2024), with science students using ChatGPT more frequently than humanities students, while both groups tended to proofread ChatGPT's answers. These findings suggest that the central tendency observed among physics students within the ABC model framework cannot be attributed solely to their academic discipline. Rather, we propose that students' attitudes may also be shaped by temporal developments and regional or country-specific factors. The temporal dimension is particularly relevant considering that Ajlouni et al. (2023) represents the earliest study among those discussed. Meanwhile, cross-national differences align with the results of Abdaljaleel et al. (2024) and Oyelere and Aruleba (2025), who both reported significant variation in students' attitudes toward ChatGPT across different countries. The temporal explanation appears especially plausible when comparing the timeframes of the studies. For instance, the investigations by Ahmad et al. (2024), Ajlouni et al. (2023), and Estrada-Araoz et al. (2024) were conducted well before the present study, which took place between October 2024 and January 2025. During this intervening period, students likely gained more exposure to and hands-on experience with ChatGPT. This idea is supported by Köhler and Hartig (2024), who found that increased knowledge about ChatGPT is associated with more critical attitudes. However, these trends are not uniform across all contexts. For example, Fadillah et al. (2024) found that high school physics students generally hold very positive perceptions of ChatGPT. In their study, the length of exposure did not significantly affect attitudes. Instead, gender and academic level played a more decisive role: female students expressed more favorable views, whereas more advanced students were more critical.

### Attitudinal Comparison within Physics: ABC Model vs. Alternative Frameworks

To date, no prior research specifically examining physics students' attitudes toward ChatGPT has been identified. However, several studies have addressed closely related psychological constructs such as perceptions or intentions to use ChatGPT–components that align with the behavioral aspect of the ABC model of attitudes. In this regard, many studies rely on newly developed surveys based on literature reviews (cf. Fadillah et al., 2024; Ravšelj et al., 2025) or employ custom-designed instruments (cf. Kregear et al., 2025). For example, Agyare et al. (2025) utilized the technology acceptance model (TAM) to explore students' perceptions, as did Yilmaz et al. (2023) in their investigation of students' attitudes toward ChatGPT. Overall, the TAM appears to be a frequently applied framework in studies examining attitudes and perceptions of ChatGPT in educational contexts (cf. Abdaljaleel et al., 2024; Acosta-Enriquez et al., 2024a; Agyare et al., 2025; Al Darayseh & Mersin, 2025; Fajt & Schiller, 2025; Mariñas et al., 2025; Sallam et al., 2023; Yilmaz et al., 2023).

Beyond these acceptance-based perspectives, recent work in STEM education has increasingly framed students' engagement with AI tools through the lens of AI literacy. AI literacy frameworks, such as the SEAME model or UNESCO's AI competency framework(cf. Biagini, 2025; Waite & Garside, 2023), emphasize that meaningful AI use in education involves not only operational skills but also critical evaluation and ethical awareness. Within this broader view, the balanced combination of cognitive skepticism, moderate behavioral engagement, and ethical concern observed among our physics students may reflect emerging forms of AI literacy rather than simple reluctance or resistance. In other words, students' attitudes might indicate not only whether they accept ChatGPT, but also how well they can critically appraise its limitations, evaluate its output, and position it appropriately in their learning process. This interpretation aligns with contemporary AI literacy perspectives in STEM, which frame reflective and selective use of AI tools as a desirable educational outcome(cf. Leon et al., 2025; Rupnik & Avsec, 2025).

