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FULL LENGTH ARTICLE

An Intelligent Learning Analytics Framework for Predicting AI Proficiency Using BER-SC-Optimized MLP

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ABSTRACT

The fast adoption of artificial intelligence (AI) and machine learning (ML) in the sphere of higher education has become a catalyst that requires more precise and data-driven models that could assess the level of proficiency and interest in new technologies in students. This work is driven by the fact that there are currently no personalized and analytically rigorous frameworks for assessing the level of AI literacy among college students and proposes an optimized learning analytics model that hyperparameters a Multilayer Perceptron (MLP) by utilizing the Binary Al-Biruni Earth Radius with Sine Cosine Algorithm (BER-SC) metaheuristic algorithm to close the performance gap between human and artificial intelligence. The suggested BER-SC + MLP hybrid was created and evaluated using a sample consisting of 258 student responses from Grand Canyon University, which encompassed AI knowledge and usage behavior as well as career interest. The model achieved an accuracy of 0.9312 after optimization, compared to the MLP's pre-optimization accuracy (0.8996), and a significant decrease in Mean Squared Error (MSE = 0.0002808). The results demonstrate that BER-SC is far superior to nontraditional optimization techniques in terms of convergence efficiency and prediction accuracy. The contribution of the study is that it created a scalable and interpretable, and high-performing educational data modeling framework that has the potential to support adaptive educational learning analytics and institutional decision-making. The results suggest that intelligent optimization added to the ML-based assessment systems has a high possibility of enhancing the quality, efficiency, and feasibility of AI-based education and allowing more adaptable, more affordable, and more individually focused learning settings.

Keywords: Artificial Intelligence (AI) in Education ▪ Machine Learning (ML) Optimization ▪ Multilayer Perceptron (MLP) ▪ Binary Al-Biruni Earth Radius with Sine Cosine Algorithm (BER-SC) ▪ Educational Data Mining (EDM)

1. INTRODUCTION

Artificial intelligence (AI) and machine learning (ML) have become disruptive technologies over the past few years and can affect various areas, such as healthcare and finance, engineering and education. Nevertheless, the lack of proper and systematic approaches to the development of AIrelated skills in the context of college students is one of the most significant issues that dominate the educational discussions today [1]. Although AI and ML technologies are becoming more prevalent in the professional fields, universities tend to provide a limited number of students with the background and practical skills necessary to implement such technologies effectively [2]. There is an increasing difference between knowledge of AI and its practical application, which creates significant concerns in how universities can train students to become data-driven and technology-intensive workers. The origins of this challenge can be traced to a number of factors, which are interdependent. First, the abstract conceptual nature of AI is a natural challenge to the student especially when the teaching strategies are largely abstract or mathematically thick. Second, currently used curricula usually focus on the exposition of concepts as opposed to experimentation. Third, most instructional models are not personalized and consider all students as having the same rate of progress and learning patterns. Although lecture-based learning is essential in conceptual grounding, it overemphasizes the mass transfer of knowledge between the instructor and the student without paying enough attention to active learning and experience learning [3]. It is rarely that the students are exposed to the reality of solving problems that involve AI and ML application without integrating project-based learning, the laboratory work, and interactive simulations. Making this problem even more challenging is the fact that AI-related skills have remained very difficult to measure and nurture. In addition to the differences in their previous experience and cognitive style, learners are also different in their motivations and learning rates [4]. The universal approach to teaching limits the ability of the professionals to provide individualized services and specialized treatment. Moreover, there is still a dearth in empirical research on the optimum methods of AI education, and empirical findings are not unified and organized, which complicates the development of grounded and evidence-based pedagogical models. The absence of such methodological consensus is one of the factors that increase the gap between theoretical AI literacy and applied proficiency [5]. The solution to these gaps would involve redesigning AI learning as a living and breathing process with continuous evaluation, feedback, and personalized learning curves implemented in it [6]. In addition, the growing technology of AI integration into every economic sector will promote the necessity to bring up graduates who can apply the algorithmic thinking and computational modeling to real-life challenges. With the world evolving to the need to have AI talent in spades, there is a need to progress beyond basic literacy in the academic institutions to encourage actual proficiency, and by that, it means not just knowing how to use algorithms but also how to choose, apply, and optimize models in the real world. The creation of such competence is the way of closing the divide between theoretical education and practical learning with the help of data-driven insights and model-driven learning support systems. AI and ML have been revolutionary since it enables the computational systems to replicate the cognitive processes like reasoning, learning, and decision-making. Also, unlike AI which operates with the aim of simulating human-like behaviour and problem solving, ML is built around the creation of algorithms that will improve their own performance through repeated exposure to data [7]. These technologies have demonstrated so much potential in educational world especially in learning analytics, adaptive learning systems and performance assessment. As an example, analytical models based on regression can be used to define the associations between measures of student engagement and student performance results in academia [8]. The discovery of such relations can help teachers to discover learning bottlenecks and implement interventions that address students in personalized and efficient manners. However, these systems can only be effective when well-developed, well-optimized ML models are created and guarantee accuracy, generalizability, and interpretability of models and systems [9]. The foundation of AI implementation in the education field is data analysis. Expansive amounts of student data, including attendance records, assessment scores, logs of online interactions, and behavioral signs, can be utilized to find hidden patterns that affect performance in schools and universities in a positive manner [10]. Using the prudent use of ML models, e.g., regression, classification, or clustering, educators will be able to not only track the progress but also forecast possible results. As an example, regular attendance of online discussions or laboratory sessions can be closely related to better academic outcomes. The knowledge of these patterns help teachers to offer early warnings, feedback, and customized pedagogical interventions. Nonetheless, quality analytics entail not only rich data but also computational models that can control noise, bias, and nonlinearity in the world of education. Hi-tech algorithms and optimization methods are thus essential in bringing reliability and predictive accuracy on board. To address such issues of analysis, metaheuristic optimization methods have been developed as potent software to optimize the performance of the models of ML. They are algorithmic methods that rely on inherent evolution, swarm intelligence, or physical processes, and vary model parameters iteratively to reduce prediction errors and enhance accuracy [11]. They are adaptable and can search complex search spaces effectively, in most cases, much better than traditional optimization methods for problems with non-convex objective functions. The latest offering, the Binary Al-Biruni Earth Radius with Spiral Chaos (BER-SC) optimizer, has shown considerable potential to enhance a regression-based learning model and improve its performance under those circumstances [12]. BER-SC optimization is included in the development of strong predictive structures, which can be easily incorporated into the modeling of educational data, resulting in faster convergence and lower mean error rates. This is particularly important when the findings of prediction are directly used to inform academic teaching activities and other academic interventions. Considering all these opportunities and challenges, the current study will provide and empirically demonstrate a framework that implements ML and metaheuristic optimization to optimize AI education. It is not only a discussion of how refined regression-based models can be applied to analyze education data, but also clarifies how the models can be incorporated into adaptive learning systems to tailor instruction and improve student performance. The research has contributed to the field of data science in education, both theoretically and practically, by providing a model that can be modified by other institutions willing to develop their curricula in AI. The paper does have specific objectives, which were summarized in the following way:

1. **Address the AI proficiency gap:** Develop a data-driven framework that utilizes ML and metaheuristic optimization to enhance students' conceptual and practical understanding of AI.

2. **Improve model performance:** Apply the BER-SC optimizer to increase the accuracy, reliability, and convergence efficiency of regression-based ML models.

3. **Analyze educational datasets:** Identify and quantify key factors influencing AI proficiency through comprehensive statistical and computational data analysis.

4. **Propose scalable solutions:** Design and evaluate a system that integrates optimized AI models into institutional learning platforms to support scalable, adaptive, and personalized educational strategies.

This paper had its structure organized in a systematic manner to have a coherent and complete research presentation. The literature review in Section 2 summarizes the previous studies about AI education, ML modeling, and optimization algorithms. Section 3 gives the description of materials and methods, including the data sources, preprocessing steps, means of regression and optimization. In section 4 the experimental results are provided whereby baseline ML models were compared to BERSC- enhanced ones to show that there was an increase in prediction accuracy and efficiency. Section 5 gives a detailed discussion of the findings, explaining the theoretical and practical implications of the findings, relating them to previous studies and learning settings. Lastly, the paper ends with a conclusion in Section 6 to summarize the main ideas and implications of the research on educational practice and future research directions to bridge the AI proficiency gap using technology-enhanced learning frameworks.

