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# Intención de uso de la inteligencia artificial con fines académicos entre estudiantes de educación física

*Intention to Use AI for Academic Purposes among Physical Education Students*


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## Abstract

Introduction: The use of AI tools has revolutionized education systems, but adoption of these tools in physical education remains underexplored.
Objective: This study investigates the intention of physical education students to use AI for academic purposes by using an extended Technology Acceptance Model (TAM) incorporates additional three constructs that is subjective norms, trust, and ethical concerns to reflect the collaborative and ethically sensitive nature of physical education learning contexts.
Methodology: A quantitative and cross-sectional research design was used and, with the help of structured online questionnaire used to collect data from 392 undergraduate and postgraduate physical education students studying in Kerala, India, who had prior experience with generative AI tools. Data were analyzed using PLS-SEM via Smart PLS 4.1 to assess the reliability, validity, and structural relationships among the constructs.
Results: The study revealed that all the five independent variables significantly influencing on Attitude toward AI use. Both attitude and external variables such as subjective norms, trust, and ethical concerns significantly influencing usage intention.
Conclusion: The study concludes that subjective norms, trust, and ethical concern are key factors of physical education students' intention to adopt AI for academic purposes.



## Keywords

artificial intelligence; physical education; PLS SEM; technology acceptance model



## Resumen

Introducción: El uso de herramientas de IA ha revolucionado los sistemas educativos, pero su adopción en educación física aún está poco explorada.
Objetivo: Este estudio investiga la intención del alumnado de educación física de utilizar la IA con fines académicos mediante un Modelo de Aceptación de Tecnología (TAM) ampliado que incorpora tres constructos adicionales: normas subjetivas, confianza y preocupaciones éticas, para reflejar la naturaleza colaborativa y éticamente sensible de los contextos de aprendizaje de la educación física.
Metodología: Se empleó un diseño de investigación cuantitativo y transversal, y mediante un cuestionario estructurado en línea se recopilaron datos de 392 estudiantes de educación física de pregrado y posgrado de Kerala, India, con experiencia previa en herramientas de IA generativa. Los datos se analizaron mediante PLS-SEM a través de Smart PLS 4.1 para evaluar la fiabilidad, la validez y las relaciones estructurales entre los constructos.
Resultados: El estudio reveló que las cinco variables independientes influyen significativamente en la actitud hacia el uso de la IA. Tanto la actitud como las variables externas, como las normas subjetivas, la confianza y las preocupaciones éticas, influyen significativamente en la intención de uso. Conclusión: El estudio concluye que las normas subjetivas, la confianza y la preocupación ética son factores clave de la intención de los estudiantes de educación física de adoptar IA con fines académicos.



## Palabras clave

inteligencia artificial; educación física; PLS-SEM; modelo de aceptación de la tecnología

## Introduction

AI is changing educational field by offering various tools and services particularly in generative AI tools like Chat GPT. Such technologies provide customized learning experiences and content generation features that allow students to connect with learning materials in more valuable and accessible ways (Pesovski et al., 2024). Although the use of AI for academic purpose has been extensively developed in the science and technology-oriented fields, it remains as a gap in physical education. Compared to other educational domains, AI in physical education is still mostly unexplored. In physical education, where learning focuses on movement and physical performance rather than just cognitive outcomes, the ability of AI to personalize learning, gather data, and provide real-time feedback is very beneficial (Bofill et al., 2025). In this field, AI offers promising opportunities to improve instructional strategies, personalize training, and create engaging technology-enhanced learning environments (Cui et al., 2025). However, the adoption of AI in physical education must be understood in the context of its unique emphasis on kinesthetic, experiential, and collaborative learning environments (Shekerbekova et al., 2025).

