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Impact of intelligent tutoring on emotion and academic performance of systems engineering students at the national university of central Peru

Kevin Taype Soriano[a], Miguel Fernando Inga-Avila[a*] and Roberto Líder Churampi-Cangalaya[a]

[a]*Universidad Nacional del Centro del Perú, Peru*

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This paper investigates the impact and implementation of Intelligent Tutoring Systems (ITS) on enhancing educational outcomes for engineering students at the Universidad Nacional del Centro del Perú. The model emphasizes the role of ITS in improving academic achievement, student satisfaction, and engagement, considering critical dimensions like emotional attitude, cognitive receptivity, and reflective strategy. Using SmartPLS for data analysis and an application developed in Flutter, the study demonstrates that ITS can positively influence student emotion and performance. Reliability metrics confirm robustness, with Cronbach's alpha values between 0.76 and 0.876 and AVE scores above 0.7. Predictive power is supported by R-squared values of 0.746 for student emotion and 0.723 for ITS impact on academic performance. Path coefficients underscore significant relationships, such as ITS influence on emotional engagement (0.549) and academic satisfaction (0.384). Findings suggest that integrating ITS with emotional and cognitive dimensions can foster higher academic satisfaction and achievement.

1. Introduction

The tutoring program at the Universidad Nacional del Centro del Perú (UNCP) faces significant challenges due to a lack of student interest and the difficulties tutors experience in fostering positive changes and sustained support among students. Low engagement rates and limited interactive feedback hinder the effectiveness of tutoring sessions, resulting in minimal long-term academic and emotional support for students (Lawson et al., 2021; Katz et al., 2021). Despite the recognized potential of tutoring programs to enhance educational outcomes, current practices often lack consistent mechanisms for capturing and addressing student needs in real-time, leading to a gap between the intended educational goals and student experiences (Shuo et al., 2020; Clancey & Hoffman., 2021). These challenges are compounded by a broader issue in Latin America, where educational systems struggle to provide equitable and effective learning experiences. Peruvian students often enter higher education with insufficient preparation, as indicated by low scores on international assessments like PISA, reflecting both academic and motivational barriers (Serrano et al., 2023). The absence of data-driven approaches in tutoring further limits the potential for personalized intervention, hindering the use of AI and predictive analytics to monitor and support students' academic and emotional development in real-time (Rodriguez et al., 2020; Kochmar et al., 2022). To address these issues, this study proposes a model that leverages Intelligent Tutoring Systems (ITS) combined with emotional and cognitive dimensions to bridge the engagement gap in tutoring. By incorporating AI-driven data analytics, the model aims to provide continuous, personalized support, addressing both academic and emotional needs to enhance student satisfaction and academic achievement (Zhang & Begum, 2021). The integration of ITS allows for real-time feedback, helping tutors to adaptively engage students, ultimately fostering an emotionally supportive learning environment conducive to academic success (Taub et al., 2021; Rodríguez et al., 2022, 2023).

* Corresponding author
E-mail address miguelinga@uncp.edu.pe (M. F. Inga-Avila)

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2. Methodology

This study adopts a quasi-experimental design, using an existing dataset to develop a predictive model aimed at improving academic performance in the Faculty of Systems Engineering at UNCP. The dataset includes tutoring records, tutor evaluation records, tutor evaluation records, grades, and academic averages (Schmitt, 2023).

2.1 Data collection

Academic Records:

Academic records were used to collect data on indicators of student performance, including academic achievement, pass rates, and GPA. These indicators are essential for assessing academic outcomes in relation to tutoring, as they reflect the direct impact of academic support on student success (Katz et al., 2021). Each indicator is normalized on a scale from 0.0 to 1.0, providing a quantifiable measure of academic progress aligned with prior studies highlighting the importance of academic monitoring in tutoring contexts (Torshizi & Bahraman, 2019; Veeramanickam et al., 2023).