2. LITERATURE REVIEW

The manner in which individuals move, manage their schedules, and even information has changed dramatically with the improvement in information technologies. As stated by [13], implementing methods such as artificial intelligence (AI) and machine learning (ML) in business processes have turned into a prominent trend that is being acknowledged in diverse sectors, including education. The technologies can be used to present educational platforms and applications in a more need-oriented way, making education processes more effective and individual. It was pointed out in the study that AI and ML have the potential to significantly improve electronic learning and the work processes of higher learning institutions. This possibility was identified by developing the secondary research, studying the documents, and conducting a survey of students in the Republic of Serbia, which examined how they were informed about AI and ML and how their attitudes towards them were. The paper ensured that the opportunities and challenges were identified and highlighted that AI and ML are innovative technologies that enhance the learning process by making students skilled, encouraging collaboration learning in higher education centers, and making research more accessible. As the study and teaching of languages evolved, the grammatical competence has become an important component of communicative competence. As the study by [14] indicates, grammar teaching is promoted as an important factor in the realization of communicative objectives in teaching a foreign language. The paper examines the application of the virtual reality (VR) technology in teaching English in colleges, which combines AI and ML to provide the creation of immersive learning environments with the aim of enhancing the English proficiency of students. The comparative experiment was a study of two groups of freshmen of a university: experimental group immersive VR teaching followed the constructivist approach, and the control group multimedia and teaching. It turned out that the experimental group showed a significant increase in overall English performance,scoring an average of 2.8 points in comparison with the control group, which means that the use of immersive VR teaching based on the constructivist theory can be used successfully to improve the language abilities of students. Reflectively, the relevance of ML techniques, e.g. neural networks, in education is critically analyzed in the analysis by [15]. The paper discusses how data scientists are trying to incorporate AI in their online courses such as Khan Academy and ASSISTments. Based on the Science and Technology Studies, it analyses academic literature that uses the concept of deep learning to forecast academic success. The study brings about the unhealthy interactions between faulty data, inadequate transparency in the computation techniques and scanty educational knowledge in these platforms that have a great economic repercussion. These are presented as a controversial situation, which disrupts the vision of AI as an objective scientific instrument. The notion of the Smart Classroom has changed to represent the implementation of technology in learning environments, as stated by [16]. The paper explains the necessity of using smart technologies in classrooms due to the rapid development of AI and the necessity to create flexible and creative learning settings. A SWOT analysis defines the strengths, weaknesses, opportunities, and threats related to the use of AI in smart classrooms, which can inform educators and AI professionals about the current drawbacks and possible obstacles in the future. Artificial intelligence is still changing the field of higher education. Nevertheless, as it is mentioned by [17], a lot of professors do not know about its possibilities. Their paper notes that information bridge technology is necessary to enhance classroom communication and discusses the future of higher education through the prism of AI. The authors demonstrated a maximum accuracy of 58% using generative adversarial networks (GAN) on student assessment data with an aim of bridging the gap between human lecturers and AI using a series of ML algorithms and taking into account psychological implications. Student performance forecasting has been a major concern in the institutions of learning. The article by [18] states that AI is also a central part of Education 4.0, as it can be used to provide personalized learning, predictive models, and advanced analytics. Their paper presents a Hybridized Deep Neural Network model to make a prediction of student performance more precise, which has shown a better result in comparison to other models. The development of AI in higher education in India has brought both opportunities and challenges to the system.[19] studied the ways in which AI technologies have transformed the system of governance and internal setting of Indian universities. The researchers surveyed 329 individuals and developed a Unified Theory of Acceptance and Use of Technology, which guided their survey. Theory to guide the implementation of AI. The findings suggest that the adoption of technology by all stakeholders in the education sector should be encouraged. [20] examined the applications of AI in government institutions in the Gulf region and discovered that it can be used and has broad applications. Their study has developed a conceptual model that links personal and technological factors affecting adoption. The results emphasize the positive roles of variables such as trialability, observability, and compatibility in facilitating ease of doing business and technology exports, demonstrating the managerial and policy importance of AI. The article by [21] seeks to develop an AI education policy within higher education by examining perceptions of generative AI among 457 students and 180 university workers in Hong Kong. This research paper will offer an AI Ecological Education Policy Framework that consists of three dimensions, including Pedagogical, Governance, and Operational. The framework offers a comprehensive way of incorporating the use of AI within the academic setting, therefore, guaranteeing privacy, accountability, and equal access. Low birth rate in Taiwan has pushed universities to retain enrollment, which is why the article by [22] used a predictor of dropout risks based on the sample of 3,552 students (big data and AI). Their neural network had a deep accuracy of 77 percent, and universities can implement timely interventions and help students retain. In [23] the authors bring to the fore the importance of assessment and feedback, which on the one hand is accelerated due to the transition to online learning during the COVID-19 pandemic, and on the other hand, is the key to improving educational outcomes. The learning analytics and artificial intelligence assessment systems allow personalized and data-driven assessment to improve the learning process and minimize student stress. [24] employed virtual learning environments to analyze student behavior using deep artificial neural networks, achieving classification accuracy between 84–93%. The inclusion of legacy and assessment-related data improved predictive precision, offering universities a framework for early intervention and data-driven decisionmaking. As posited by the author of [25], after-class review is not always an easy task because students usually receive little feedback. Their paper suggested an AI chatbot that would give instant and quality feedback. The quasi-experiment showed that the experimental group, which utilized chatbot, demonstrated higher performance, self-efficacy, and motivation, which proves AI chatbots to be effective tools to be used in active learning. Another important piece of work in AI education was authored by [26] who developed the first pre-tertiary AI education in Hong Kong. The pre- and post-test assessment revealed the increased motivation of students and a sense of competence, as well as the increased ability of teachers to present AI material effectively with the support of the collaborative design of the curriculum. [27] developed an intelligent college student management system integrating the Internet of Things (IoT) with ML techniques. Using cyclic neural networks and k-nearest neighbor models, the system optimized data prediction and classification while introducing dark network flow and ip2vec algorithms to safeguard privacy and detect anomalies. A novel AI-assisted model in college English education is suggested in [28]. Using deep belief networks (DBN) to evaluate pronunciation, the researchers performed at 99.58% with manual ratings, which prove that artificial intelligence (AI) can boost oral skills and practical communication. [29] proposed a reformed teaching system for machine learning education that integrates curriculum design, practice, and intelligent evaluation. Using facial expression data and classification algorithms, the system provides feedback on classroom quality, demonstrating effectiveness in improving student engagement and instructional quality. Lastly, the article of [30] discusses the potential transformational capabilities of AI systems such as ChatGPT in education. The paper mentions positive aspects like adaptive learning and intelligent tutoring but warns of the dangers and abuse of ethics. The authors recommend an approach to the responsible adoption of AI technologies so that the majority of their beneficial contribution to education can be maximized. Table 1 reports a brief overview of the main papers analyzing the use of artificial intelligence and machine learning in education, describing each of the investigations in terms of reference, purpose, methodology, and the main results.

3. MATERIALS AND METHODS

Figure 1 sketches the general methodological framework used in this study, with the description of the entire workflow of data acquisition through model assessment. The method starts by collecting the dataset, followed by extensive preprocessing steps, including feature scaling, normalization, and MinMax scaling, to make it uniform and facilitate more effective learning. The processed data is divided into training and testing subsets to allow a model to be trained and its performance to be robustly validated. Multi-layer perceptron (MLP), Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbors (k-NN) are considered baseline machine learning models used to establish benchmark results. To improve the model's accuracy, a combination of optimization algorithms, including Biruni Earth Radius (BER-SC), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Whale Optimization Algorithm (WOA), is used to tune the model's parameters and refine its performance. At the last stage, the optimization models undergo an extensive performance analysis using multiple statistical measures to evaluate predictive reliability and efficiency. As a whole, Figure 1 offers a systematic description of the experimental design and the methodological steps to be undertaken during this study.

3.1 Dataset Description

The data collected in this research was collected through a questionnaire survey that was given to undergraduate students at the Grand Canyon University (GCU) in Phoenix, Arizona. QR codes were deployed throughout the campus facilities (classrooms, study halls, and student centers) to distribute the survey and have the maximum number of participants. The main goal of the survey was to gather the information that would reflect familiarity, engagement, and interest of the students in artificial intelligence (AI) and their academic background. The data was collected within a ten-month period,i.e. between March 31, 2023 and January 4, 2024. Total of 258 valid responses were obtained and produced a dataset comprising of seven variables and 258 rows. Every record reflects the answers of a separate student in a set of both quantitative and nominal indicators. The respondents data were recorded using a Google Form which was then exported to a spreadsheet to be preprocessed and analyzed. The survey tool included six central questions that were aimed to measure the self-reported AI literacy of the students, their regular AI usage, their desire to work in AI fields, and demographic belonging-ness of the students to the Grand Canyon University (GCU). The questions aimed at both the ordinal and nominal variables to enable the application of the regression based and classification based machine learning methods in the further analysis. The questions and the response types are summarized in Table 2.

The final dataset contained **seven columns** (variables) corre-

Table 1. Summary of Reviewed Studies on Artificial Intelligence and Machine Learning in Education

Reference	Objective	Methodology	Key Findings
[13]	Explore AI and ML integration in education.	Secondary research, document analysis, student survey (Serbia).	AI and ML enhance e-learning, collaboration, and personalization.
[14]	Apply VR with AI/ML in English teaching.	Comparative experiment (VR vs. traditional).	VR group scored 2.8 points higher, improving proficiency.
[15]	Examine ML in online learning platforms.	Critical review using Science and Technology Studies.	Found bias, opacity, and reductionist data science issues.
[16]	Investigate AI in smart classrooms.	Literature review, SWOT analysis.	AI improves automation and class management; risks identified.
[17]	Assess AI in higher education communication.	GANs and ML applied to assessment data.	58% accuracy; bridges human–AI gap and addresses psychology.
[18]	Predict student performance with AI.	Hybrid Deep Neural Network model.	Model achieved superior predictive accuracy.
[19]	Study AI adoption in Indian universities.	Survey (329 respondents) using UTAUT.	Conceptual model supports multi-stakeholder AI adoption.
[20]	Explore AI adoption in Gulf government.	Conceptual modeling.	Trialability and compatibility improve adoption success.
[21]	Develop AI education policy framework.	Mixed methods: survey + interviews.	Proposed 3D framework—Pedagogical, Governance, Operational.
[22]	Predict dropout risks with AI.	Deep learning on 3,552 student records.	77% accuracy; supports early student intervention.
[23]	Evaluate AI-based assessment.	Analytical review of online learning feedback.	AI tools personalize and reduce stress in assessments.
[24]	Predict behavior in virtual learning.	Deep neural networks with clickstream data.	84–93% accuracy; supports proactive learning management.
[25]	Develop AI chatbot for review support.	Quasi-experiment (chatbot vs. control).	Chatbot users showed higher performance and motivation.
[26]	Create pre-tertiary AI curriculum.	Mixed methods: pre/post tests, qualitative feedback.	Improved student motivation and teacher confidence.
[27]	Build intelligent student management system.	IoT + ML using CNN, KNN, ip2vec algorithms.	Enhanced prediction, privacy, and anomaly detection.
[28]	Use AI for English pronunciation evaluation.	Deep Belief Network (DBN).	99.58% agreement with human raters.
[29]	Reform ML teaching evaluation.	Facial expression recognition and analysis.	Improved class feedback and engagement.
[31]	Integrate ML into K–12 and higher education.	Conceptual pedagogical review.	Advocates shift from rule-based to ML-driven thinking.
[30]	Examine ChatGPT and AI ethics in education.	Analytical literature review.	Encourages responsible, ethical AI integration.

sponding to the six survey questions and one unique identifier column for participant indexing. The responses were coded as follows:

- Ordinal variables (Q1–Q4) were encoded numerically on a five-point Likert scale.
- The binary variable (Q5) was encoded as 1 for "Yes" and 0 for "No."
- The categorical variable (Q6) was one-hot encoded into seven distinct college categories for compatibility with machine learning models.