For the effective incorporation of AI in physical education environment, it is crucial to identify how physical education students' perception and intention towards use of AI is crucial for academic purposes. The Technology Acceptance Model (TAM) was proposed by (Davis, 1989) is providing a theoretical framework for examining these usage intentions especially related to technology. It relies on two constructs, that are PU and PEOU. PU refers to the perception of user that if he using AI technologies it will improve the effectiveness, efficiency, or performance of their tasks (Kelly et al., 2023), in this study it refers to how students perceive that using AI tools like Chat GPT enhance their academic learning, productivity, or problem-solving capabilities (Almogren et al., 2024). PEOU is the belief of individuals that interacting with an AI system is effort- free, including how easily they can learn, use, and manage the technology without requiring substantial training or technical competence (Kelly et al., 2023). These constructs have proven effective in estimating usage intentions across educational contexts, including AI-enabled learning systems (Mustofa et al., 2025; Saif et al., 2024). PU is associated with improvements in academic outcomes such as content creation and study assistance (Sallam et al., 2024). PEOU relates to the intuitive design and minimal learning curve of AI interfaces like Chat GPT (Noh et al., 2021).

Depending only on the TAM constructs not sufficient to provide complete understanding the intention to use AI among physical education students. To examine this limitation this study extended TAM model by incorporating subjective norms, trust in AI, and ethics concerns as determinants of user acceptance. These three variables are critical determinants of AI adoption in academic contexts, as previous research demonstrated that subjective norms significantly predict actual AI usage, while trust and ethics exert direct positive effects on students' adoption behaviour (Mustofa et al., 2025). These variables are especially relevant in collaborative and morally sensitive domains such as physical education. Subjective Norms refer to the expectations from peers, instructors, or academic communities, that shape usage intention towards a particular technology (Ajzen, 1991). In group-oriented fields like physical education, where peer influence is a central feature of the learning environment, subjective norms can significantly shape usage intention (Ashraf et al., 2025). Social and educational norms within physical education contexts significantly shape teachers' and students' willingness to adopt AI-based learning tolos (Lee and Lee, 2021). Trust in AI systems such as reliability, fairness, and data security is another important determinant of user acceptance, especially when students rely on these systems for academic decision-making (Foroughi et al., 2025; Mustofa et al., 2025). It is an important factor shaping usage intention, without trust students may avoid AI tools even though it has many functional benefits. In physical education setting, teachers' trust in AI systems has a important role in shaping users intention to adopt such technologies (Zha et al, 2025). Ethical concern refers to students' understanding and self-assessment of the ethical consequences in relation with using AI tools like Chat GPT, particularly regarding issues such as academic integrity, plagiarism, misinformation, and user privacy in their educational activities (Acosta-Enriquez et al., 2024). For physical education students, who often integrate digital tools in practical environment, the perceived ethical implications can influence the acceptance and responsible use of AI (Abdulhajar et al., 2024; Mustofa et al., 2025). ChatGPT and other similar AI tools has great potential to enhance learning personalization and instructional efficiency in physical education (Genç, 2024). Therefore, incorporating ethics into the TAM framework is important to understanding students' motivations regarding AI usage for academic purpose in the context of physical education.

Attitude denotes a person's favorable or unfavorable assessment of using a technology such as AI tools like Chat GPT for academic purposes, which significantly mediates the effect of PU and PEOU on usage intention (Alshammari & Babu, 2025). PU positively shapes user attitude toward AI tools like Chat GPT (Alshamy et al., 2025; Sallam et al., 2024) and PEOU also contributes to favorable attitudes, especially among digital-native students (Abdi et al., 2025). Subjective norms as a social influence factor, where perceived peer or instructor endorsement significantly increases students' attitude toward AI usage in learning environment (Wang et al., 2025). Trust in AI's reliability and fairness has emerged as a key determinant of attitude, particularly in education systems where data security and algorithmic transparency are concerns (Foroughi et al., 2025). Ethical concerns can influence attitude both positively and negatively, depending on students' awareness and institutional guidelines (Abdulhajar et al., 2024; Niekerk et al., 2025). All these five independent variables converge to shape students' attitudes, and this attitude mediate their intention to use AI tools for academic purposes (Bunea et al., 2024; Mustofa et al., 2025).