The limited use of theory-based psychological survey instruments may be attributed to the fact that most existing scales–such as the attitudes toward artificial intelligence scale (Sindermann et al., 2021) or the general attitudes towards artificial intelligence scale (Schepman and Rodway, 2023)–were not specifically designed for educational settings. A domain-specific instrument tailored to educational contexts was only recently developed by Marengo et al. (2025). Nonetheless, the absence of such scales in earlier research is not necessarily problematic: findings by Montag and Ali (2025) demonstrate that even single-item measures of attitude show strong correlations with the aforementioned multi-item scales. Accordingly, we include studies that employ single-item or related constructs in our comparative analysis. Agyare et al. (2025) found that university physics students with stronger ethical concerns tend to use ChatGPT less frequently, as ethical concerns negatively mediate the relationship between behavioral intention and actual use. This may help explain the limited usage of ChatGPT in the sample presented in this study, where participants expressed significant doubts about the accuracy of ChatGPT's responses. Similarly, Tafhi et al. (2025) observed generally positive perceptions of ChatGPT among physics students, despite limited actual engagement with the tool. In samples consisting of students from various disciplines, Farinosi and Melchior (2025) identified complex and occasionally contradictory attitudes within the TAM framework–an observation that aligns with our findings. Among high school students, Fadillah et al. (2024) reported positive perceptions of using ChatGPT for learning physics. These students also expressed a strong need to verify ChatGPT's answers, a sentiment mirrored in item $A_5$ ("I feel concerned about using ChatGPT when learning physics, because it may generate inaccurate results") of our survey. In both studies, this concern ranks among the most strongly endorsed items. Interestingly, while programming students reported increased self-confidence through ChatGPT use (Yilmaz & Yilmaz, 2023), physics students in our study expressed contrasting views. Specifically, **Table 5** shows that over 50% of participants disagreed with item $C_4$ ("ChatGPT strengthens self-confidence with regard to physics"), which assesses whether ChatGPT boosts their self-confidence.

Stoyanova et al. (2025) found that programming students generally agreed that ChatGPT supports critical thinking, problem formulation, and problem-solving. However, they were ambivalent regarding its effect on creativity, with an average rating of 3.29 on a 5-point Likert scale. In contrast, our physics students exhibited a more pessimistic view: item $C_9$ ("The use of ChatGPT promotes the development of creativity") had a mean score of 2.23 and a median of 2, indicating a more critical stance on ChatGPT's support for creativity. In samples with students from diverse academic backgrounds, overreliance on ChatGPT has been associated with concerns about declining writing skills and creativity (Farinosi and Melchior, 2025). Consistent with these concerns, our findings (cf. item $C_5$ and item $C_9$ in **Table 5**) also suggest skepticism about the tool's effect on creativity. However, attitudes toward its impact on writing skills were more neutral.

### Limitations

There are several limitations that merit consideration in order to better contextualize our results. Firstly, the factors in the ABC model show very high intercorrelations and–in combination with medium values for average extracted variance–thus violate the Fornell-Larcker criterion, indicating insufficient discriminant validity.

However, investigating this potential overlap among constructs by combining components did not lead to a better model. In fact, all two-factor models as well as the one-factor model exhibited significantly worse model fit (cf. **Table 2** and **Table 3**). In other words, even though the three components can be empirically separated, they are closely related and should not be inspected independently from one another. In this regard it is noteworthy that the ABC model is not a model of orthogonal constructs–the components are also theoretically interdependent(cf. Eagly & Chaiken, 1993; Rosenberg et al., 1960).

Additionally, as already mentioned, AEV for the factors A (0.45) and C (0.36) were found to be below the established threshold of 0.50 (Fornell & Larcker, 1981). Lastly, the quotient $\chi 2/\mathrm{df}$ should not take values above 3.00 according to Schermelleh et al. (2003). All models except the three-factor model vastly exceed this limit, and with $\chi 2/\mathrm{df} = 2.92$ even the three-factor model shows barely acceptable fit. However, the $\chi 2$ statistic as well as the degrees of freedom are very sensitive to sample size and should therefore not be considered alone when evaluating model fit. Since the more robust statistics (CFI, SRMR, and RMSEA) all clearly indicate good model fit, the three-factor model can still be considered an adequate representation of the data despite the marginal $\chi 2/\mathrm{df}$ ratio.