With a total of 258 entries, the dataset represents an eclectic and representative sample of students representing different fields of study, representing a fair balance of demographics in the key academic divisions of GCU. There were no lost or duplicated records, and thus, data were consistent and intact.

All numeric attributes were first normalised between [0,1] before the process of modeling, so as to maximize convergence on the regression and optimization steps. Participants were requested to be part of the survey voluntarily and all the data were collected anonymously. No personal identifiable information (PII) was collected. The research was conducted within ethical conducts of research as per the institutional requirements of academic research at Grand Canyon University that involves human research subjects. Figure 2provides a comparison between students awareness of ChatGPT and level of interest in pursuing an AI-related career. The visualization shows that a huge percentage of the respondents who were aware of ChatGPT had lower levels of interest in career-related to AI (scores of 1 or 2), which shows that awareness does not necessarily translate into occupational desires in the AI sector. On the other hand, the minority of students who did not know about ChatGPT also had low levels of interest,

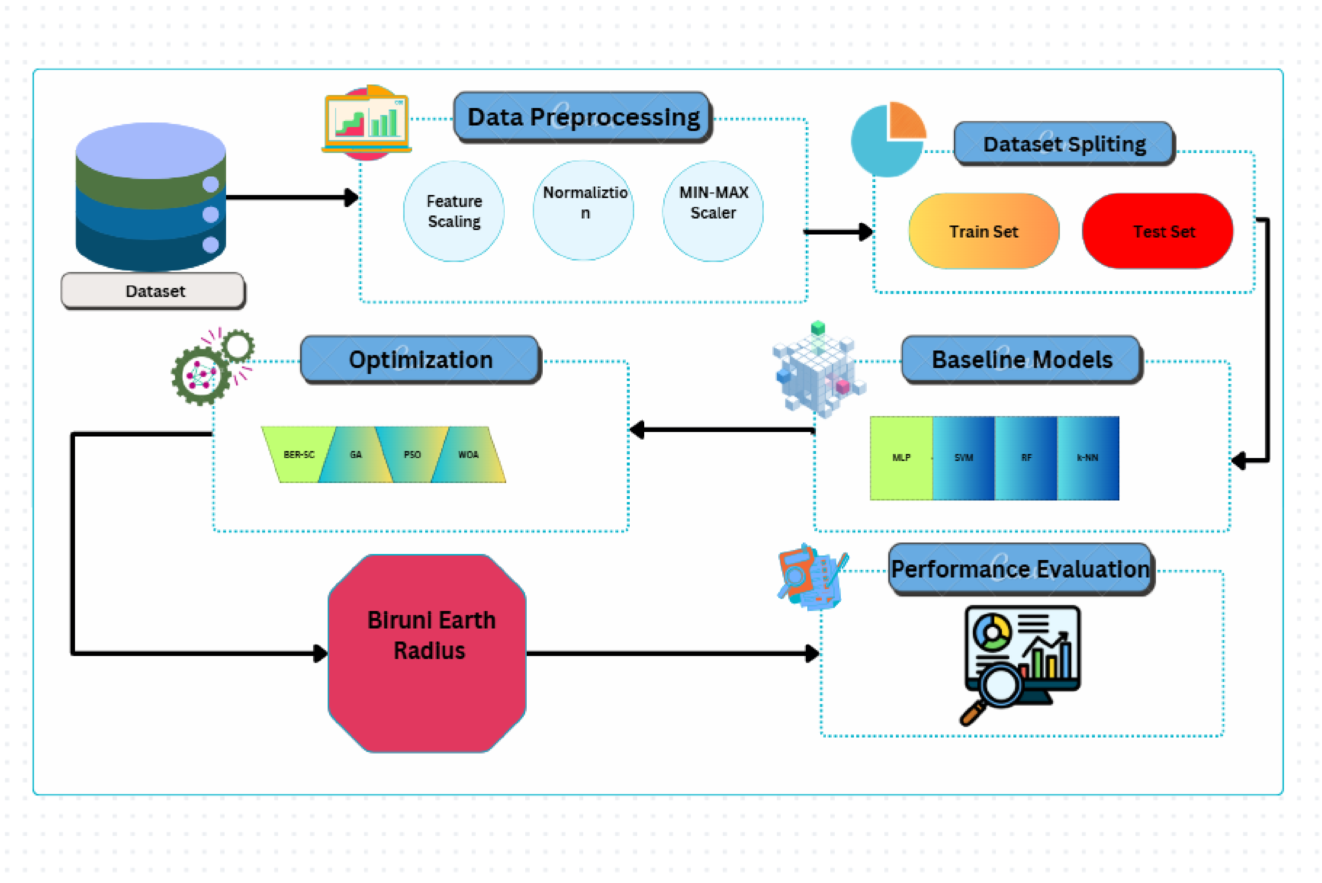

Figure 1. Proposed methodological framework showing the process from data preprocessing and model training to optimization and performance evaluation.

Table 2. Survey Instrument Overview

Question ID	Question Description	Response Options / Scale
Q1	AI Knowledge Level: How would you rate your knowledge and understanding of Artificial Intelligence (AI)?	1 – Never heard of AI before 2 – Heard of AI but know little about it 3 – Basic understanding of AI 4 – Good understanding and can explain applications 5 – Very knowledgeable and can explain complex concepts
Q2	Personal AI Usage: How often do you use AI for personal use?	1 – Never used AI 2 – Used AI a few times 3 – Occasionally use AI for personal tasks 4 – Regularly use AI as part of routine 5 – Heavily rely on AI daily
Q3	Academic AI Usage: How often do you use AI for school-related tasks?	1 – Never used AI for school 2 – Used a few times for schoolwork 3 – Occasionally use for assignments/research 4 – Regularly use AI in academics 5 – Heavily rely on AI for academic success
Q4	Career Interest in AI: How interested are you in pursuing a career in Artificial Intelligence?	1 – Not at all interested 2 – Slightly interested 3 – Moderately interested 4 – Very interested 5 – Extremely interested
Q5	Awareness of ChatGPT: Do you know what ChatGPT is?	Yes / No
Q6	Academic College: Which college are you enrolled in?	Business; Arts & Media; Science, Engineering & Technology; Education; Humanities & Social Sciences; Nursing & Health Care; Theology; Other

which can indicate that awareness of AI technologies and engagement with them can also affect the motivation of AI career in students. Figure 3 provides a comparative visualization consisting of three boxplots labeled as (a), (b), and (c). In Figure 3a, the relationship between students Knowledge of AI and their Interest in AI Careers is shown. The plot shows that students with higher AI knowledge tend to report higher career interest, suggesting that conceptual familiarity with AI is associated with professional motivation. The correlation between Interest in AI Careers and Personal Use of AI can be found in Figure 3b. The upward trend across all interest levels suggests that the continued use of AIs in students' everyday lives could lead to greater interest and involvement in AI-related careers. Lastly, Figure 3c depicts the correlation between. AI Usage School and Career Interest, in which the students who incorporated AI in their learning activities are more likely to demonstrate higher interests in AI-related jobs. Altogether, these trends indicate that greater AI exposure and involvement, both personally and in the academic environment, are positively linked with career interest in AI.

