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Accessing the Impact of Autonomous Robotic Software for Students' Academic Performance Prediction in Tertiary Education Using TAM

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Abstract

In recent years, artificial intelligence (AI) has gained significant attention in education for its potential to enhance learning, teaching and performance evaluations. However, despite existing studies on student performance analytics and prediction, 99% of their works have focused on other branches of AI such as Natural Language Processing, Deep Learning, Reinforcement Learning and Machine Learning. This gap highlights the need for an autonomous AI-driven framework that combines predictive modeling with behavioral analysis for effective educational outcomes via Robotics. The primary aim of this study is to design an AI Robotic Autonomous Students' Academic Performance Prediction System based on the Technology Acceptance Model (TAM), focusing on constructs such as Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Behavioral Intention to Use (BI), and Actual System Use (ASU). The methodology adopted a three-phase approach involving a comprehensive literature review, framework formulation, and architectural design using EdrawMax. The key contribution of this research lies in designing a schematic and autonomous architecture that integrates AI-based decision intelligence with educational robotics for continuous monitoring and adaptive prediction. The system's architecture enables real-time data analysis and performance tracking, offering valuable insights for academic planners and educators. It is recommended that future implementations can incorporate large datasets and IoT-enabled learning environments to improve scalability and adaptability. Also, employing a hybrid ensemble of Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN) algorithms to enhance prediction accuracy and ensure model reliability is recommended.

***Keywords*:** Autonomous Robotics, Perceived Ease of Use, Perceived Usefulness, Behavioral Intention to Use, Actual System Use

INTRODUCTION

Quality education is essential as it lays the foundation for social and societal equality. Equally important is the commitment of educational institutions to monitor and enhance the academic performance of every student Karim-Abdallah *et al*., (2025). Predicting student academic performance has gained significant attention in the education sector. However, while learning outcomes are recognized as vital for enhancing both teaching and learning, predicting students' achievements of these outcomes is still relatively underexplored Namoun, A., & Alshanqiti, (2020). Student retention poses a major challenge for higher education institutions (HEIs). Since a significant proportion of university dropouts result from academic underperformance, institutions are increasingly motivated to develop learning analytics tools that leverage predictive models of academic success. However, the scalability of these models remains constrained, as students' performance, engagement, and the factors affecting them are highly dependent on the specific educational context Quimiz-Moreira *et al*., (2025).

The incorporation of Artificial Intelligence (AI) into educational systems holds great potential to revolutionize academic practices while fostering sustainability and long-term improvement in the education sector López-Zambrano *et al*., (2021). University students frequently encounter challenges in balancing academic responsibilities, including difficulties in time management, task prioritization, and the adoption of effective study strategies Stasolla *et al*., (2025). Determining the critical factors that influence students' academic performance is essential for improving the teaching and learning process. Artificial intelligence (AI) techniques hold great promise in this domain, fostering a new era of innovation in education. Nonetheless, despite significant advancements, there is still considerable debate regarding the most suitable machine learning model for accurately predicting student performance trends Bressane *et al*., (2022).

Robotics has evolved into a transformative and interdisciplinary field that bridges engineering, computer science, and cognitive sciences. This state-of-the-art review examines the latest advancements, prevailing methodologies, and key challenges shaping contemporary robotics research and education. It highlights how innovations in artificial intelligence, machine learning, and human-robot interaction are redefining automation, learning environments, and skill development, ultimately driving the integration of robotics into diverse academic and industrial domains Nnadi *et al*., (2024).

Robots are intelligent systems capable of autonomously executing complex sequences of actions, primarily powered by computer programs and machine learning algorithms. In the educational context, robots are purposefully designed to facilitate teaching and learning, fostering learners' interest in science, technology, engineering, arts, and mathematics (STEAM) Ryalat *et al*., (2025). The recent integration of humanized robots into educational settings holds transformative potential for enhancing teaching and learning experiences. However, for their effective adoption, it is crucial to identify and address the educational and human-centric challenges associated with their implementation, such as ethical considerations, emotional interaction, and adaptability to diverse learning environments You *et al*., (2025).

A. Prediction of Students' Academic Performance

This section reviews the key related studies focused on predicting students' academic performance. Models for predicting students' academic performance can be categorized as those applied in blended learning environments.

B. On-Campus Learning Environments

The early prediction of students' learning performance using data mining techniques has become an increasingly important research topic in recent years (Ngulube, 2025 and Ali & Butt, 2025). Their studies utilized supervised machine learning algorithms to identify factors that adversely affect academic performance among college students. The most frequently used predictive algorithms included J48, Random Forest, Support Vector Machine (SVM), and Naïve Bayes for classification tasks, as well as logistic and linear regression for regression analysis. The findings revealed that the key factors influencing early prediction were linked to student assessments, interactions within Learning Management Systems (LMS), duration of study at the university, and prior academic performance in assessing students who were at risk.

In a study by Ahmed, (2025), the author tried to predict students' overall academic performance at the end of the semester by employing video learning analytics combined with data mining techniques. The study further highlighted that the CN2 Rule Inducer and multivariate projection methods could help faculty members interpret the generated rules to better understand student interaction patterns. The findings revealed that the Random Forest algorithm achieved an accuracy of 88.3% in predicting successful students, utilizing both equal-width discretization and the information gain ratio.

Alnaqeeb *et* al., (2025) introduced a hybrid model that integrates Linear Regression and K-Means Clustering to predict students' academic performance. The Linear Regression component demonstrated strong predictive capability, achieving an R^2 of 0.9842, a Mean Squared Error (MSE) of 0.00077, and an F-statistic of 10,448.24. Similarly, the Clustering model yielded favorable results, with between-cluster error, within-group error, and variance values of 462.27, 197.12, and 0.70, respectively. Overall, the proposed hybrid approach exhibited significantly enhanced performance, with the analysis confirming that the ensemble model delivers superior prediction accuracy.