Considering all of these social and moral dimensions are especially relevant for physical education students, whose learning environments emphasize collaboration, physical engagement, and values such as fairness and integrity (Rus & Radu, 2014). This study examines the usage intention of physical education students to use generative AI for academic purposes by applying an extended TAM framework that considers both basic TAM elements and additional influential factors that are trust, ethics, and social norms. Through examining the impact of these factors on usage intention, the research aims to address critical gaps in the literature and offer findings targeted at the unique learning requirements of physical education students. Based on the gap the study formulated following objectives;

a) To examine the effect of PE on physical education students' attitude toward using AI for educational purposes.
b) To investigate the influence of PEOU on students' attitude toward the AI usage for academic purposes.
c) To analyze the impact of subjective norms on students' attitude and usage intention regarding AI tool adoption in physical education.
d) To explore how trust in AI affecting students' attitude toward and intention to use AI for academic purposes.
e) To assess impact of ethical concern on students' attitude toward and intention to adopt AI in physical education learning environments.
f) To evaluate the mediating role of Attitude toward AI use in the relationship between PE, PEOU, subjective norms, trust in AI, and ethical concerns, and students' Usage Intention.

On the basis of the objectives the study proposed the following hypotheses;

H1: PU positively influencing the physical education students' attitude toward using AI for educational purposes.

H2: PEOU positively influencing the physical education students' attitude toward using AI in learning activities.

H3a: Subjective norms have a positive effect on physical education students' attitude toward using AI.

H3b: Subjective norms have a positive effect on physical education students' usage intention toward using AI.

H4a: Trust in AI has a positive effect on physical education students' attitude toward using AI.

H4b: Trust in AI has a positive effect on physical education students' usage intention toward using AI.

H5a: Ethical concerns have an effect on physical education students' attitude toward using AI.

H5b: Ethical concerns have an effect on physical education students' usage intention toward using AI.

H6a: Attitude toward AI use mediates the relationship between PU and usage intention.

H6b: Attitude toward AI use mediates the relationship between PEOU and usage intention.

H6c: Attitude toward AI use mediates the relationship between subjective norms and usage intention.

H6d: Attitude toward AI use mediates the relationship between trust and usage intention.

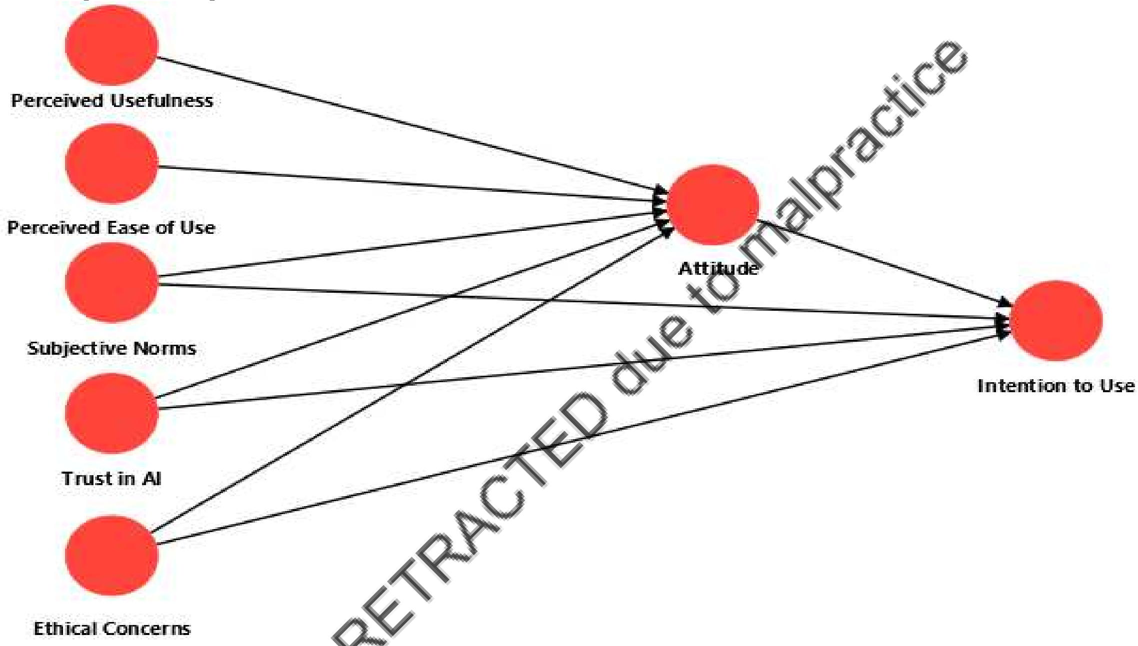
H6e: Attitude toward AI use mediates the relationship between ethical concerns and usage intention.