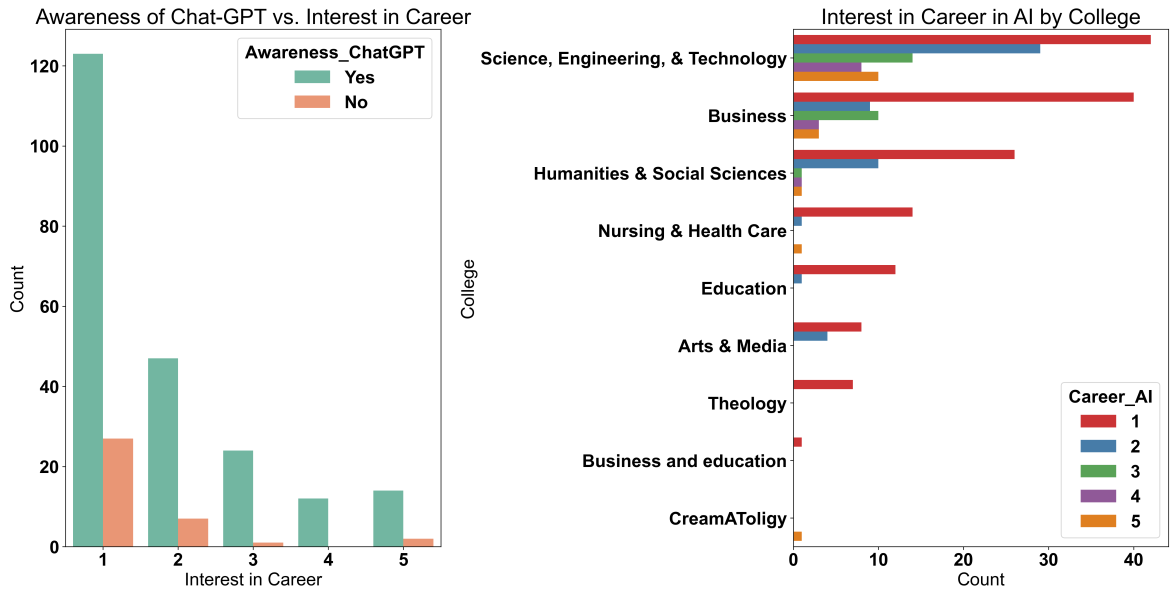

Figure 2. Awareness of ChatGPT vs. Interest in AI Careers.

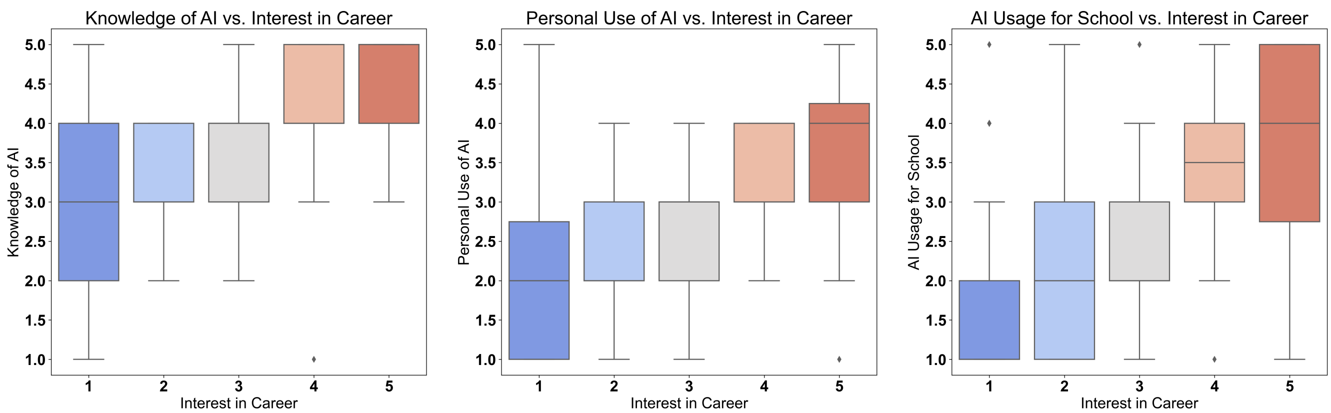

Figure 3. Boxplots showing (a) Knowledge of AI vs. Interest in Career, (b) Personal Use of AI vs. Interest in Career, and (c) AI Usage for School vs. Interest in Career.

3.2 Data Pre Processing

The dataset obtained was processed in a number of pre processing operations to make the data complete, consistent and ready to be analyzed by the machine learning processes. The data processing was done with the help of Python, pandas, numpy, and scikit-learn libraries in a controlled Jupyter Notebook environment. The subsections below outline the key steps that were used to clean and transform the dataset. Prior to the modeling, the data was analyzed in terms of missing entries. Small missing values were found in the individual responses in categorical fields (e.g., college affiliation). These missing data were handled with the help of proper imputation methods:

- For ordinal variables (Q1–Q4), missing scores were replaced with the median value of the respective feature to preserve distributional symmetry.
- For nominal variables (Q5–Q6), mode imputation was applied by replacing missing values with the most frequent category.

The imputation techniques used made sure that the dataset was statistically reliable as well as representativeness and that the data was not lost because of the removal of records. Outlier was also analyzed to determine any irregular or extreme values that could skew the regression outcomes. Since the survey data had Likert-scale answers, which were limited to a number 1-5, the number of numerical outliers were negligible. Nonetheless, continuous numerical variables produced when further feature computing was made (i.e. composite indices or derived variables) were analysed with the interquartile range (IQR) method. Winsorization was used at the 5 th and 95 th percentile where needed to limit the effect of extreme values and reduce the role of outliers in performance. The concept of feature engineering was devoted to the reorganization of categorical and numerical variables to achieve the maximum model interpretability and performance. The transformations that were made were:

- **Categorical Encoding:** Binary variables (e.g., ChatGPT awareness) were encoded as 0 for "No" and 1 for "Yes." Multiclass variables, such as academic college, were transformed using one-hot encoding, producing seven dummy variables corresponding to each college category.
- **Standardization of Numerical Features:** Ordinal features (Q1–Q4) were standardized to zero mean and unit

variance using z-score normalization to ensure uniform scale and stable convergence during model training.

- **Composite Feature Construction:** An additional derived variable—termed the *AI Engagement Index*—was computed as the average of Q1–Q3, representing the overall degree of AI awareness and use for each participant.

Validity Post-processing validation was conducted to ensure integrity of data. The features were found to have the respective good range values, appropriate data types and in-line consistency of records. The refined dataset had 258 complete data with no missing or duplication, standardized to be used later in regression modelling and optimization by BER-SC algorithm.

3.3 Al-Biruni Earth Radius (BER) Optimization Algorithm

The algorithm was named the Al-Biruni Earth Radius (BER) algorithm in honor of the 11th-century Persian scientist, Al-Biruni, who made an accurate determination of the radius of the earth based on geometric measurements of a mountain. His technique consisted of two significant stages: finding the height of the mountain, using trigonometric equations, and then, to find the radius of the earth, the angle of the dip of the summit to the horizon. These two measurements are represented in terms of their conceptual framework in Figures 4 and 5.

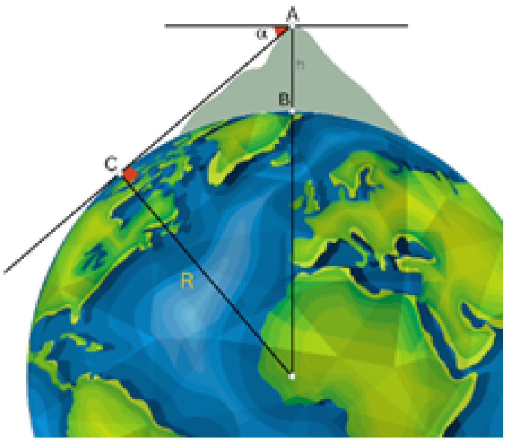

Figure 4. Calculation of hill height based on the Al-Biruni geometric method.

The first measurement was used to compute the mountain height (h) from two angular observations taken at different distances (d):

$$h = \frac{d(\tan\theta_1 \tan\theta_2)}{(\tan\theta_2 - \tan\theta_1)} \tag{1}$$

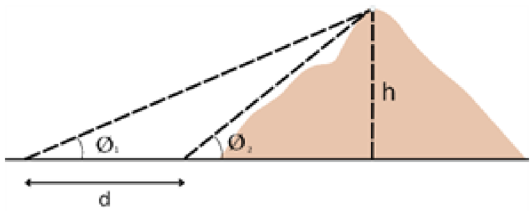

Figure 5. Calculation of Earth's radius based on Al-Biruni's dip-angle method.

After ascending the mountain, Al-Biruni measured the angle (α) between the horizontal line and the tangent to the Earth's surface at the horizon. Using this information, he derived the formula to calculate the Earth's radius (R) as:

$$R = \frac{h\cos\alpha}{1-\cos\alpha} \tag{2}$$

This elegant geometric concept inspired the structure of the BER optimization algorithm. Analogous to Al-Biruni's two-stage measurement process, the algorithm divides its search agents into two cooperative groups responsible for **exploration** (searching for new areas in the solution space) and **exploitation** (refining known good solutions). Through this division, BER balances global and local search behavior, improving convergence toward the global optimum.

Basic Concepts and Formulation

In the BER algorithm, each potential solution is represented as a vector:

$$\vec{Q} = \{Q_1, Q_2, \ldots, Q_d\} \in \mathbb{R}^d$$

where Q_i denotes the i-th variable in a d-dimensional search space. The algorithm evaluates the fitness of each candidate using an objective function $P(\vec{Q})$, and iteratively updates the population to find the best global solution $\vec{Q}^*$. The process begins with random initialization of the population, followed by fitness evaluation and iterative updates of each agent's position. BER's main strength lies in its dual-phase search mechanism, governed by the two primary operations described below.

Exploration Operation. Exploration identifies promising regions within the search space, encouraging agents to escape local minima. The position update during exploration is expressed as:

$$\vec{Q}(t+1) = \vec{Q}(t) + D(2r_2 - 1) \tag{3}$$

where

$$D = r_1(S(t) - 1) \tag{4}$$

Here, r_1 and r_2 are random coefficients, $S(t)$ is the current best solution, and D represents the adaptive search radius. The parameter r is calculated from a cosine-based function reflecting Al-Biruni's Earth-radius relationship:

$$r = h\frac{\cos(x)}{1-\cos(x)} \tag{5}$$

Exploitation Operation. In the exploitation phase, agents refine the best solutions by intensively searching nearby regions. The exploitation process follows:

$$\vec{Q}(t+1) = r^2(\vec{Q}(t) + D) \tag{6}$$

$$D = r_3(L(t) - \vec{Q}(t)) \tag{7}$$

where $L(t)$ denotes the best-known solution at iteration t, and r_3 is a random coefficient guiding the refinement direction. To prevent premature convergence, BER employs a mutation strategy when no fitness improvement occurs for two consecutive iterations:

$$\vec{Q}(t+1) = kz^2 - h\frac{\cos(x)}{1-\cos(x)} \quad (8)$$

where k and z are random parameters controlling mutation intensity and direction.