Tutoring Session Logs:

Consistent with findings that student engagement in structured tutoring contributes significantly to academic and emotional growth, tutoring session logs provided data on student-tutor interactions across dimensions such as emotional attitude and receptivity (Lawson et al., 2021; Taub et al., 2021). Tutors evaluated students on indicators like attendance, punctuality, and engagement in the tutoring process. Additionally, these logs enabled measurement of the "student model" dimension by capturing information on self-reflection and reflection processes (Castro-Schez et al., 2021). Scored on a scale of 0.0 to 1.0, these logs were critical for assessing real-time student responsiveness and the tutor's ability to foster positive change.

Tutoring Evaluation Sheets:

To assess the overall quality and effectiveness of tutoring, evaluation sheets were used to collect data on key indicators. Supporting the "interface model" dimension, these sheets recorded students' alignment with the learning methodology and their learning strategies (Matsuda et al., 2020). Additionally, to substantiate the "learning satisfaction" dimension (Sychev, 2024), indicators such as attentive listening, topics of student interest, and experiential learning were considered. This approach, with each aspect scored on a scale from 0.0 to 1.0, enabled a structured evaluation of the tutoring impact on student satisfaction, reinforcing the role of qualitative feedback in the continuous improvement of tutoring programs (Shuo et al., 2020; Kim & Kim, 2020).

Tutor Evaluation Forms:

Tutor evaluations collected data on key indicators, including the work plan and tutoring plan, to substantiate the "tutoring model" dimension. Additionally, indicators such as scheduled changes, clear learning feedback, and punctual sessions were used to support the "academic achievement" dimension (Hardt et al., 2023). This evaluation, scored similarly to other components on a 0.0 to 1.0 scale, provided essential insights into the tutor's effectiveness in meeting academic and emotional needs. These findings reinforced the alignment of the tutoring process with students' educational objectives, underlining the importance of structured tutor-student interactions for positive learning outcomes (Woo-Hyun & Jong-Hwan, 2020).

2.2 Data analysis and model development

1. Framework: The model was developed using the Scrum methodology, facilitating iterative progress and continuous feedback. This agile approach is well-suited to educational settings, promoting adaptive learning and collaborative feedback mechanisms, which are essential for enhancing student engagement and support (Jianfeng et al., 2020).
2. Technologies:
- Front-End: Flutter was selected for its efficiency in creating user-friendly interfaces that facilitate seamless interactions for both students and instructors. Its ability to deliver a consistent and engaging user experience is critical in educational applications (Bhangale et al., 2021; Aziz et al., 2022).
- Back-End: The model relies solely on Flutter for application development, eliminating the need for Python. This streamlined approach enhances application performance and user interaction while simplifying the development process (De Barros et al., 2023; Bhangale et al., 2021).
3. Steps:
- Data Preparation: The dataset was meticulously prepared to ensure consistency and accuracy in the information gathered from academic records, tutoring logs, and evaluations.
- Model Development: Rather than using machine learning for predictions, the focus shifted towards building an analytical framework that integrates student feedback and performance data (Guenther et al., 2023). This framework is designed to assess and improve tutoring effectiveness based on real-time input from both students and tutors.

- Validation: The model's reliability was assessed through the collection of qualitative feedback from tutoring sessions, ensuring that the insights gained align with the educational goals of enhancing student performance and satisfaction (Huybrechts et al., 2023).
- Evaluation: Instead of utilizing a confusion matrix, the evaluation process now emphasizes qualitative metrics such as student satisfaction ratings and engagement levels, ensuring a comprehensive understanding of the tutoring program's impact.

2.3 Implementation

The model guides tutoring strategies and interventions to improve students' academic performance, emotional engagement, and academic satisfaction, aligning with the overarching goal of enhancing educational quality (Schmitt, 2023). In recognizing that thought experimentation can lead to a deeper and more lasting understanding of the material, students are encouraged to propose their own tutoring topics, fostering a more engaging learning environment (Guenther et al., 2023). Furthermore, the implementation of artificial intelligence tools must consider ethical aspects, particularly regarding privacy, equity, and student rights. This approach advocates for a holistic model that weighs both the benefits and potential risks associated with the use of AI in educational contexts (Tsai et al., 2020; Hardt et al., 2023; Huybrechts et al., 2023).