The findings from the study will be provide educators, policymakers, and AI developers with a view to incorporating AI technologies into physical education curricula responsibly and productively.

## Method

A quantitative, cross-sectional research design was used to determine how students in physical education intend to use AI for educational purposes. Based on the extended Technology Acceptance Model (TAM), this research examines not only the direct effects of PU and PEOU but also integrates Subjective Norms, Trust, and Ethics as key external variables. Critically, the model includes Attitude Toward AI Use as a mediating variable, consistent with second-generation TAM research (Saadé & Bahli, 2005; Venkatesh & Davis, 2000). The study attempts to deliver a deeper understanding of the factors responsible for the adoption of AI in physical education by investigating the direct and indirect links between these constructs and Usage Intention. Based on the hypothetical relationship, the study proposed following model;

Figure 1. Proposed conceptual model






### *Participants*

The participants were recruited based on purposive sampling, a non-probability technique valid when the population is undefined or difficult to count (Etikan, 2016). The population of interest was undergraduate and postgraduate students of physical education in Kerala, India, who had prior experience working with generative AI tools for activity purposes such as assignment writing, feedback generation, or concept explanation. A total of 392 eligible responses were obtained. This sample size is adequate based on the requirements for Partial Least Squares Structural Equation Modeling (PLS-SEM), which suggests a minimum sample size of 10 times the number of structural paths pointing to any latent construct (Hair et al., 2019).

### *Procedure*

Data were collected through a structured questionnaire created using Google Forms. The questionnaire link was circulated through physical education teachers who assisted in reaching undergraduate and postgraduate students enrolled in recognized physical education colleges across Kerala. Only participants who were actively enrolled in UG or PG physical education programs were included in the study, while incomplete responses were excluded from the final dataset. A total of 411 responses were received, of which 392 valid responses were used for further analysis. The participant group consisted solely of students, with 71% male and 29% female respondents, aged between 18 and 25 years. The minimum sample size, as per Cochran's equation (385 at a 95% confidence level for an unknown population), was therefore adequately met (Asenahabi & Ikoha, 2023). Informed consent was obtained before participation, and all responses were completely voluntary and anonymous. Only quantitative findings are presented in this paper.

*Instrument*

The survey was developed using previously tested scales of TAM and its extensions. Items for PU, PEOU, Attitude and Usage Intention were adapted from Davis (1989), while other constructs such as, Subjective Norms, Trust, and Ethics were derived from recent studies focusing on AI in higher education (Abdulhajar et al., 2024; Foroughi et al., 2025; Mustofa et al., 2025). Each construct was carefully adapted to the context of physical education by rephrasing items to reflect AI-supported academic learning and instructional applications. Content relevance was verified through expert consultation with faculty specializing in educational technology and physical education. A questionnaire consists with 35 questions including 7 demographic questions and 7 construct are measured using 4 questions each used for data collection. Every item was measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Before the main study a pilot test was carried out with 30 students to verify clarity and internal consistency of the questionnaire. Expert reviews of faculty members in physical education field were employed to validate content validity. This study consists with 392 undergraduate and postgraduate physical education students aged 18–25 years. Out of this 71% male, and 29% of respondents are female, who enrolled in recognized institutions across Kerala. Respondents represented a balanced mix of universities and colleges from multiple districts, to ensure diversity and representativeness.

### *Data analysis*

Partial Least Squares Structural Equation Modeling (PLS-SEM) with Smart PLS 4.1 was used for analyzing the data (Magno et al., 2024). PLS-SEM was chosen because to its capability to handle advanced models with non-normal data distributions, small to intermediate sample sizes, and latent constructs (Hair et al., 2019). In the initial stage, the measurement model was tested for reliability using Cronbach's alpha, composite reliability, convergent validity based on average variance extracted, and discriminant validity using the Fornell-Larcker criterion and HTMT ratio. In the second stage, the structural model was tested using bootstrapping with 10,000 resamples, path coefficients, and $R^2$ values.

## Results

*Demographic Statistics*

Out of the total 392 respondents, 278 were male (71%) and 114 were female (29%). Regarding educational level, 323 students (82%) were enrolled in undergraduate (UG) programs, while 69 students (18%) were pursuing postgraduate (PG) studies. In terms of daily internet usage, 109 respondents (28%) reported using the internet for less than 2 hours, 243 respondents (62%) used it for 2 to 6 hours, and 40 respondents (10%) used it for more than 6 hours per day.