In a study by Abulail *et al*., (2025), five machine learning algorithms were employed Random Forest (RF), Gradient Boosted Regression Tree (GBRT), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost). The results demonstrate that AugmentED effectively predicts academic performance with high accuracy. Moreover, the performance of the five algorithms (RF*, GBRT*, KNN*, SVM*, and XGBoost*) was relatively consistent, all achieving strong predictive outcomes. Specifically, examining the precision values, the respective values for the five algorithms were 0.873, 0.877, 0.863, 0.889, and 0.871. This indicates that (i) the lowest precision value is 0.863, meaning AugmentED achieves at least 86.3% precision, and (ii) the difference between the highest and lowest precision values is only 0.026 a minimal variation, highlighting the stable performance across all models.

In a related study by Al-Alawi *et al*., (2023), the authors employed a hybrid classification approach combining Decision Tree and Support Vector Machine (SVM) algorithms to predict students' academic performance. Through statistical analysis, several key factors influencing student outcomes were identified. The experimental results showed accuracy rates of 71.79%, 74.04%, and 78.85% for the Decision Tree model, and 69.87%, 74.04%, and 71.15% for the SVM model across different data splits. The study further highlighted seven major factors directly impacting student performance, particularly those linked to educational environments and social network activities. Notably, variables such as "time spent on social networks," "type of mobile games played," and "time spent playing mobile games" were found to have significant effects on students' academic achievement.

Similarly, Hasan *et al*., (2020) focused on predicting students' academic performance to help educational institutions improve overall academic outcomes. The research employed classification algorithms, specifically Support Vector Machines (SVM) and Random Forest (RF), to analyze student data. Experimental results demonstrated that both algorithms achieved high prediction accuracy, with the binary classification task reaching up to 93% accuracy. In regression analysis, the Random Forest model produced the lowest Root Mean Square Error (RMSE) of 1.13, indicating strong predictive performance.

In a recent study by Folorunso *et al*., (2024), a new Hybrid Ensemble Learning Algorithm (HELA) was introduced to predict students' academic performance. The model integrates prediction results from several base classifiers Gradient Boosting, Extreme Gradient Boosting, and Light Gradient Boosting Machine along with various combinations of these algorithms, which are then fed into a Super Learner algorithm. Experimental findings revealed high predictive accuracy, achieving 96.6% for the Mathematics course and 91.2% for the Portuguese course.

In another recent study by Zhao *et al*., (2020), the authors aimed to develop a more holistic approach to predicting students' academic performance by integrating study habits and sleep patterns into the analysis. Various machine learning algorithms including Logistic Regression, Random Forest, Support Vector Machine (SVM), and Decision Tree were employed to forecast academic outcomes based on these variables. The results revealed that both study duration and sleep hours have a significant impact on academic achievement, with each model demonstrating different levels of predictive accuracy. The study underscores the importance of these behavioral factors in academic prediction and emphasizes the potential of machine learning as an effective tool for the early identification of at-risk students.

In the study by Hussain *et al*., (2022), multiple machine learning models were applied to perform regression-based predictions of student performance and classification tasks to determine individual performance levels. Ultimately, these models were integrated into a comprehensive framework designed to predict students' academic outcomes effectively. This framework can be implemented within digital student management systems to provide actionable decision support for academic early warning and to guide students' learning progress and development.

Similarly, Leena *et al*., (2021) introduced an innovative framework for predicting student performance by combining metaheuristic-based hyperparameter optimization with explainable artificial intelligence (XAI) to enhance learning analytics. A rigorous experimental setup employing 5-fold cross-validation and 20 independent runs was implemented, with performance evaluated using multiple metrics, including Coefficient of Determination (R^2), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Relative Absolute Error (RAE), and Mean Error (ME). The results indicate that metaheuristic optimization substantially improves predictive accuracy, with the SCSO-LightGBM model achieving the best performance, attaining an R^2 value of 0.941. Furthermore, SHapley Additive exPlanations (SHAP) analysis enhanced the interpretability of the model, identifying Attendance, Hours Studied, Previous Scores, and Parental Involvement as the most influential predictors providing valuable, data-driven insights for educators and policymakers.

C. Online Learning Environment

In the study by Keser & Aghalarova, (2022), the authors applied multiple machine learning models namely Multilayer Perceptron (MLP), Decision Tree (DT), Random Forest (RF), Extreme Gradient Boosting (XGBoost), CATBoost, K-Nearest Neighbour (KNN), and Support Vector Classifier (SVC) on two benchmark Virtual Learning Environment (VLE) datasets.

Results from Experiments 1 and 2 revealed that class imbalance was a major factor contributing to the reduced performance of the models. To mitigate this issue, Experiment 3 was designed to address the imbalance problem using various Synthetic Minority Oversampling Techniques (SMOTE) and generative models such as Generative Adversarial Networks (GANs). Among the SMOTE variants, the SMOTE-NN approach demonstrated the best classification performance. Moreover, when combined with generative models, the SMOTENN-GAN–generated Coursera dataset yielded the highest results, enabling machine learning models to achieve approximately 90% classification accuracy. Overall, MLP, XGBoost, and CATBoost emerged as the top-performing models across the experiments.

In the work by Alnassar, (2023), features were categorized into four groups: demographic attributes, previous academic performance, current academic performance, and learning behavior or activity features. The analysis indicated that Deep Neural Networks (DNNs) and hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) models were the most frequently employed techniques. Furthermore, studies utilizing deep learning approaches such as CNNs, DNNs, and LSTMs demonstrated superior performance, achieving prediction accuracies exceeding 90%, while other models attained accuracy levels ranging between 60% and 90%.