2.4 Evaluation

The effectiveness of the implemented model is evaluated in terms of its impact on educational outcomes and student engagement. While traditional predictive accuracy measures like confusion matrices are not utilized, the focus remains on qualitative assessments, ensuring that the developed model aligns with real-world educational needs (Woo-Hyun & Jong-Hwan, 2020; Veeramanickam et al., 2023). This methodology allows for a comprehensive approach to harness AI for educational improvement while addressing existing deficiencies in the tutoring program (Matsuda et al., 2020; Taub et al., 2021). To measure the relationships between different variables effectively, advanced modeling techniques in PLS-SEM (Partial Least Squares Structural Equation Modeling) are employed. This approach provides a deeper understanding of the interactions within the data, enhancing the robustness and validity of the results (Aziz et al., 2022). By utilizing SmartPLS, the study aims to establish meaningful connections between emotional engagement, academic performance, and the effectiveness of tutoring interventions. This comprehensive evaluation strategy ultimately contributes to the overall improvement of educational quality within the tutoring program (Shuo et al., 2020).

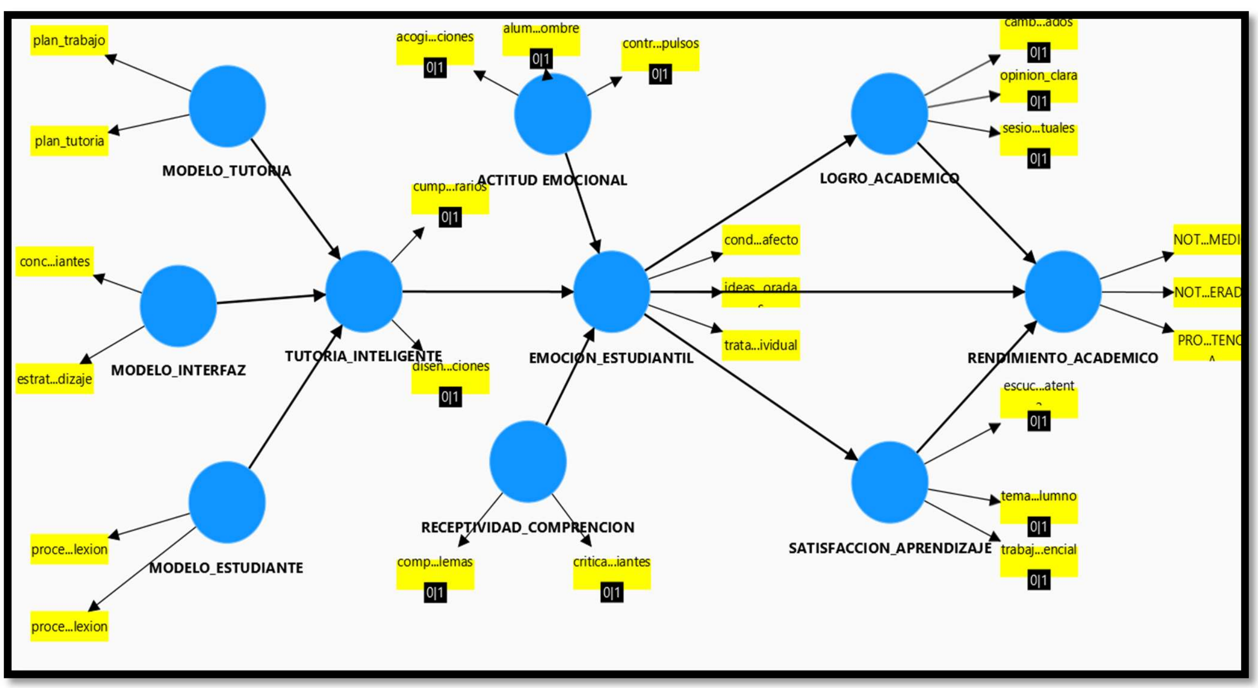

Fig. 1. The proposed study

In the SmartPLS model, the intelligent tutoring variable is assessed through the indicators of "schedule adherence" and "session design," structured into three dimensions: tutoring model (indicators: "work plan," "tutoring plan"), student model (indicators: "self-reflection process," "reflection process"), and interface model (indicators: "student alignment," "facilitating learning strategies"). An intermediate variable is introduced, including indicators for "affective behavior" and "individual treatment," divided into emotional attitude (indicators: "impulse control," "emotion acceptance") and receptivity and comprehension (indicators: "problem understanding," "student critique"). The dependent variable of academic performance is measured through "average grade," "weighted average," and "pass rate," divided into academic achievement (indicators: "timely sessions," "clear understanding of sessions") and learning satisfaction (indicators: "active listening," "student interest topics," "experiential work"). This model explores the relationships between the quality of intelligent tutoring and academic performance, mediated by emotional and behavioral factors of the student.

3. Results

The study conducted a comprehensive analysis using SmartPLS to evaluate the relationships between various dimensions of intelligent tutoring, including the tutoring model, interface model, student model, learning preferences, and academic performance. The analysis focused on understanding how these constructs interact to enhance student engagement and educational outcomes.