Table 1. Reliability and Convegent Validity Test Results

| | Cronbach's alpha | rho_a | rho_c | AVE |
|---|---|---|---|---|
| **Attitude** | 0.820 | 0.821 | 0.881 | 0.649 |
| **Ethical Concerns** | 0.755 | 0.763 | 0.844 | 0.574 |
| **Intention to Use** | 0.814 | 0.817 | 0.878 | 0.643 |
| **PEOU** | 0.842 | 0.866 | 0.893 | 0.677 |
| **PU** | 0.864 | 0.870 | 0.907 | 0.709 |
| **Subjective Norms** | 0.849 | 0.858 | 0.898 | 0.689 |
| **Trust in AI** | 0.770 | 0.775 | 0.852 | 0.591 |

*Smart PLS 4 Output*

Table 1 presents the reliability and convergent validity test result for the variables used in the proposed conceptual model based on extended TAM. The reliability of the constructs was evaluated using 2 methods namely, Cronbach's alpha and composite reliability, and convergent validity was assessed using Average Variance Extracted (AVE). Cronbach's alpha values are within the range of 0.755 to 0.864, more than the required value of 0.70 (Hair et al., 2019), showing good internal consistency among the items measuring each construct. In the same way, composite reliability that is rho_a and rho_c values for all constructs exceeded 0.70, which ensure the consistency and reliability of the latent variables.

In terms of convergent validity, all constructs exhibited AVE values above the minimum limit of 0.50, indicating that more than 50% of the variance is explained by the latent variable rather than by measurement error (Fornell & Larcker, 1981). The AVE ranged from 0.574 to 0.709, confirming that the indicators for each construct adequately represent the basic theoretical concept. These results collectively justify the conclusion that the measurement model possesses strong reliability and adequate convergent validity, allowing for valid and reliable structural model assessment in further analysis.

Table 2. Discriminant validity- FORNELL- LARCKER Criterion

| | Attitude | Ethical Concerns | Intention to Use | PEOU | PU | Subjective Norms | Trust in AI |
|---|---|---|---|---|---|---|---|
| **Attitude** | 0.806 | | | | | | |
| **Ethical Concerns** | 0.399 | 0.758 | | | | | |
| **Intention to Use** | 0.550 | 0.463 | 0.802 | | | | |
| **PEOU** | 0.309 | 0.155 | 0.333 | 0.823 | | | |
| **PU** | 0.409 | 0.371 | 0.381 | 0.320 | 0.842 | | |
| **Subjective Norms** | 0.501 | 0.381 | 0.557 | 0.310 | 0.474 | 0.830 | |
| **Trust in AI** | 0.445 | 0.322 | 0.457 | 0.161 | 0.231 | 0.319 | 0.769 |

*Smart PLS 4 Output*

Table 2 demonstrates discriminant validity based on the Fornell–Larcker criterion, as per this criterion square root of the Average Variance Extracted (AVE) for each construct exceeds its inter-construct correlations (Fornell & Larcker, 1981). These results indicate acceptable discriminant validity, confirming that the latent variables measure distinct concepts and supporting the validity of the measurement model for structural analysis.

Table 3. Discriminant validity- HTMT Ratio

| | Attitude | Ethical Concerns | Intention to Use | PEOU | PU | Subjective Norms | Trust in AI |
|---|---|---|---|---|---|---|---|
| **Attitude** | | | | | | | |
| **Ethical Concerns** | 0.492 | | | | | | |
| **Intention to Use** | 0.672 | 0.580 | | | | | |
| **PEOU** | 0.364 | 0.194 | 0.390 | | | | |
| **PU** | 0.482 | 0.452 | 0.451 | 0.371 | | | |
| **Subjective Norms** | 0.597 | 0.470 | 0.667 | 0.359 | 0.548 | | |
| **Trust in AI** | 0.555 | 0.414 | 0.569 | 0.199 | 0.283 | 0.385 | |

*Smart PLS 4 Output*

Table 3 shows discriminant validity assessed using the Heterotrait–Monotrait (HTMT) ratio of correlations. The table clearly shows that all the Heterotrait-Monotrait values are less than 0.85, which means they are within the acceptable limit (Henseler et al., 2015), indicating good discriminant validity. These results confirm there is no discriminant validity issues and it is possible proceed with further analysis.