In a recent study by Zou (2025), the authors introduced a hybrid machine learning framework for predicting students' academic performance by employing eight classification algorithms alongside three ensemble methods Bagging, Boosting, and Voting to identify the most effective predictive model. Additionally, both filter-based and wrapper-based feature selection techniques were applied to extract the most relevant features influencing student performance. The results demonstrated that ensemble methods achieved superior predictive accuracy compared to individual classifiers. Moreover, the incorporation of feature selection techniques further enhanced the overall model performance.

Similarly in Abukader *et al*., (2025), the study introduces a student performance prediction model based on multidimensional time-series data analysis, incorporating diverse data types such as students' learning behaviors, assessment scores, and demographic information. The model effectively extracted behavioral patterns and identifies relationships among multiple characteristics to better understand how various factors influence academic outcomes. Experimental evaluations using the Open University Learning Analytics Dataset (OULAD) demonstrated that the model achieved 74% accuracy and a 73% F1 score in a four-class prediction task, and an impressive 99.08% accuracy and 99.08% F1 score in early risk prediction. Compared to benchmark models, the proposed approach exhibited superior performance in both multi-class prediction and early risk detection.

In the study by Murtaza *et al*., (2025), the authors employed a statistical analysis approach to identify the key factors influencing students' performance and subsequently utilized Artificial Neural Networks (ANNs) to predict academic outcomes within the blended learning environment of Saudi Electronic University (SEU). The analysis revealed four major factors that significantly impact academic performance. Based on these findings, a new ANN model was developed to predict students' performance using these four identified factors.

The algorithm by Bayan *et al*., (2024), the authors employed machine learning techniques to predict student performance by analyzing various factors such as behavioral patterns, educational history, and demographic characteristics. The findings demonstrated the effectiveness of machine learning models in forecasting academic outcomes and identifying the key determinants of student success. This information can assist educators and academic institutions in designing personalized interventions, tailored learning experiences, and targeted recommendations, ultimately contributing to improved educational performance and student achievement.

In the study by Shou *et al*., (2024), the authors proposed a solution for analyzing student engagement and predicting academic performance by employing a Random Forest classifier combined with the SMOTE data-balancing technique. The proposed approach achieved a 5% improvement in performance when using SMOTE compared to models without data balancing. Additionally, the model attained an Area Under the Curve (AUC) value of 0.96 on the ROC curve, highlighting its strong predictive capability and overall effectiveness.

Similarly, Hamadneh *et al*., (2022) presented a novel approach for predicting student performance by converting one-dimensional online learning behavior data into two-dimensional images using four different text-to-image encoding methods: Pixel Representation (PR), Sine Wave Transformation (SWT), Recurrence Plot (RP), and Gramian Angular Field (GAF). The transformed images were analyzed using Convolutional Neural Networks (CNN) and Fully Convolutional Networks (FCN), both individually and within an ensemble architecture called EnCF. For comparison, traditional machine learning algorithms including Random Forest, Naive Bayes, AdaBoost, Decision Tree, SVM, Logistic Regression, Extra Trees, K-Nearest Neighbors, Gradient Boosting, and Stochastic Gradient Descent were applied to the original, untransformed data with the SMOTE technique for data balancing. Experimental findings revealed that the Recurrence Plot (RP) method achieved superior performance compared to other transformation techniques, yielding the highest classification accuracy of 0.9528 within the EnCF ensemble framework.

In a similar study, Hasan *et al*., (2020) and Alboaneen *et al*., (2022), the authors presented the development of a web-based system designed to predict students' academic performance and identify those at risk of failure using both academic and demographic factors. Several machine learning algorithms were employed, including Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), and Linear Regression (LR). The proposed model was applied to a dataset comprising 842 records from 168 female students in the Computer Science Department at Imam Abdulrahman bin Faisal University (IAU). The experimental results revealed a Mean Absolute Percentage Error (MAPE) of 6.34%, indicating high prediction accuracy. Furthermore, the analysis showed that academic factors had a greater influence on students' performance compared to demographic variables, with midterm exam scores emerging as the most significant predictor.

In a related study by Jawad *et al*., (2022) and Wen & Juan, (2023), the authors introduced an innovative approach for representing students' partial sequences of learning activities and developed an early performance prediction model based on a deep neural network. The experimental findings revealed that: (1) compared to demographic attributes and assessment scores, utilizing 20% and complete online learning activity sequences yields classifier accuracies of 0.5 and 0.84, respectively, enabling effective early prediction of students' academic outcomes; (2) the proposed autoencoder efficiently extracts latent features from raw activity sequences, enhancing prediction accuracy by over 30%; and (3) by applying distance-based oversampling to address dataset imbalance, the end-to-end prediction model achieves accuracy exceeding 80%, demonstrating improved predictive performance, particularly for non-major academic courses.

Existing studies have focused majorly on other branches of AI for students' academic performance prediction such as machine learning, blockchain, deep learning and natural language processing. While educational robots have been increasingly adopted across various disciplines for teaching in higher education, their potential for enhancing student performance and learning outcomes via prediction remains unexplored, presenting a promising avenue for future research and practical application. Thus, this study aims to assess the impact of adopting robotics for students' academic performance prediction in higher institution using the Technological Acceptance Model. The contributions of this study lie on the proposal of conceptual framework for AI Robotic Software acceptance for the improvement of students' outcome using TAM.

MATERIALS AND METHODS

A. Materials

i. Technological Acceptance Model (TAM)

TAM is an adaptation of the Theory of Reasoned Action (TRA) to the field of Information System (IS). TAM posits that perceived usefulness and perceived ease of use determine an individual's intention to use a system with intention to use serving as a mediator of actual system use. Perceived usefulness is also seen as being directly impacted by perceived ease of use. Attempts to extend TAM have generally taken one of three approaches: by introducing factors from related models, by introducing additional or alternative belief factors, and by examining antecedents and moderators of perceived usefulness and perceived ease of use as shown in figure 1. Researchers have simplified TAM by removing the attitude construct found in TRA from the current specification Venkatesh *et al*., (2003).