3.1 Validity and Reliability

Table 1 displays the results of reliability and construct validity metrics for each dimension analyzed in the study. Cronbach's Alpha values for all dimensions are above 0.7, suggesting high internal consistency among the items within each construct. Additionally, composite reliability values (rho_a and rho_c) exceed 0.8, indicating that the constructs consistently measure the theoretical aspects they represent. The average variance extracted (AVE) for all dimensions is over 0.7, confirming high convergent validity for each dimension. This suggests that the items composing each construct adequately reflect the concepts they aim to represent.

Table 1
Reliability and Validity Indicators

Dimension	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Emotional Attitude	0.843	0.848	0.905	0.761
Student Emotion	0.815	0.818	0.89	0.73
Student Model	0.855	0.874	0.932	0.872
Tutoring Model	0.876	0.876	0.942	0.89
Interface Model	0.76	0.768	0.892	0.806
Academic Achievement	0.843	0.845	0.905	0.761
Receptivity Comprehension	0.804	0.807	0.91	0.835
Academic Performance	0.826	0.825	0.9	0.753
Learning Satisfaction	0.831	0.835	0.898	0.747
Intelligent Tutoring	0.826	0.827	0.92	0.852

3.2 Model Fit and R-squared values

The R-square and adjusted R-square values in Table 2 assess the explanatory power of the structural models. Student Emotion has an R-square of 0.746, indicating that the model explains 74.6% of the variance in this variable. Similarly, Learning Satisfaction and Intelligent Tutoring show high R-square values (0.740 and 0.723, respectively), demonstrating that a large proportion of the variance in these dimensions can be explained by the associated constructs. However, Academic Performance has a low R-square value (0.057), suggesting that additional factors may influence this outcome.

Table 2
R-squared values

Dimension	R-Square	R-Square Adjusted
Student Emotion	0.746	0.738
Academic Achievement	0.486	0.481
Academic Performance	0.057	0.027
Learning Satisfaction	0.74	0.738
Intelligent Tutoring	0.723	0.714

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3.3 Path Coefficients and total effects

Table 3 presents the coefficients of the structural relationships between constructs in the model. The strongest relationship is observed between Emotional Attitude and Student Emotion (coefficient of 0.857), indicating that a change in students' emotional attitude has a significant impact on their emotions in the academic environment. A positive relationship is also notable between Student Emotion and Learning Satisfaction (0.384) and between Academic Achievement and Academic Performance (0.365), suggesting that academic achievement positively contributes to overall performance. The negative relationship between Learning Satisfaction and Academic Performance (-1.172) is atypical, suggesting that external or mediating effects might be affecting this relationship.