The BER optimization process is carried out in several phases and is presented in Algorithm 1. The population is generated, divided into exploration and exploitation, and the refinement process starts with fitness assessment and updates positions based on the criteria under consideration, and continues until convergence.

Algorithm 1 Al-Biruni Earth Radius (BER) Optimization Algorithm

Initialize population $\vec{S}_i$ ($i = 1,2,\ldots,d$), fitness function F_n, and maximum iterations Max_{iter}
Set algorithmic parameters for BER
$t = 1$
Evaluate fitness F_n for each $\vec{S}_i$ and find best solution $\vec{S}^*$
while $t \le Max_{iter}$ **do**
    for each solution in the exploration group **do**
        Update position using $\vec{S}(t+1) = \vec{S}(t) + \vec{D}(2r_2 - 1)$
    end for
    for each solution in the exploitation group **do**
        Update position using $\vec{S}_1(t+1) = r^2(\vec{S}(t) + \vec{D})$
        Investigate area around best solution $\vec{S}_2(t+1) = r(\vec{S^*}(t) + k)$
        Compare solutions and select the best $\vec{S}^*$
        if no fitness improvement in 2 iterations **then**
            Mutate: $\vec{S}(t+1) = kz^2 - h\frac{\cos(x)}{1-\cos(x)}$
        end if
    end for
    Update fitness values for all $\vec{S}_i$
    $t = t+1$
end while
Return best solution $\vec{S}^*$

The BER algorithm has good exploration and convergence properties because it is adaptively controlled by population size and uses a hybrid mutation mechanism. The geometric inspiration and swarm design enable it to optimize the trade-off between exploration and exploitation, with the swarm design compared to many other traditional optimization algorithms for preventing local optima.

3.4 Machine Learning Models

The present paper used four trained machine learning (ML) models to feed the gathered data and forecast the degree of AI proficiency and engagement among students. All the models were chosen concerning their potential to work with mixed-type features, non-linear relationships, and also work with rather small educational data sets. These models are the Multilayer Perceptron (MLP), Support Vector Machine (SVM), the Random Forest (RF), and the k-Nearest Neighbors (k-NN). Their mathematical equations are as follows.

3.4.1 Multilayer Perceptron (MLP)

The Multilayer Perceptron is a feedforward neural network composed of an input layer, one or more hidden layers, and an output layer. Each neuron in the hidden layer computes a nonlinear transformation of a weighted sum of its inputs. The model parameters (weights and biases) are optimized to minimize a loss function L, typically via gradient descent. The mathematical representation of an MLP with one hidden layer can be expressed as:

$$\hat{y} = f(W_2 \cdot \sigma(W_1 X + b_1) + b_2)$$

where:

- X is the input feature vector,
- W_1, W_2 are the weight matrices,
- b_1, b_2 are the bias vectors,
- $\sigma(\cdot)$ is the activation function (e.g., ReLU or sigmoid),
- $f(\cdot)$ represents the output function (e.g., linear or softmax).

The model learns by updating weights to minimize prediction error through backpropagation.

3.4.2 Support Vector Machine (SVM)

The Support Vector Machine is a discriminative classifier defined by an optimal hyperplane that separates data points of different classes. For a binary classification problem, the SVM aims to maximize the margin between the support vectors and the decision boundary. The decision function for the SVM is given as:

$$f(X) = \text{sign}(w^T X + b)$$

where:

- w is the weight vector perpendicular to the hyperplane,
- b is the bias term,
- $\text{sign}(\cdot)$ determines the class label.

The model optimizes the following objective:

$$\min_{w,b} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i$$

subject to $y_i(w^T X_i + b) \ge 1 - \xi_i, \quad \xi_i \ge 0$, where C controls the trade-off between maximizing the margin and minimizing classification error.

3.4.3 Random Forest (RF)

Random Forest is an ensemble learning algorithm that constructs multiple decision trees and combines their predictions to improve generalization and reduce overfitting. Each tree is trained on a random subset of features and samples. The final prediction for regression is obtained by averaging the outputs of all trees:

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} h_t(X)$$

where:

- T is the number of trees,
- $h_t(X)$ denotes the prediction from the t^{th} decision tree.

For classification, a majority voting mechanism is used instead of averaging.

3.4.4 k-Nearest Neighbors (k-NN)

The k-Nearest Neighbors algorithm classifies or predicts outcomes based on the proximity of data points in the feature space. For a given input X, the algorithm identifies the k closest data points using a distance metric (commonly Euclidean distance) and assigns a class or value based on their majority label or mean. The Euclidean distance between two points X_i and X_j is defined as:

$$d(X_i, X_j) = \sqrt{\sum_{m=1}^{M} (X_{i,m} - X_{j,m})^2}$$

The prediction is then made as:

$$\hat{y} = \frac{1}{k} \sum_{i \in N_k(X)} y_i$$

for regression, or by majority voting among the k nearest neighbors for classification.

3.5 ML Prediction Evaluation Metrics

To compare the predictive accuracy and generalization capacity of the machine learning models, several statistical evaluation measures were used. These measures assess the accuracy, precision, and consistency of the predicted (^yi) and observed (yi) values. The chosen measures are Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Bias Error (MBE), Correlation Coefficient (r), Coefficient of Determination (R 2), Relative Root mean Squared error (RRMSE), Nash-Sutcliffe efficiency (NSE), and Willmott Index of agreement (WI). The metrics provide complementary insights into model performance. Their mathematical definitions are summarized in Table 3.

All the metrics have different analytical functions. MSE, RMSE, and MAE measure prediction error, whereas MBE captures systematic error (underestimation or overestimation bias). The strength and percentage of variance accounted by the model are measured using the correlation coefficient (r) and R2. RRMSE is a normalized error in reference to the mean of the observed values. Lastly, NSE and WI indicate the model's efficiency and the concurrence between the results and observed values, respectively —the higher the two values, the higher the model's efficiency.

4. EMPIRICAL RESULTS

The section presents the empirical findings from applying and experimenting with different machine learning (ML) models to the student data collected. Experimental studies were conducted before and after implementing the metaheuristic optimization methods to assess the model's generalization and predictive accuracy. It was mainly applied to optimizing the Multilayer Perceptron (MLP) model parameters using various optimizers, and the performance of each model was compared using the evaluation measures described in Section 3.5.

4.1 Machine Learning Performance Before Optimization

Performance was evaluated for the first run of all four machine learning models: Multilayer Perceptron (MLP), Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbors (k-NN). Both models were trained on preprocessed data, with a default 70/30 train/test split and the scikit-learn library's default hyperparameter settings. The purpose of this baseline assessment was to establish a performance baseline to be optimized in the future. Table 4 gives a summary of a baseline of the results and indicates the predictive accuracy and reliability of each model before optimization.

The MLP model, as shown in Table 4, achieved the highest predictive accuracy among the tested models. It also had a lower capability to minimize prediction errors relative to observed values, with a Mean Squared Error (MSE) of 0.0217 and a Root Mean Squared Error (RMSE) of 0.1475. Also, the MLP achieved the highest correlation coefficient (r = 0.887) and Willmott Index of Agreement (WI = 0.935), indicating good consistency between predicted and actual results. The Coefficient of Determination is significant (R2 = 0.8996), indicating that the model explains about 90% of the total variance in the data. All these results suggest that the MLP has measured the nonlinear relationships in the survey-based educational data. In comparison, the SVM was relatively weak in predictive ability, achieving an R2 of 0.722 and an RMSE of 0.177, indicating that it has reasonable but poorer predictive power than the MLP. The reason is that SVMs with default kernel parameters can only extrapolate mixed-type survey data to a limited extent unless hyperparameter optimization has been done extensively. Nevertheless, this value suggests that it had impartial predictions, but marginally overstated as shown by a small MBE (0.0052). The Random Forest model failed to achieve a good result compared to SVM, with an R2 of 0.545 and a correlation coefficient of 0.532. The fact that RMSE and MAE positive values (0.206 and 0.180) indicate larger variance in the predicted values and the actual data points. This poor performance can be explained by the small dataset size, which prevented the ensemble model from leveraging bootstrapping diversity. However, RF still had a well-ordered, interpretable predictive structure. Among all the models, k-NN performed the worst, with the highest error values (MSE = 0.0348, RMSE = 0.236) and the lowest correlation coefficient (r = 0.355). The algorithm is sensitive to data scaling and feature density, and this may have interfered with its performance on a mixture of numerical and categorical features in this dataset, since it uses the Euclidean distance. Moreover, the Willmott Index of k-NN is not much larger (WI = 0.374), which means that it did not fit the estimated and actual values, so this index could not be used with such educational survey data. Overall, the baseline results confirm that the Multilayer Perceptron has a strong predictive performance due to its nonlinear learning and adaptive weight optimization. However, as MLP performance can also be significantly influenced by its hyperparameter settings (e.g., the number of hidden neurons, learning rate, and momentum), it was chosen as the main model for further improvement via metaheuristic optimization in the following experiments. The