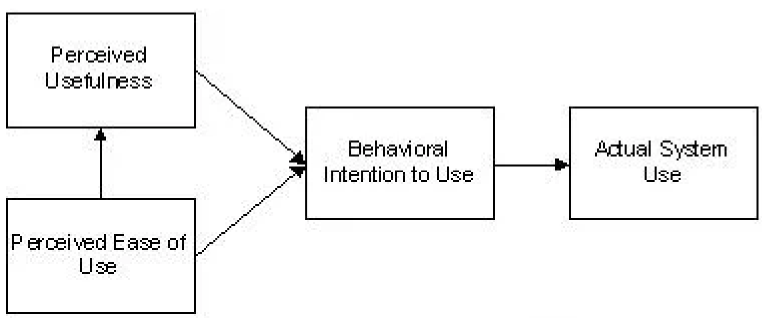

Fig. 1: Diagram of TAM Venkatesh *et al*., (2003).

- Perceived Ease of Use

The integration of technology has profoundly reshaped higher education, transforming how students engage with academic content and pursue their learning objectives. Thus, Shahraniza & Abubaker, (2025) explored the influence of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) on students' Academic Performance (CGPA). Guided by the Technology Acceptance Model (TAM), the study aims to (1) examined the relationship between PU, PEOU, and CGPA, and (2) assessed the mediating effect of Motivation on this relationship. The results indicated a strong positive correlation between PU, PEOU, and CGPA, confirming that the adoption of technology plays a significant role in enhancing students' academic performance.

Similarly, Mata *et al*., (2025) conceptually identified and categorized the most influential factors from previous research within the frameworks of the Technology Acceptance Model (TAM) and Expectation Confirmation Theory (ECT). The main objective was to investigate how blockchain system perceived quality and perceived usability influence student academic performance (SAP), considering the mediating role of student satisfaction and the moderating role of continuance intention. The findings revealed that the direct effect of perceived quality on SAP is positive and significant, while perceived usability shows no significant effect. Moreover, the study offers a novel contribution by demonstrating how student satisfaction mediates, and continuance intention moderates, the relationship between blockchain system attributes and academic performance.

In a related study by Jeilani & Abubakar, (2025) sought to gain insights into the relationship between perceived institutional support and students' perceptions of AI-supported learning. It further examines the mediating role of perceived learning outcomes and the moderating effect of technology self-efficacy within this framework. The research model was developed and validated based on Social Cognitive Theory (SCT) and students' learning outcomes. The results indicated that perceived institutional support has a significant influence on students' perceptions of AI-supported learning ($\beta = 0.200$, C.R. = 2.291, $p = 0.022$), technology self-efficacy ($\beta = 0.492$, C.R. = 9.671, $p < 0.001$), and learning outcomes. These findings emphasized the critical interaction between perceived institutional support, technology self-efficacy, and perceived learning outcomes in shaping students' perceptions of AI in higher education, highlighting the importance of cultivating supportive academic environments for successful AI integration.

Similarly, Shuhaimi *et al*., (2025) explored how key attributes of blockchain technology relative advantage (RA), compatibility (COM), and complexity (CPX) affect teachers' readiness for adoption, with perceived ease of learning (PEOL) serving as a mediating factor. The findings contributed to the broader objectives of the Industrial Revolution (IR) 5.0 by emphasizing the importance of human-centered and cognitively accessible technological integration strategies in education, particularly in promoting systemic reforms in assessment practices.

- Perceived Usefulness

Algerafi *et al*., (2023) examined the influence of artificial intelligence-based assessment (AIBA) on student performance (SP) in higher education, with a focus on the mediating role of digital competence (DC). The findings indicated that AIBA has a significant and positive impact on student performance, while digital competence acts as a strong mediator in this relationship. Specifically, engagement with AIBA enhances learning outcomes through personalized feedback and adaptive evaluation, while simultaneously strengthening students' digital skills, which are crucial in today's technology-driven educational landscape. These results suggested that the effectiveness of AIBA is largely contingent on learners' digital readiness, emphasizing that technology alone cannot guarantee improved academic outcomes without the parallel development of essential digital competencies.

The purpose of Al-Adwan *et al*., (2025) was to examine the intentions of Chinese higher education students to adopt AI-based robots for educational purposes. Guided by the Technology Acceptance Model (TAM 3), the study proposed 14 hypotheses to analyze the factors influencing students' willingness to integrate AI-based robots into their learning experiences. The findings were expected to offer valuable insights for university administrators on the importance of AI-based robots in modern education. Additionally, the results assisted robot developers, policymakers, and institutional leaders in designing and implementing AI-based robotic systems that effectively address contemporary educational needs and enhance the overall learning experience.

- Behavioral Intention to Use

In the study by Alnaqeeb *et al*., (2025), the studies introduced an Integrated Technology Continuance Model (ITCM) designed to explain teachers' Continuous Use Intention (CUI) of technology in higher education institutions (HEIs). The study emphasized the positive effects of facilitating conditions and management support on TPACK, which in turn positively influence self-efficacy, perceived usefulness, and perceived ease of use. Moreover, perceived usefulness, perceived ease of use, self-efficacy, and social influence are found to significantly affect teachers' continuous intention to use technology in HEIs. The study offered valuable insights into the factors shaping the integration of technological innovations into teaching practices and classroom environments, aligning with key objectives of Sustainable Development Goal 4 (SDG4). Based on the findings, implications and directions for future research were also discussed.