Table 3
Route Coefficients

Relationship	Path Coefficient
Emotional Attitude → Student Emotion	0.857
Student Emotion → Academic Achievement	0.309
Student Emotion → Academic Performance	0.323
Student Emotion → Learning Satisfaction	0.384
Student Model → Intelligent Tutoring	0.235
Tutoring Model → Intelligent Tutoring	0.092
Interface Model → Intelligent Tutoring	0.102
Academic Achievement → Academic Performance	0.365
Receptivity Comprehension → Student Emotion	0.695
Learning Satisfaction → Academic Performance	-1.172
Intelligent Tutoring → Student Emotion	0.549

3.4 Reliability

Table 5 shows the results of the Cramér-von Mises test, which evaluates the fit of the data to the expected theoretical distributions. The test statistic values are significant ($p < 0.05$) for all dimensions except Academic Performance, indicating that most dimensions do not follow a strict normal distribution. This result is significant because it justifies using analytical methods that do not assume normality in the data. The Academic Performance dimension is the only one with a p-value of 0.024, showing a closer approximation to normality than the other dimensions.

Table 5
The results of the p-value

Dimension	Cramér-von Mises Test Statistic	Cramér-von Mises p-value
Emotional Attitude	2.685	0.000
Student Emotion	1.659	0.000
Student Model	2.593	0.000
Tutoring Model	2.616	0.000
Interface Model	2.31	0.000
Academic Achievement	2.494	0.000
Receptivity Comprehension	3.032	0.000
Academic Performance	0.149	0.024
Learning Satisfaction	2.253	0.000
Intelligent Tutoring	3.062	0.000

5. Discussion and results

The results illustrate, through path coefficients of 0.857 and 0.384, the positive relationship that emotional attitude has with intelligent tutoring and learning satisfaction. These findings indicate that a supportive emotional environment significantly enhances both intelligent tutoring experiences and overall student satisfaction. Consequently, we conclude that the relationship between academic engagement and learning outcomes is positively influenced by emotional support, adaptability to individual needs, and student involvement, aligning with Chevalere's (2020) insights on the role of emotions in fostering engagement in learning. Moreover, this study highlights significant enhancements in educational results through the implementation of an AI-driven intelligent tutoring model, reflecting the trends identified by Zhang and Aslan (2020). Our findings extend previous research by providing empirical evidence of AI's effectiveness in enhancing academic performance, thus validating observed trends, particularly in the realms of student profiling and learning analytics as highlighted by Guan et al. (2021).

To support the learning satisfaction dimension, we observed a path coefficient of 0.384 in the relationship between intelligent tutoring and learning satisfaction. This indicates a robust positive connection that correlates with improved academic outcomes, resonating with Mayer's (2019) assertions regarding effective learning environments. Furthermore, the emphasis on personalized learning experiences, reflected in various indicators, alongside performance evaluations, has aided in identifying areas where AI interventions can significantly enhance the learning experience (Chong et al., 2021).

In terms of the emotional attitude dimension, the R-Squared value of 0.746 indicates substantial explanatory power. The path coefficients related to intelligent tutoring, student emotion, and learning satisfaction are 0.235, 0.857, and 0.549 respectively. These values suggest improvements in emotional support and satisfaction, corroborating the findings of Jeon et al. (2022).

The findings of this study underscore the significance of implementing intelligent tutoring systems to improve the academic performance of systems engineering students, especially when these systems consider emotional and satisfaction-related factors. The analysis, based on PLS-SEM models, reveals a significant correlation between personalized learning and increased student engagement and satisfaction. This trend is consistent with previous research exploring the relationship between adaptive learning and academic performance in advanced educational settings (Chen et al., 2020; Li & Zhao, 2021).