Table 4. Collinearity test results (Inner Model)

| | VIF |
|---|---|
| Attitude -> Intention to Use | 1.581 |
| Ethical Concerns -> Attitude | 1.297 |
| Ethical Concerns -> Intention to Use | 1.285 |
| PEOU -> Attitude | 1.159 |
| PU -> Attitude | 1.424 |
| Subjective Norms -> Attitude | 1.473 |
| Subjective Norms -> Intention to Use | 1.419 |
| Trust in AI -> Attitude | 1.181 |
| Trust in AI -> Intention to Use | 1.298 |

*Smart PLS 4 Output*

The results of the collinearity test shown in Table 4 reveal that the Variance Inflation Factor (VIF) values for all the predictor variables fall between 1.159 and 1.581. Since these values are well below the commonly accepted threshold of 5, it means that there is no serious multicollinearity problem among the variables (Hair et al., 2019). Specifically, the relationships between ethical concerns, PEOU, PU, subjective norms, trust in AI, attitude, and intention to use AI show low collinearity, supporting the robustness of the structural model analyzed via Smart PLS 4 (Sarstedt et al., 2020).

Table 5. $R^2$ Results

| | R-square | R-square adjusted |
|---|---|---|
| Attitude | 0.398 | 0.394 |
| Intention to Use | 0.476 | 0.472 |

*Smart PLS 4 Output*

The R-square values in Table 5 indicate that the model explains 39.8% of the variance in attitude towards AI usage and 47.6% of the variance in intention to use AI for academic purpose. These moderate values suggest the predictors provide a meaningful explanation of students' attitudes and their intention to adopt AI technologies, reflecting a good model fit in behavioural research contexts (Cohen, 1988).

Table 6. $f^2$ Results

| | Attitude | Intention to Use |
|---|---|---|
| Attitude | | 0.067 |
| Ethical Concerns | 0.028 | 0.054 |
| Intention to Use | | |
| Perceived Ease of Use | 0.021 | |
| Perceived Usefulness | 0.020 | |
| Subjective Norms | 0.077 | 0.125 |
| Trust in AI | 0.099 | 0.055 |

*Smart PLS 4 Output*

From table 6 showing effect size ($f^2$) that explains how much each independent construct contributes to explaining the dependent construct when it is included in the model. It measures a predictor's incremental impact on $R^2$. The recommended cut-off values for $f^2$ are 0.02, 0.15, and 0.35 for small, medium, and large effect sizes respectively (Guenther et al., 2023). All the values below 0.15 means all contrcust has small effect sizes. Trust in AI and Subjective Norms show relatively higher influence on Attitude, while Subjective Norms has the strongest effect on Intention to Use.



Table 7. Path Analysis

| | Path Coefficient | Standard deviation | T statistics | P values |
|---|---|---|---|---|
| Attitude -> Intention to Use | 0.236 | 0.047 | 5.036 | 0.000 |
| Ethical Concerns -> Attitude | 0.147 | 0.054 | 2.727 | 0.003 |
| Ethical Concerns -> Intention to Use | 0.190 | 0.051 | 3.749 | 0.000 |
| PEOU -> Attitude | 0.121 | 0.042 | 2.852 | 0.002 |
| PU -> Attitude | 0.131 | 0.051 | 2.549 | 0.005 |
| Subjective Norms -> Attitude | 0.261 | 0.058 | 4.472 | 0.000 |
| Subjective Norms -> Intention to Use | 0.305 | 0.058 | 5.296 | 0.000 |
| Trust in AI -> Attitude | 0.265 | 0.048 | 5.578 | 0.000 |
| Trust in AI -> Intention to Use | 0.193 | 0.045 | 4.274 | 0.000 |