Beyond these statistical limitations, the study is further limited in terms of design and sample. The cross-sectional study design does not capture how attitudes develop or change over time. This is particularly relevant since ChatGPT is rapidly evolving and students' exposure is vastly deepened over time. Thus, different results are to be expected when conducting a follow-up study in the future. In addition, the sample was composed exclusively of physics students from German universities. Cultural, linguistic, or disciplinary factors were not considered and may thus limit the generalizability of our findings to other student populations or subject areas. For example, since there is no uniform national AI policy for higher education in Germany, students may encounter differing rules between institutions and even courses–a patchwork solution that might foster ambivalence or central-tendency response patterns, which our data reflect. However, such speculations are beyond the scope of our study and, thus, require further investigation. A last but important inherent limitation relates to the questionnaire–data were collected through self-reported questionnaire responses, which are subject to social desirability effects and individual interpretation of items. This is particularly relevant for emerging technologies like ChatGPT: In the absence of established social norms, students may respond based on perceived acceptability rather than actual attitudes or behaviors. Rapidly shifting public discourse, variable familiarity with the technology, and uncertainty about the implications of their responses can further distort how participants interpret and answer survey items, thus compromising the validity of the data.

### Outlook

While our cross-sectional study provides a snapshot of physics students' attitudes toward ChatGPT, future research should explore how these attitudes evolve over time. A longitudinal study could capture such temporal dynamics, e.g., in response to increased exposure, instructional integration, or changes in institutional policies surrounding AI. Such data would complement our findings and clarify whether the overall moderate attitudes observed in our study are stable or subject to change–and what dependencies this possible change is linked with. Furthermore, our study focused on latent attitudinal structures but did not address how these attitudes manifest in students' everyday academic behavior.

Qualitative research–such as interviews, think-aloud protocols, or open-ended questions specifically tailored to the three components of the ABC model–could provide valuable insight into how the students' attitudes about ChatGPT manifest into actions. This would help determine whether and how the affective, behavioral, and cognitive components identified through factor analysis translate into actual use patterns and learning behaviors. In addition, it would be worthwhile to complement the students' views by investigating instructors' attitudes toward ChatGPT. A potential mismatch between students' perceived utility and instructors' acceptance could result in friction or underutilization of AI tools in educational settings. Since "educational processes must closely follow and effectively utilize emerging technologies" (Coban et al., 2025, p. 24), exploring this dual perspective could inform more coherent, inclusive strategies for integrating GenAI into physics education, ensuring alignment between pedagogical goals and technological competencies.

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**AI statement:** The authors stated that Generative AI tools (e.g., ChatGPT by OpenAI) were used to check the English language clarity of the manuscript only. No content generation was performed by AI.

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## APPENDIX A

**Table A1.** Overview of all indicators and the corresponding statements that students were asked to agree or disagree with on a 5-point rating scale

| Indicator (item) | Statement |
|---|---|
| A1 | I like learning about ChatGPT. |
| A2 | I enjoy using ChatGPT. |
| A3 | I feel comfortable using ChatGPT when learning physics. |
| A4 | I feel at ease employing ChatGPT for physical learning tasks. |
| A5 | I feel concerned about using ChatGPT when learning physics, because it may generate inaccurate results. |
| A6 | I feel nervous if I can't access ChatGPT when learning physics. |
| B1 | I inform friends and fellow learners about the benefits of learning physics with ChatGPT. |
| B2 | I use ChatGPT in physics as an educational resource. |
| B3 | I use ChatGPT for practicing and preparing for exams in physics. |
| B4 | I use ChatGPT to summarize and analyze educational material in physics. |
| B5 | I use ChatGPT to achieve my learning goals in physics. |
| C1 | Learners should be able to use ChatGPT when learning physics. |
| C2 | The use of ChatGPT supports learning processes in physics. |
| C3 | The use of ChatGPT improves the learning experience in physics. |
| C4 | ChatGPT strengthens self-confidence with regard to physics. |
| C5 | The use of ChatGPT promotes the ability to write about physical topics. |
| C6 | ChatGPT supports lifelong learning of physics. |
| C7 | The use of ChatGPT promotes the development of abstract thinking. |
| C8 | The use of ChatGPT promotes the development of evaluation skills. |
| C9 | The use of ChatGPT promotes the development of creativity. |