Similarly, Aziz & Sabri, (2024) aimed to explore the factors influencing academicians' behavioral intention towards the adoption of blended learning (BL) systems using an Artificial Neural Network (ANN) approach. The results indicated that performance expectancy and perceived playfulness are the most influential factors affecting academicians' intentions to adopt BL systems. Furthermore, the ANN model demonstrated superior predictive accuracy compared to traditional regression models, suggesting that non-linear relationships better capture the complexities of technology adoption behavior among academicians.

- Actual System Use

In a study Momani, (2020), the author aimed to examine the relationship between the constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM) in the context of AI technology and AI-based application adoption within the education sector. The results revealed that the magnitude of relationships among the TAM constructs remained strong across all paths (Perceived Usefulness → Attitude Toward Use, Perceived Ease of Use → Attitude Toward Use, Perceived Usefulness → Behavioral Intention, and Perceived Ease of Use → Behavioral Intention). These findings provide valuable insights for IT companies and educational decision-makers in designing, developing, and implementing effective AI technologies and AI-based applications tailored to enhance teaching and learning processes.

Similarly, Abulail *et al*., (2025) investigated the key technological and socio-environmental factors that influence the adoption intentions of AI-powered technologies at the corporate level within higher education institutions. A conceptual model integrating the Diffusion of Innovation Theory (DOI), the Technology–Organization–Environment (TOE) framework, and the Technology Acceptance Model (TAM) was proposed and empirically tested using data collected from 367 participants, including students, faculty members, and administrative employees. The findings indicate that factors such as Compatibility (C), Complexity (CX), User Interface (UX), Perceived Ease of Use (PEOU), User Satisfaction (US), Performance Expectation (PE), AI introducing new tools (AINT), AI Strategic Alignment (AIS), Availability of Resources (AVR), Technological Support (TS), and Facilitating Conditions (FC) significantly affect the intention to adopt AI technologies. These results provided valuable insights for policymakers, technology developers, and institutional leaders seeking to enhance AI integration and digital transformation within higher education.

ii. Data Collection and Analysis

- Data Collection

A dataset of 30 participants comprising students and staff for the constructs and sub-factors in table 1 was collected using google form in a public institution in Delta State as depicted on table 1. Each variable was placed on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

TABLE 1: Reduced Dataset of the Study

PEOU	**PU**	**BI**	**ASU**
5	5	5	5
4	4	4	4
3	3	4	3
5	5	4	5
2	3	2	2
4	4	4	4
5	4	5	5
3	3	3	3
4	4	4	4
2	3	3	2
5	5	5	5
3	3	3	3
4	4	4	4
5	5	5	5
2	2	2	2
4	4	4	4
3	3	3	3
5	5	5	5
4	4	4	4
2	2	2	2
5	5	5	5
3	3	3	3

4	4	4	4
5	5	5	5
3	2	2	2
4	4	4	4
5	5	5	5
3	3	3	3
4	4	4	4
2	3	2	2

iii.

Analysis

- Statistical Package for the Social Sciences (SPSS)

SPSS is a powerful software package used for statistical analysis, data management, and data visualization. The Pearson Correlation, also known as the Pearson Product-Moment Correlation Coefficient (PPMCC), is one of the most widely used statistical methods for measuring the strength and direction of a linear relationship between two continuous variables in SPSS. Correlation Matrix is a square matrix that presents the pairwise correlation coefficients such as Pearson's coefficient r between variables. The value of the correlation coefficient ranges from –1 to +1, indicating the direction and strength of the relationship.

Mathematically, it is expressed as

$$r = \frac{\Sigma(X - \bar{X})(Y - \bar{Y})}{\sqrt{[\Sigma(X - \bar{X})^2 \, \Sigma(Y - \bar{Y})^2}} \quad (1)$$

Where:

- X and Y = Variables being compared
- and $\bar{Y}$ = Means of X and Y
- Σ = Sum of all Observations

B. Methods

The methodological approach adopted in this study follows a systematic three-phase process comprising Literature Review, Framework Formulation, and Design of Architecture for the Proposed System.

The first phase, the Literature Review, involved an in-depth examination of previous studies and theoretical models, particularly the Technology Acceptance Model (TAM). This phase focused on identifying key variables such as perceived ease of use, perceived usefulness, behavioral intention to use, and actual system use, as well as their sub-factors. The review provided a theoretical foundation for developing a predictive and adaptive learning framework.

The second phase, the Framework Formulation, focused on constructing a conceptual structure based on the TAM model and findings from related literature. The framework outlined the relationships among variables influencing technology acceptance and use within a higher education context. This stage formed the foundation for modeling the intelligent system to enhance student performance prediction and engagement through AI and robotic integration.

RESULTS

Table 2: Theoretical Background Summary Table (Authors)

Variable	Factors (from studies [32]–[41]	Description
Perceived Ease of Use (PEOU)	- Ease of Learning (PEOL) - Compatibility (COM) - Complexity (CPX) - Relative Advantage (RA) - Institutional Support - Technology Self-Efficacy - User Interface (UX) - Facilitating Conditions (FC)	Factors that enhance users' perception of how easily a technology can be used. High institutional support, intuitive interfaces, and low complexity improve PEOU, increasing adoption likelihood.
Perceived Usefulness (PU)	- AI-Based Assessment (AIBA) - Digital Competence (DC) - Perceived Quality - Perceived Usability - Learning Outcomes - Technology Self-Efficacy - Performance Expectancy (PE)	These reflect users' belief that technology enhances learning or work performance. Digital competence and effective AI-based systems improve PU, reinforcing positive user attitudes.
Behavioral Intention to Use (BI)	- Motivation (Mediator) - Self-Efficacy (SE) - Social Influence (SI) - Performance Expectancy (PE) - Perceived Playfulness (PP) - Management Support (MS) - TPACK - Facilitating Conditions (FC)	Reflects individuals' willingness to use a system. Strongly affected by perceived usefulness, self-efficacy, motivation, and social context.
Actual System Use (ASU)	- Compatibility (C) - Complexity (CX) - User Satisfaction (US) - AI Introducing New Tools (AINT) - AI Strategic Alignment (AIS) - Availability of Resources (AVR) - Technological Support (TS) - Facilitating Conditions (FC)	Represents real adoption or utilization behavior. Determined by technical, organizational, and environmental enablers that ensure continued technology use and alignment with institutional goals.