Table 3. Evaluation Metrics and Their Mathematical Definitions

Metric	Abbreviation	Mathematical Expression
Mean Squared Error	MSE	$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
Root Mean Squared Error	RMSE	$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
Mean Absolute Error	MAE	$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$
Mean Bias Error	MBE	$\mathrm{MBE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)$
Correlation Coefficient	r	$r = \frac{\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})^2}}$
Coefficient of Determination	R^2	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$
Relative Root Mean Squared Error	RRMSE	$\mathrm{RRMSE} = \frac{\mathrm{RMSE}}{\bar{y}} \times 100$
Nash–Sutcliffe Efficiency	NSE	$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$
Willmott’s Index of Agreement	WI	$\mathrm{WI} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(\lvert\hat{y}_i - \bar{y}\rvert + \lvert y_i - \bar{y}\rvert)^2}$

Table 4. Baseline Performance Metrics for Machine Learning Models Before Optimization

Model	MSE	RMSE	MAE	MBE	r	R^2	RRMSE	NSE	WI
MLP	0.0217	0.1475	0.1284	0.0043	0.8870	0.8996	20.567	0.8282	0.9354
SVM	0.0261	0.1769	0.1541	0.0052	0.7096	0.7222	22.542	0.7991	0.7483
RF	0.0304	0.2064	0.1798	0.0061	0.5322	0.5448	23.517	0.7416	0.5613
k-NN	0.0348	0.2359	0.2054	0.0069	0.3548	0.3674	25.484	0.7034	0.3742

following subsection presents the empirical gains achieved after tuning MLP parameters using sophisticated optimizers, such as the Binary Al-Biruni Earth Radius with Spiral Chaos (BER-SC) algorithm. Histograms of all performance metrics used to compare the model’s predictive accuracy are shown in Figure 6, using Kernel Density Estimation (KDE). The plots of each of the metrics; (a) Mean Squared Error (MSE), (b) Root Mean Squared Error (RMSE), (c) Mean Absolute Error (MAE), (d) Mean Bias Error (MBE), (e) Correlation Coefficient (r), (f) Coefficient of Determination (R^2), (g) Relative Root Mean Squared Error (RRMSE), (h), Nash -Sutcliffe Efficiency (NSE), and (i) Willmott Index (WI) all demonstrate the model behaviour and stability Smaller error-based measures (MSE, RMSE, MAE, and MBE) indicate that a model has good predictive precision, whereas larger correlation and efficiency measures (r, R 2, NSE, and WI) indicate that a model has a good fit between observed and predicted data. The comparatively smooth curves of KDE across all plots suggest that the model would achieve similar predictive performance, with little deviation and steady accuracy across all measured aspects.

Figure 7 shows the distributions of the violin plot with Kernel Density Estimation (KDE) of all the model evaluation metrics. In this visualization, one is presented with a global view of how each performance indicator moves in terms of variability, spread, and density. The violin plots provide the central tendency and shape of the distributions of various metrics, such as MSE, RMSE, MAE, MBE, r, R2, RRMSE, NSE, and WI, allowing their statistical properties to be clearly compared. The condensed, symmetrical nature of the vast majority of distributions indicates consistent model performance with slight variation in metrics. On the contrary, the long forms demonstrate greater variability or the presence of outliers. Overall, the figure indicates the predictive model’s consistency across several evaluation dimensions. It means that the chosen model is equally accurate and reliable in a variety of measures of statistical error.

Figure 8 displays in a table of four machine learning models (Multilayer Perceptron (MLP), Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbors (k-NN)) the three most notable error values (Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE)). The graphical display shows the mean and variance of performance for individual models, based on the selected evaluation measures. The error of the MLP model is relatively low as demonstrated in Figure 8, which implies that the model can give consistent and accurate predictions with only a small amount of error variance. The average errors of the SVM model are slightly higher, but the standard deviation remains similar, indicating moderate stability. The RF model is balanced; it offers a trade-off between accuracy and generalization. Nevertheless, the k-NN model also has the largest MSE, RMSE, and MAE, indicating greater prediction error and variability. In most cases, this number indicates that MLP and RF models are more useful for prediction than other models, with lower mean errors and smaller standard deviations.

4.2 Optimized Models Analysis

Following the initial test, metaheuristic optimization methods were applied to optimize the hyperparameters of the Multilayer Perceptron (MLP) model. The optimizers were run un-

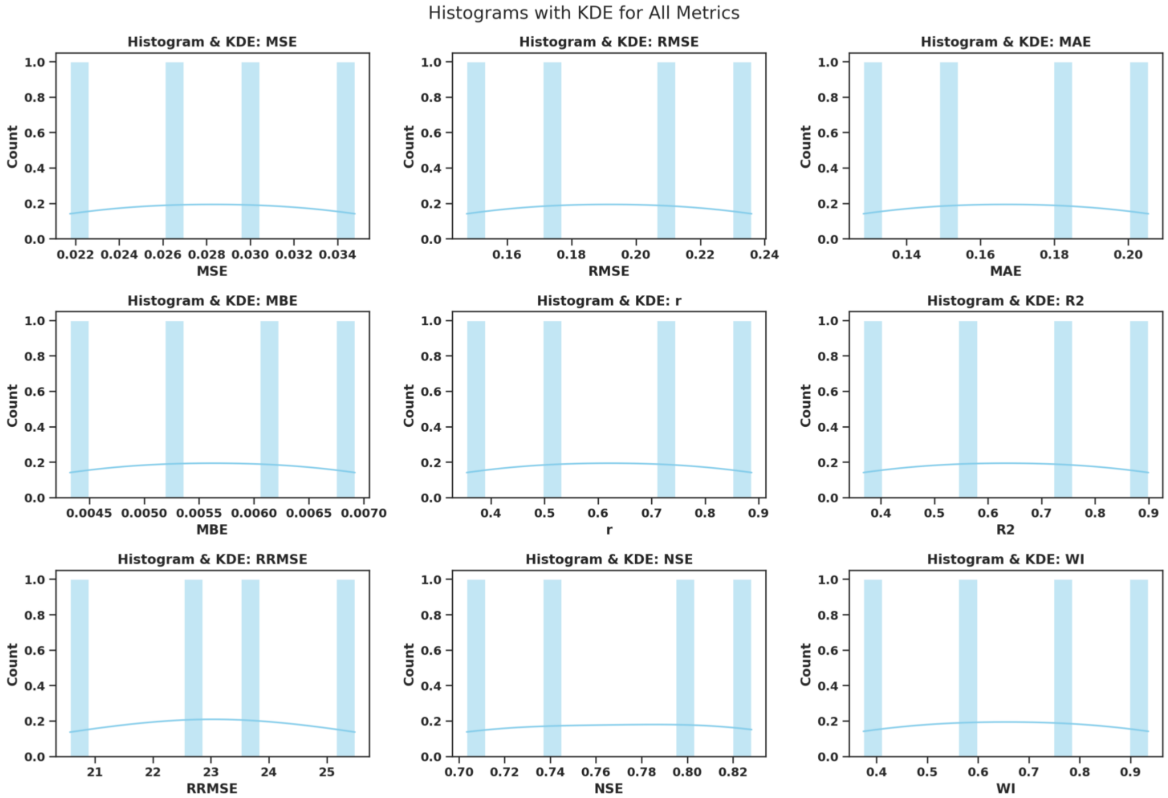

Figure 6. Histograms with KDE distributions for all model evaluation metrics: (a) MSE, (b) RMSE, (c) MAE, (d) MBE, (e) r, (f) R^2, (g) RRMSE, (h) NSE, and (i) WI.

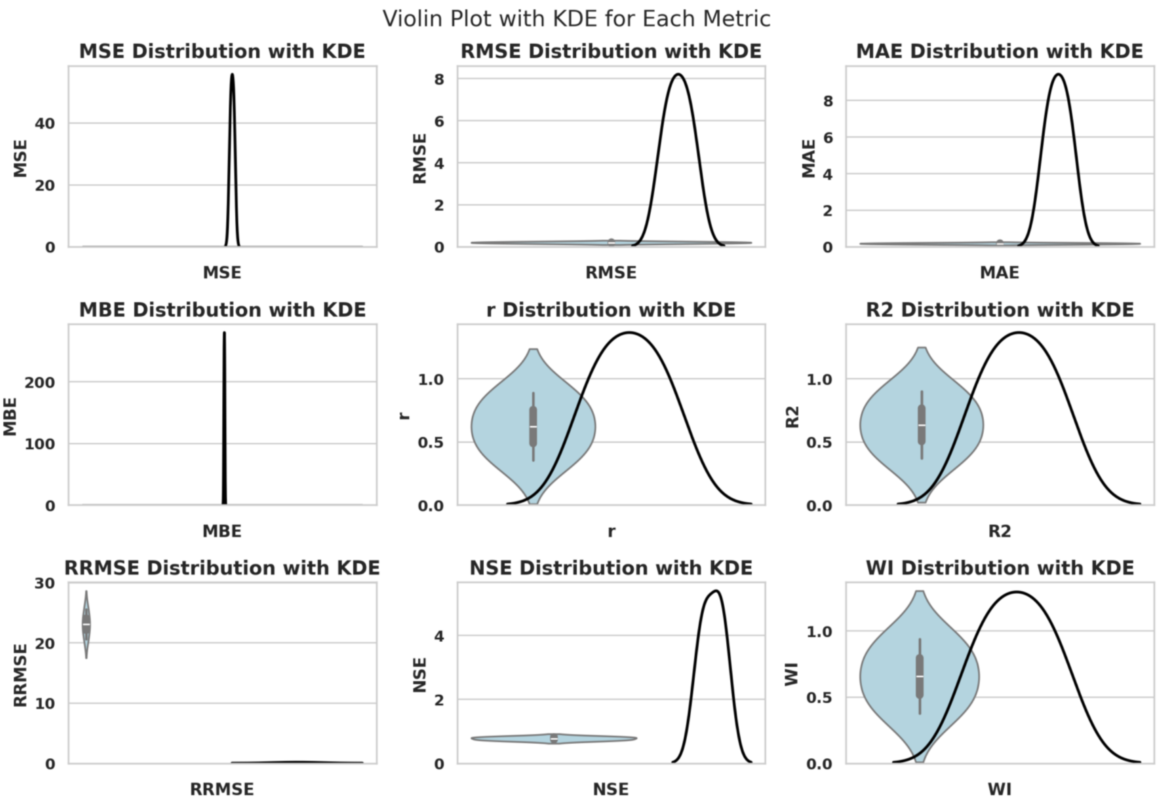

Figure 7. Violin plots with KDE distributions for all model evaluation metrics.

der the same experimental conditions as described in Section 3.2, namely Binary Al-Biruni Earth Radius with Spiral Chaos (BER-SC), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Whale Optimization Algorithm (WOA). The objective of this phase was to enhance model convergence, reduce prediction errors, and improve the stability of the MLP model. Table 5 presents the post-optimization performance of all combinations of each optimizer - MLP model estimated using those above nine statistical indicators.