*Smart PLS 4 Output*

Figure 2. Path diagram with R square value

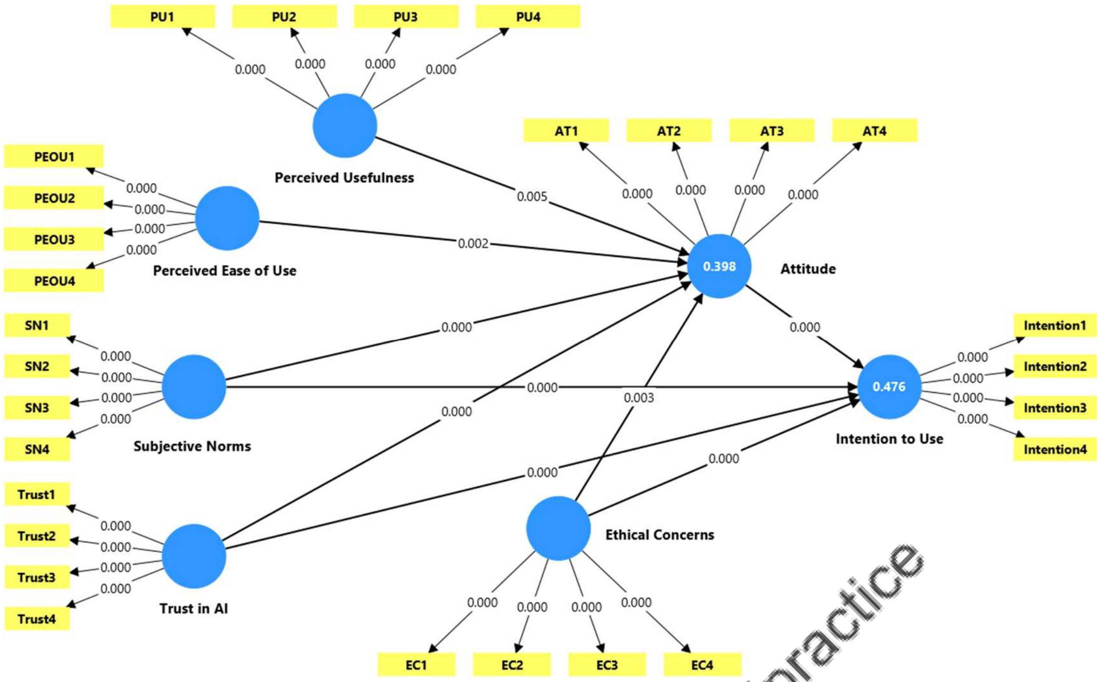





Table 7 demonstrates path analysis results that confirm that all proposed relationships in the extended TAM model are statistically significant because all the P values are less than 0.05 which means alternatives hypothesis H1, H2, H3a, H3b, H4a, H4b, H5a and H5b are accepted at 95% confidence level. Favourable attitude toward AI use significantly influences physical education students' intention to use AI for educational purposes. Trust in AI, subjective norms, ethical concerns, PU, and PEOU all have significant positive effects on physical education students' attitudes toward AI. Subjective norms, trust in AI, and ethical concerns also exhibit direct, positive effects on the intention to use AI. Students' attitudes and intentions regarding AI use are significantly shaped by both subjective norms and their trust in AI. This suggests that the endorsement of AI in physical education is heavily dependent on the support provided by educators, fellow students, and educational institutions, as well as on students' confidence in the precision and dependability of AI applications. These findings demonstrate that both attitude and external factors independently contribute to students' intention to adopt AI tools in physical education learning environment.

Table 8. Specific indirect effect

| | Path Coefficient | Standard deviation | T statistics | P values |
|---|---|---|---|---|
| **Ethical Concerns -> Attitude -> Intention to Use** | 0.035 | 0.016 | 2.193 | 0.014 |
| **PEOU -> Attitude -> Intention to Use** | 0.029 | 0.012 | 2.417 | 0.008 |
| **PU -> Attitude -> Intention to Use** | 0.031 | 0.014 | 2.195 | 0.014 |
| **Subjective Norms -> Attitude -> Intention to Use** | 0.061 | 0.017 | 3.559 | 0.000 |
| **Trust in AI -> Attitude -> Intention to Use** | 0.062 | 0.018 | 3.555 | 0.000 |

*Smart PLS 4 Output*

The mediation results from table 8 indicate that attitude toward AI use partially mediates the relationships between all five antecedent variables and students' intention to use AI. Specifically, the indirect effects of ethical concerns, PEOU, PU, subjective norms, and trust in AI on intention to use AI through attitude are all statistically significant and from table 7 it is clear that the direct relationship between these variables are also significant, which means there exists partial mediation.