A. Sub-Factors and Constructs

Table 3 presents the distribution of sub-factors across the four key constructs derived from the Technology Acceptance Model (TAM) Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Behavioral Intention to Use (BI), and Actual System Use (ASU) which form the basis for the study's conceptual and architectural framework. The construct Perceived Ease of Use (PEOU) comprises eight sub-factors, emphasizing user-friendly attributes such as ease of learning, compatibility, and system simplicity that enhance the perceived effortlessness of technology adoption. Perceived Usefulness (PU) contains seven sub-factors, focusing on elements like AI-based assessment, digital competence, and perceived quality, which collectively determine the user's belief in the technology's ability to improve performance outcomes. Similarly, Behavioral Intention to Use (BI) encompasses eight sub-factors, addressing motivational and contextual drivers such as self-efficacy, social influence, and management support that shape individuals' willingness to adopt and continue using the system. The final construct, Actual System Use (ASU), also includes eight sub-factors, representing the real implementation and sustained utilization of the system, influenced by factors such as compatibility, user satisfaction, and availability of resources.

Table 3: Sub-Factors and Constructs Table

Construct	Number of Sub-Factors
Perceived Ease of Use (PEOU)	8
Perceived Usefulness (PU)	7
Behavioral Intention to Use (BI)	8
Actual System Use (ASU)	8

B. Proposed Conceptual Framework

The proposed conceptual framework shown in figure 4, based on the Technology Acceptance Model (TAM), illustrates the interaction between four major constructs: Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Behavioral Intention to Use (BI), and Actual System Use (ASU) in predicting students' academic performance. The framework integrates factors such as Ease of Learning, Compatibility, Complexity, Digital Competence, Motivation, and Technological Support to explain how students perceive, adopt, and utilize AI-based learning systems. It posits that when students find the AI robotic system easy to use and beneficial to their learning goals, their intention to engage with it increases, ultimately leading to consistent and effective system use. Furthermore, the framework embeds AI-driven data analysis and feedback mechanisms, enabling continuous monitoring of student performance and adaptive learning interventions. This holistic design not only aligns with TAM principles but also extends it by incorporating autonomous robotic processes and predictive analytics, making it a dynamic tool for enhancing personalized learning and performance prediction in higher education.

D. The Relationship between Perceived Ease of Use and Behavioral Intention

TABLE 4: Correlation Matrix Table

Correlations			
		BI	PEOU
BI	Pearson Correlation	1	.940**
	Sig. (2-tailed)		.000
	N	30	30
PEOU	Pearson Correlation	.940**	1
	Sig. (2-tailed)	.000	
	N	30	30
**. Correlation is significant at the 0.01 level (2-tailed).			

E. The Relationship between Perceived Usefulness and Behavioural Intention

TABLE 5: Correlation Matrix Table

Correlations			
		PU	BI
PU	Pearson Correlation	1	.919**
	Sig. (2-tailed)		.000
	N	30	30
BI	Pearson Correlation	.919**	1
	Sig. (2-tailed)	.000	
	N	30	30
**. Correlation is significant at the 0.01 level (2-tailed).			

F. The Relationship between Behavioural Intention and Actual System Use

TABLE 6: Correlation Matrix Table

Correlations			
		BI	ASU
BI	Pearson Correlation	1	.959**
	Sig. (2-tailed)		.000
	N	30	30
ASU	Pearson Correlation	.959**	1
	Sig. (2-tailed)	.000	
	N	30	30
**. Correlation is significant at the 0.01 level (2-tailed).			