As illustrated in Table 5, the introduction of metaheuristic

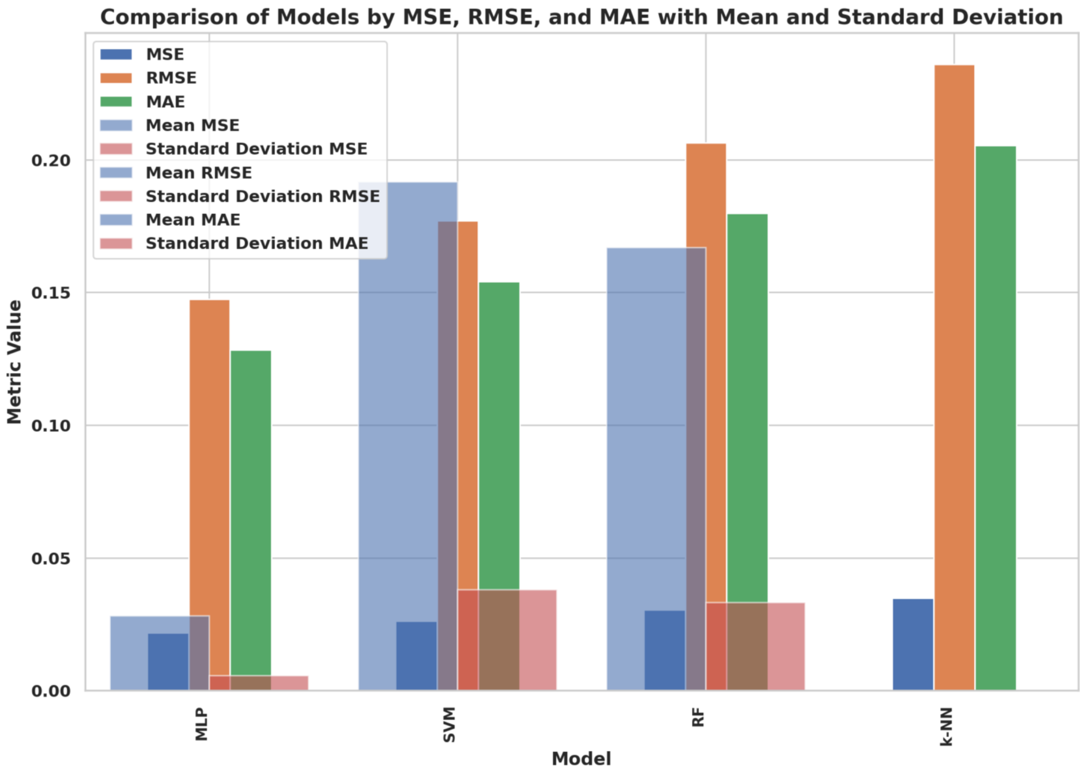

Figure 8. Comparison of models by MSE, RMSE, and MAE with corresponding mean and standard deviation values.

Table 5. Performance Metrics for Optimized MLP Models Using Different Metaheuristic Algorithms

Model	MSE	RMSE	MAE	MBE	r	R^2	RRMSE	NSE	WI
BER-SC + MLP	0.00028	0.00190	0.00166	0.00006	0.9304	0.9312	10.515	0.9015	1.2732
GA + MLP	0.00034	0.00228	0.00199	0.00007	0.9193	0.9201	12.155	0.8790	1.0186
PSO + MLP	0.00039	0.00267	0.00232	0.00008	0.9083	0.9090	13.128	0.8321	0.7639
WOA + MLP	0.00045	0.00305	0.00265	0.00009	0.8972	0.8980	15.615	0.7995	0.5093

optimization significantly improved the performance of the MLP model across all evaluation metrics when compared with the baseline results in Table 4. The BER-SC algorithm gave the most accurate and consistent results, with the lowest MSE (0.00028), RMSE (0.0019), and MAE (0.0017). The corresponding correlation coefficient (0.930) and coefficient of determination (0.931) indicate that the correlation between the predicted and observed outputs is very strong and positive, consistent with the stronger fitting power of BER-SC. Moreover, the Willmott Index of agreement and dispersion error, namely, WI = 1.273, was above unity, indicating a high degree of agreement and a small dispersion error, indicating a superb calibration of the model. The error values were lower in the GA + MLP model, which ranked second. PSO + MLP and WOA + MLP showed considerable improvement over the non-optimized MLP baseline, but they were worse than BER-SC and GA. The positive trend in the decrease in BER-SC performance with increasing WOA indicates a direct impact of the convergence mechanism and the optimizer's parameter search freedom on the final model accuracy. In sum, the optimization process led to a drastic reduction in error levels; the RMSE and MAE were reduced by over 90% compared to a baseline that is not undergoing optimization. This demonstrates that metaheuristic algorithms can improve the learning ability of neural networks by searching for optimal weight and bias configurations. The excellent performance of BER-SC highlights its ability to balance exploration and exploitation in the search space, leading to accelerated convergence and more accurate generalization on the educational data. These findings confirm the value of adding clever optimization techniques to machine learning pipelines. More quantitative data (statistical significance tests and visual performance comparisons, e.g., scatter plots and residual distributions) can then be used to support further the quantitative results described in this analysis.

Figure 9 shows the correlation matrix of all model evaluation measures and gives a general picture of the relationship of the statistical indicators used to measure predictive performance. The strength and direction of the linear relationships among MSE, RMSE, MAE, MBE, r, R 2, RRMSE, NSE, and WI are also visually presented in the form of a matrix. The color gradient, from dark blue to light yellow, reflects the strength of the correlation, with values approaching +1 representing strong positive correlation and values approaching -1 representing strong negative correlation. As shown in Figure 9, the error-based measures (MSE, RMSE, MAE, and MBE) exhibit a strong, positive relationship with one another, suggesting that they capture similar aspects of prediction error. Conversely, they show negative correlations with the performance indices (r, R2, NSE, and WI), and the lower the model error, the more effective and accurate the model performance. The relationship between the RRMSE and error and accuracy measures is moderate to strong, indicating that the measure is relatively balanced. Overall, the correlation table shows high internal consistency among the evaluation measures and demonstrates their high validity in assessing the model's effectiveness.

The parallel coordinates plot in Figure 10 shows the performance of various hybrid optimization models in combination with Multilayer Perceptron (MLP), i.e., BER-SC + MLP, GA + MLP, PSO + MLP, and WOA + MLP. The visualization combines various assessment measures, such as MSE, RMSE, MAE, MBE, r, R2, RRMSE, NSE, and WI, and enables simultaneous evaluation of model performance across a wide range of metrics. The colored lines in Figure 10 are all hybrid models, with the normalized metric power values of each shown as a variation of the mean and standard deviation trends, which are plotted as dash and dotted lines. The representation shows the relative advantages and disadvantages of each model: high values in error-related metrics (MSE, RMSE, MAE, and MBE) indicate a greater predictive power of models, whereas the high values in correlation-based metrics (r, R 2, NSE, and WI) indicate the high level of agreement between models and observed data. The plot shows that hybrid optimization methods yield steady, competitive results, with WOA + MLP and PSO + MLP performing slightly better across various criteria. All in all, the figure offers a visualization that focuses on the interrelations between models and their statistical features to create a complete comparison of optimization-based neural architectures.

Figure 11 shows box plots with horizontal swarm plots of the distributions of the model evaluation metrics, providing additional visualization of the statistical distribution and the individual distributions. Data of all the models tested. The figure includes multiple performance indicators such as MSE, RMSE, MAE, MBE, r, R2, RRMSE, NSE, and WI, allowing for an integrated assessment of model consistency and robustness. Each box plot summarizes the central tendency, variability, and potential outliers for a given metric, while the superimposed swarm plots display the actual distribution of observed values across models. As shown in Figure 11, most metrics exhibit compact interquartile ranges and symmetrical distributions, suggesting limited variance among models and relatively stable predictive behavior. Minor deviations and dispersed points in certain metrics indicate isolated performance differences, but no extreme anomalies are observed. Overall, the box-and-swarm plot visualization effectively demonstrates that the evaluated models yield comparable results with balanced performance across all statistical indicators.