## Discussion

This study explored the intention of physical education students in Kerala, India, to use generative AI tools such as Chat GPT for academic purposes by applying Technology Acceptance Model (TAM) by incorporating three addition variables. In addition to the traditional TAM variables that is PU and PEOU, the model incorporated trust, ethical concerns, and subjective norms to better reflect the unique sociocultural and pedagogical dynamics of physical education.

Attitude toward AI use is significant mediator across all constructs. The indirect pathways from PU, PEOU, trust, ethical concerns, and subjective norms to usage intention through attitude were all are statistically significant. This confirms the mediating role of attitude in TAM model as a central factor in the behavioural intention to adopt technology (Venkatesh & Davis, 2000).

Subjective norm is the factor which have strongest influence on students' intention to AI for academic purpose and also significantly shape their attitudes. This highlights the important role of social factors in physical education learning environments. Students are often influenced by their friends are peer group behaviour, the expectations set by their teachers and other social factors. The results are consistent with previous findings that social influence significantly shapes AI tool adoption, especially in group based or culturally collectivist educational contexts (Ashraf et al., 2025).

Trust is also has major role in influencing of both Attitude and Intention to Use which is supported by findings from (Foroughi et al., 2025; Mustofa et al., 2025). Students who viewed AI tools as fair, secure, and reliable were more likely to express intent to use them. In the context of physical education, where many learning tasks involve peer evaluations and performance monitoring, trust in algorithmic feedback mechanisms may be especially critical.

While PU and PEOU had relatively lower coefficients compared to subjective norms and trust, their effects were still statistically significant. These findings support (Davis, 1989) original TAM proposition that these two constructs are core predictors of technology adoption. Importantly, their indirect effects through attitude on usage intention further validate their inclusion in the extended model.

Ethical concerns positively influenced both Attitude and Usage Intention suggesting informed understanding among students. Rather than acting as deterrents, awareness of ethical challenges may prompt more responsible and intentional use. This aligns with the findings of (Abdulhajar et al., 2024)who argue that ethical literacy in AI use may promote rather than inhibit adoption when accompanied by sufficient guidance and institutional trust.

Despite these useful insights, several limitations need to be acknowledged. First, due to data collection with the help of self-report questionnaires, response biases or social desirability effects might be a factor in the results and may make students report exaggerated positive attitudes toward AI use. Second, since the investigation was conducted among only physical education students in Kerala, it represents a specific cultural, institutional, and technological context. Thus, the results may not be generalized to other regions or different educational systems with distinct digital infrastructures or pedagogical traditions. Third, the investigation relied solely on quantitative methods; including qualitative ones, such as interviews or focus groups, could be used to better capture the 'lived' experience of students and contextual nuances around AI adoption.

Based on practical implications, this study puts forward some actionable strategies that educators and educational technologists could take. Institutions should emphasize building students' trust in AI tools through transparent communication about data use and aspects of the tools' reliability and fairness. Ethics-focused modules can be integrated within teacher education and physical education curricula to advocate for responsible AI literacy. Positive subjective norms may also be encouraged when educators model appropriate AI use and embed the generative AI tool Chat GPT into collaborative learning activities. Lastly, policy makers and technology developers should guarantee that AI applications within education align with ethical standards that respect the human-centeredness of learning processes in physical education.

## Conclusions

This study used a quantitative approach and cross-sectional research design to understand how different factors affect the intention of physical education students to use AI tools for academic purposes. The factors examined include PU, PEOU, trust in AI, ethical concerns, and subjective norms. The study collect data from students in Kerala, India and analysed using PLS SEM. This study confirms the extended TAM model in predicting physical education students' intention to use AI tools, including Chat GPT, for education. Subjective norms, trust, ethics, PU, and PEOU significantly influence on both attitudes and usage intentions. Attitude is a consistent and significant mediator across all relationships, reinforcing its central role in technology acceptance models.

By focusing on factors such as trust and ethical concerns, the study moves beyond the conventional function-oriented acceptance models and acknowledges the socio-ethical complexities involved in physical education contexts. The findings encourage educational institutions to adopt a holistic approach to AI integration, one that promotes not only usability but also trustworthiness, ethical engagement, and peer-driven support structures.

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