Firstly, it is confirmed that students who experience greater emotional support and personalization in their learning process tend to be more engaged and satisfied. This aligns with studies by Chen and Li (2020), who observed a substantial improvement in motivation and performance when emotionally sensitive tutoring tools were applied to university students. This result also resonates with the findings of Veeramanickam and Manisha (2023), highlighting the positive role of intelligent tutoring systems in increasing participation and reducing dropout rates in high-difficulty courses.

Furthermore, the results of this study emphasize that emotional and learning satisfaction dimensions directly impact academic performance, a finding supported by the work of Sychev (2024). They observed that students with higher classroom satisfaction achieved higher academic averages. In our analysis, this learning satisfaction shows a moderate yet significant relationship with performance, underscoring the need for tutoring systems to adapt not only to knowledge and skills but also to students' emotional needs.

The application of the Cramér-von Mises test to adjust the model also yielded results that support the importance of personalization in learning. This aligns with the personalized approach studied by Shuo et al (2020), who found that students experiencing content adaptations and academic recommendations tailored to their learning style displayed higher engagement and satisfaction.

Moreover, recent studies in artificial intelligence in education highlight the relevance of expert systems and personalization algorithms in enhancing the effectiveness of learning processes. For instance, Katz et al (2021) analyzed intelligent tutoring systems in higher education and concluded that, by integrating AI and students' individual preferences, these systems could predict and adjust content to meet each student's needs, resulting in improved academic outcomes. This is consistent with our study’s findings, where AI-driven personalization showed a positive effect on performance.

Finally, the analysis of the effects of reliability and validity indicators, with path coefficients and total effects, indicates that not only are satisfaction and emotional support essential for enhancing performance, but also that integrating AI in education can foster a much more efficient and effective learning environment. This supports the perspectives of researchers such as Taub et al (2020) and Clancey et al (2020), who argue that AI enables a more holistic and student-centered approach, thereby promoting a more sustainable and needs-based academic development.

6. Conclusion

This study aimed to examine key factors influencing academic achievement, student satisfaction, and the role of intelligent tutoring systems, focusing on constructs such as emotional attitude, reflective strategies, and comprehension receptivity. The findings reveal significant relationships across several dimensions, supporting the proposed model and underscoring the importance of emotional and cognitive factors in educational outcomes.

- Reliability and validity: All constructs achieved high internal consistency, with Cronbach's alpha values ranging from 0.76 to 0.876 (Table 1). Composite reliability scores were similarly robust, confirming the reliability of the scales used. The Average Variance Extracted (AVE) scores also demonstrate strong construct validity, with values above 0.7 across dimensions. These results confirm that the constructs are well-defined and reliable, indicating that the model can accurately capture the complex relationships between student emotions, academic performance, and satisfaction.
- Predictive Power and R-Squared Values: The R-squared values (Table 2) for key outcome variables—student emotion, academic achievement, and intelligent tutoring—suggest that the model effectively explains a substantial portion of the variance in these dimensions. For instance, student emotion had an R-squared value of 0.746, while intelligent tutoring reached 0.723. The adjusted R-squared values indicate a minimal reduction in predictive power when accounting for the number of predictors, reinforcing the model's reliability and its applicability to diverse educational contexts.
- Path Coefficients and Relationships Among Constructs: The path analysis (Table 3) highlights critical relationships, such as the influence of emotional attitude on student emotion (0.857), the positive effect of student emotion on both academic achievement (0.309) and satisfaction with learning (0.384), and the link between comprehension receptivity and student emotion (0.695). Notably, intelligent tutoring significantly influences student emotion (0.549), confirming its role in enhancing affective and cognitive engagement. These insights emphasize that emotional and motivational dimensions are key to fostering improved academic outcomes and suggest that incorporating intelligent tutoring can support student satisfaction and engagement.

In summary, the results underscore the importance of integrating emotional, cognitive, and reflective dimensions within intelligent tutoring systems to maximize student satisfaction, learning outcomes, and engagement. Future work should focus on further refining intelligent tutoring strategies that target emotional engagement and academic achievement, especially in adaptive systems that cater to varied student profiles.

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