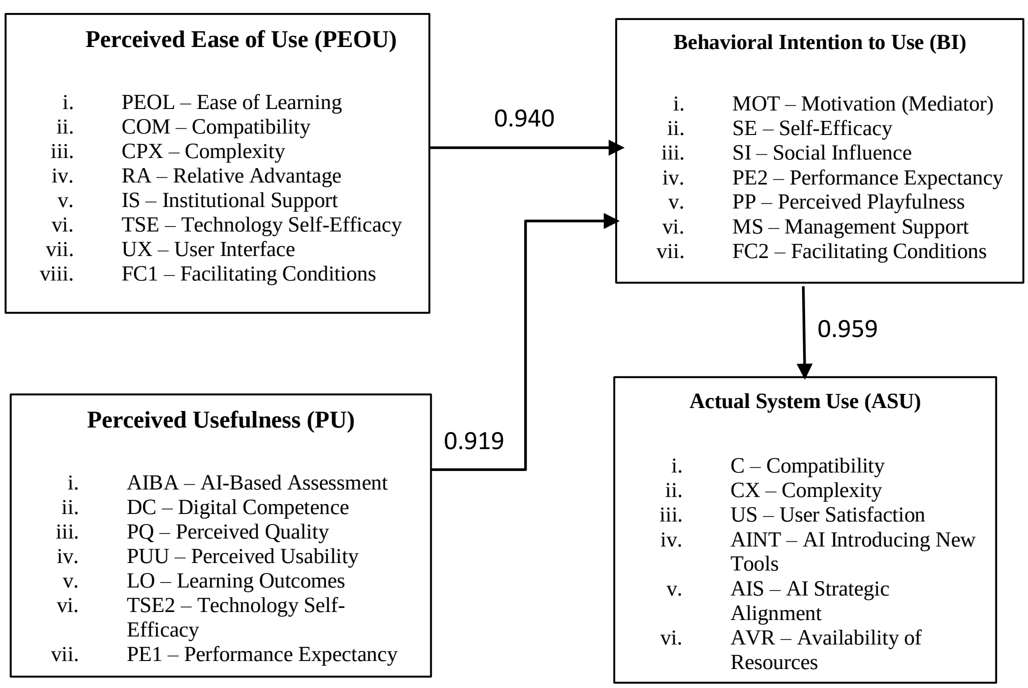

Fig. 2: Proposed TAM Conceptual Framework of the Study

DISCUSSION

There is a very strong positive correlation between PEOU and PU *(r = 0.910, p = 0.000)*, indicating that as staff perceive the system to be easier to use, they also find it significantly more useful. This suggests that perceived ease of use has a substantial influence on how useful students consider the system to be.

There is a very strong positive correlation between PU and BI *(r = 0.919, p = 0.000)*, indicating that as staff perceive the system to be more useful, their intention to use it also increases significantly. This suggests that perceived usefulness has a substantial influence on students' behavioral intention to adopt and continue using the system.

There is a very strong positive correlation between Behavioral Intention to Use (BI) and Actual System Use (ASU) (r = 0.959, p = 0.000), indicating that as staff' intention to use the system increases, their actual usage of the system also increases significantly. The correlation is statistically significant, suggesting that behavioral intention is an excellent predictor of actual system usage.

CONCLUSION

This study focused on designing an AI Robotic Autonomous Students' Academic Performance Prediction System that integrated artificial intelligence and robotic automation to enhance personalized learning and academic performance monitoring. Addressing a key research gap, the study emphasizes the need for a system that not only predicts student outcomes but also encourages continuous user interaction through a user-centered framework grounded in the Technology Acceptance Model (TAM). The research adopts a qualitative and quantitative approaches for its methodology. It incorporates four major TAM constructs Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Behavioral Intention to Use (BI), and Actual System Use (ASU) to assess system adoption and behavioral influence. The study finally recommends development of a predictive model that leverages a hybrid ensemble of Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN) algorithms, which together enhances accuracy, adaptability, and reliability in predicting students' academic performance.

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REFERENCES

Abukader, A., Alzubi, A., & Adegboye, O. R. (2025). Intelligent system for student performance prediction: An educational data mining approach using metaheuristic-optimized LightGBM with SHAP-based learning analytics. *Applied Sciences*, *15*(20), 10875.

Abulail, R. N., Badran, O. N., Shkoukani, M. A., & Omeish, F. (2025). Exploring the factors influencing AI adoption intentions in higher education: An integrated model of DOI, TOE, and TAM. *Computers*, *14*(6), 230. https://doi.org/10.3390/computers14060230

Ahmed, R. (2025). Artificial intelligence-based assessment and student performance: The mediating role of digital competence in the university context. *Journal of Research, Innovation, and Strategies for Education (RISE), 2*(5), 18–35.

Al-Adwan, A. S., Meet, R. K., Anand, S., Shukla, G. P., Alsharif, R., & Dabbaghia, M. (2025). Understanding continuous use intention of technology among higher education teachers in emerging economy: Evidence from integrated TAM, TPACK, and UTAUT model. *Studies in Higher Education, 50*(3), 505–524.

Al-Alawi, L., Al Shaqsi, J., Tarhini, A., & Al-Busaidi, A. S. (2023). Using machine learning to predict factors affecting academic performance: The case of college students on academic probation. *Education and Information Technologies, 28*(10), 12407–12432.

Alboaneen, D., Almelihi, M., Alsubaie, R., Alghamdi, R., Alshehri, L., & Alharthi, R. (2022). Development of a web-based prediction system for students' academic performance. *Data, 7*(2), 21. https://doi.org/10.3390/data7020021

Algerafi, M. A., Zhou, Y., Alfadda, H., & Wijaya, T. T. (2023). Understanding the factors influencing higher education students' intention to adopt artificial intelligence-based robots. *IEEE Access, 11*, 99752–99764.

Ali, I., Warraich, N. F., & Butt, K. (2025). Acceptance and use of artificial intelligence and AI-based applications in education: A meta-analysis and future direction. *Information Development, 41*(3), 859–874.

Alnassar, F. M. (2023). *Predicting student performance on virtual learning environment* (Doctoral dissertation, Goldsmiths, University of London).

Alnaqeeb, R. T., Abdullah, N. A., & Abdullah, N. L. (2025). Students' behavioral intentions toward teachers' use of augmented reality in higher education: Insights from the UAE. *International Journal of Information and Education Technology, 15*(9).

Aziz, K., & Sabri, M. (2024). Examining the factors influencing university students' adoption intention towards technology-enhanced learning. *Journal of Artificial Intelligence General Science, 6*, 341–358. https://doi.org/10.60087/jaigs.v6i1.259

Bayan, A., Mohammed, B., & Madini, A. (2024). The power of deep learning techniques for predicting student performance in virtual learning environments: A systematic literature review. *Computers and Education: Artificial Intelligence, 6*, 100231. https://doi.org/10.1016/j.caeai.2024.100231

Bressane, A., Spalding, M., Zwirn, D., Loureiro, A. I. S., Bankole, A. O., Negri, R. G., de Brito Junior, I., Formiga, J. K. S., Medeiros, L. C. d. C., Pampuch Bortolozo, L. A., & Moruzzi, R. (2022). Fuzzy artificial intelligence–based model proposal to forecast student performance and retention risk in engineering education: An alternative for handling small data. *Sustainability, 14*(21), 14071. https://doi.org/10.3390/su142114071

Folorunso, S. O., Farhaoui, Y., Adigun, I. P., Imoize, A. L., & Awotunde, J. B. (2024). Prediction of students' academic performance using learning analytics. In Y. Farhaoui et al. (Eds.), *Artificial intelligence, data science and applications* (Lecture Notes in Networks and Systems, Vol. 837).

Springer. https://doi.org/10.1007/978-3-031-48465-0_41

Hamadneh, N. N., Atawneh, S., Khan, W. A., Almejalli, K. A., & Alhomoud, A. (2022). Using artificial intelligence to predict students' academic performance in blended learning. *Sustainability, 14*(18), 11642.

Hasan, R., Palaniappan, S., Mahmood, S., Abbas, A., Sarker, K. U., & Sattar, M. U. (2020). Predicting student performance in higher educational institutions using video learning analytics and data mining techniques. *Applied Sciences, 10*(11), 3894.

Hussain, A., Khan, M., & Ullah, K. (2022). Student performance prediction model and affecting factors using classification techniques. *Education and Information Technologies, 27*(6), 8841–8858.

Jawad, K., Shah, M. A., & Tahir, M. (2022). Students' academic performance and engagement prediction in a virtual learning environment using random forest with data balancing. *Sustainability, 14*(22), 14795.

Jeilani, A., & Abubakar, S. (2025). Perceived institutional support and its effects on student perceptions of AI learning in higher education. *Frontiers in Education, 10*, 1548900.

Karim-Abdallah, B., Junior, M. A., Appiahene, P., Harris, E., & Binful, D. K. (2025). Application of machine learning algorithms in predicting academic performance of students in higher education institutes: A systematic review and bibliographic analysis. *African Journal of Applied Research, 11*(1), 536–559.

Keser, S. B., & Aghalarova, S. (2022). HELA: A novel hybrid ensemble learning algorithm for predicting academic performance of students. *Education and Information Technologies, 27*(4), 4521–4552.

López-Zambrano, J., Torralbo, J. A. L., & Romero, C. (2021). Early prediction of student learning performance through data mining: A systematic review. *Psicothema, 33*(3), 456–465.

Mata, M. N., Haider, S. A., Dantas, R. M., Rita, J. X., & Lucas, J. L. (2025). Blockchain technology system on student academic performance in higher education as perceived by students in Portugal. *Studies in Higher Education, 50*(4), 824–847.

Momani, A. (2020). The unified theory of acceptance and use of technology. *International Journal of Sociotechnology and Knowledge Development, 12*, 79–98. https://doi.org/10.4018/IJSKD.2020070105

Murtaza, G., Bhaumik, A., & Rehman, A. (2025). Predicting academic performance of college students based on key indicators using machine learning algorithms. *Journal of Media Horizons, 6*(3), 121–151.

Namoun, A., & Alshanqiti, A. (2020). Predicting student performance using data mining and learning analytics techniques: A systematic literature review. *Applied Sciences, 11*(1), 237.

Ngulube, P. (2025). Predicting academic success and identifying at-risk students: A systematic review of data analytics and machine learning approaches in higher education institutions. *Educational Administration: Theory and Practice, 31*(1), 117–134.

Nnadi, L. C., Watanobe, Y., Rahman, M. M., & John-Otumu, A. M. (2024). Prediction of students' adaptability using explainable AI in educational machine learning models. *Applied Sciences*, *14*(12), 5141. https://doi.org/10.3390/app14125141

Quimiz-Moreira, M., Delgadillo, R., Parraga-Alava, J., Maculan, N., & Mauricio, D. (2025). Factors, prediction, explainability, and simulating university dropout through machine learning: A systematic review (2012–2024). *Computation*, *13*(8), 198.

Ryalat, M., Almtireen, N., Al-refai, G., Elmoaqet, H., & Rawashdeh, N. (2025). Research and education in robotics: A comprehensive review, trends, challenges, and future directions. *Journal of Sensor and Actuator Networks*, *14*(4), 76. https://doi.org/10.3390/jsan14040076

Shahraniza, T., & Abubaker, Y. (2025). Influences of perceived usefulness and perceived ease of use on academic achievement: Mediating role of motivation. *Revista Conrado, 21*(105), e4718.

Shou, Z., Xie, M., Mo, J., & Zhang, H. (2024). Predicting student performance in online learning: A multidimensional time-series data analysis approach. *Applied Sciences*, *14*(6), 2522.

Shuhaimi, J., Awang, H., Jafar, M. F., Mansor, N. S., Khamis, S., & Al-Mashhadani, A. F. S. (2025). The mediating role of perceived ease of learning in teacher readiness to adopt blockchain for educational assessment. *Journal of Information and Communication Technology*, *24*(2), 66–88.

Stasolla, F., Zullo, A., Maniglio, R., Passaro, A., Di Gioia, M., Curcio, E., & Martini, E. (2025). Deep learning and reinforcement learning for assessing and enhancing academic performance in university students: A scoping review. *AI*, *6*(2), 40.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425–478.

Wen, X., & Juan, H. (2023). Early prediction of students' performance using a deep neural network based on online learning activity sequence. *Applied Sciences*, *13*(15), 8933.

You, Z., Ahmad, S. F., Yan, F., Irshad, M., Garayev, M., & Ayassrah, A. Y. B. A. (2025). Investigating the impact of safety, cultural and character traits issues in the adoption of humanized robots in education. *Humanities and Social Sciences Communications*, *12*(1), 1–14.

Zhao, L., Chen, K., Song, J., Zhu, X., Sun, J., Caulfield, B., & Mac Namee, B. (2020). Academic performance prediction based on multisource, multifeature behavioral data. *IEEE Access*, *9*, 5453–5465.

Zou, W., Zhong, W., Du, J., & Yuan, L. (2025). Prediction of student academic performance utilizing a multi-model fusion approach in machine learning. *Applied Sciences*, *15*(7), 3550.