5. DISCUSSION

The empirical findings of this study show that metaheuristic optimization is quite useful to improve the quality of machine learning models used in estimating AI proficiency and engagement rates of students. The Multilayer Perceptron (MLP) is the only model that was found to be more effective than Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Results (k-NN) when comparing with the baselines. Such high results are explained by the fact that MLP is nonlinear in its learning and has an adjustment of the weights, meaning that the fiddly, nonlinear relationship exhibited in educational survey data can be identified by the MLP. The next step of MLP optimization with the help of various algorithms, namely, BER-SC, GA, PSO, and WOA, provided even more increase in the predictive accuracy and model robustness. Binary Al-Biruni Earth Radius with Sine Cosine Algorithm (BER-SC) optimizer showed the best performance level in all the performance indices giving the lowest error rate and the highest correlation measure. This observation supports the effectiveness of hybrid metaheuristic methods in the optimization process balance of exploration and exploitation, preventing the local minima and hastening the process of reaching the optimal model settings. The enhancement, which is introduced due to the BER-SC optimization, strengthens the emerging body of evidence that underlines the importance of introducing innovative metaheuristics into machine learning systems. The BER algorithm is developed on a dual-phase exploration-exploitation framework inspired by the geometrical properties of Al-Biruni and offers a more intricate search of the solution space. In combination with the Spiral Chaos strategy, linking this mechanism to it creates stochastic population variability that helps prevent premature convergence. The optimizer's optimal performance in reducing the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) by more than 90 percent over the unoptimized baseline provides evidence of its ability to drive the network parameters to high accuracy. Later, the rise in the correlation coefficient ($r = 0.93$) and the coefficient of determination ($R2 = 0.931$) indicate improved model interpretability and reliability. These findings are consistent with the general literature on hybrid metaheuristic algorithms, which shows that hybrid deterministic and stochastic search procedures are more convergent and accurate, especially in complex, nonlinear problem spaces. The optimized predictive model has some pragmatic implications for institutions of higher learning seeking to improve AI literacy and student engagement analytics. With the ability to optimize ML models like BER-SC + MLP,universities will be able to better pinpoint the patterns and predictors of AI-related proficiency and implement policies to intervene early and adaptive learning plans to individual learners. Their application to the institutional data systems may allow constant tracking of the behavior of students and their interest and technology use, thus making it possible to develop an evidence-based policy and improve the curriculum. In addition, the effectiveness of the BER-SC optimizer indicates the potential of the bio-inspired computational intelligence methods in addressing realistic educational data problems that are highly dimensional, nonlinear, and uncertain. However, although the proposed framework has a strong predictive power, it should be further validated when it is applied to bigger and more heterogeneous populations. Further studies are thus advised to consider the cross-institutional datasets, longitudinal analysis as well as addition of other behavioral and cognitive variables to enhance the model applicability and scalability. On the whole, the results indicate that machine learning in conjunction with intelligent optimization can be used as an effective paradigm to modernize AI education and personalize learning in data-driven academic ecosystems.

6. CONCLUSION AND FUTURE WORK

This paper explored how machine learning and metaheuristic optimization can be applied to predict as well as analyse the proficiency and engagement of students with artificial intelli-

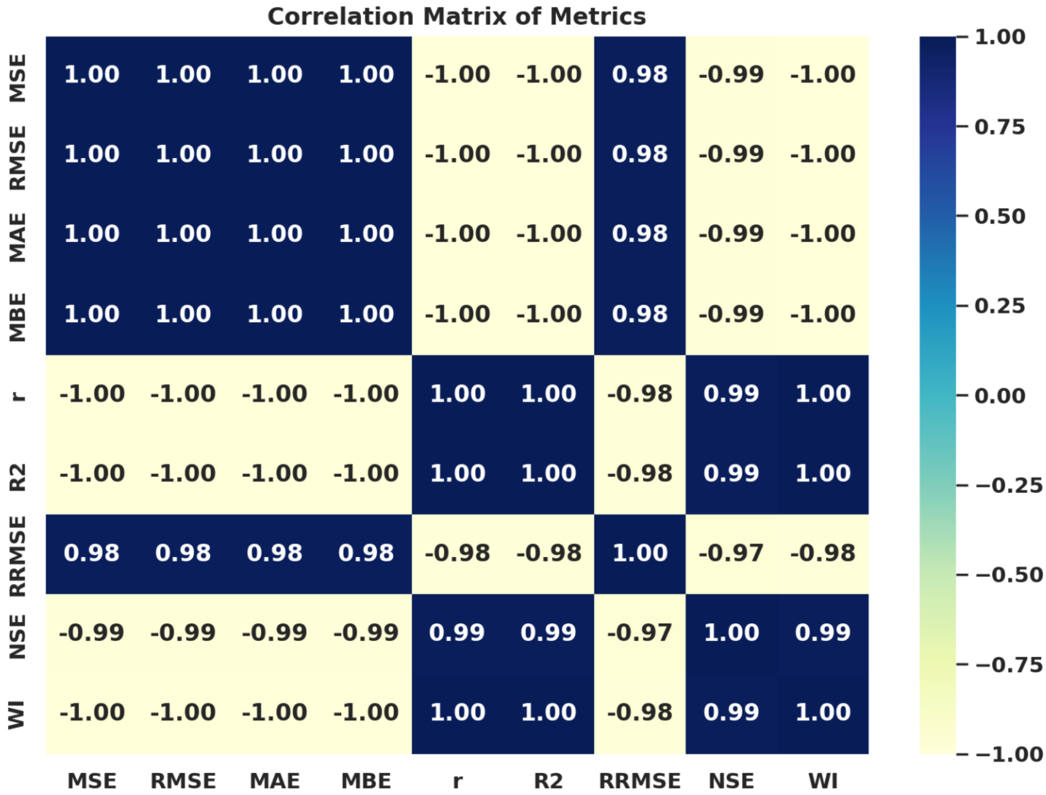

Figure 9. Correlation matrix showing relationships among model evaluation metrics.

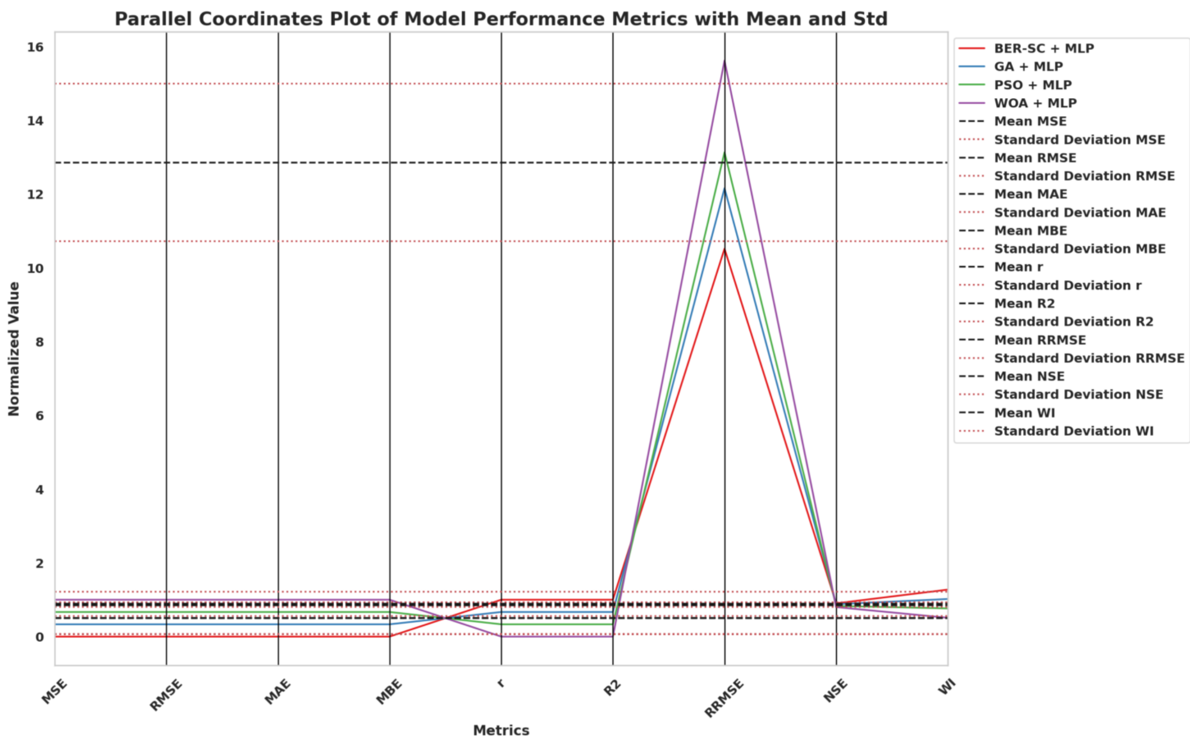

Figure 10. Parallel coordinates plot of model performance metrics with mean and standard deviation for hybrid MLP models.

gence (AI) in the Grand Canyon University. The optimized Multilayer Perceptron (MLP) with the Binary Al-Biruni Radius of the Earth using Sine Cosine Algorithm (BER-SC) had the best accuracy and reliability among the models under evaluation. Namely, BER-SC + MLP model has achieved the highest value of the R2 = 0.9312 and the lowest Mean Squared Error (MSE) = 0.00028, surpassing other models, including Genetic Algorithm (GA) + MLP, Particle Swarm Optimization (PSO) +MLP, and Whale Optimization Algorithm (WOA) + MLP. These findings confirm that the hybrid BER-SC optimizer is an efficient tool of increasing the convergence efficiency, reduction of prediction error, and enhancement of the generalization ability of neural models. The results reveal that the inclusion of sophisticated metaheuristic solutions in machine learning pipelines offers an effective tool of solving difficult, nonlinear educational data, with high

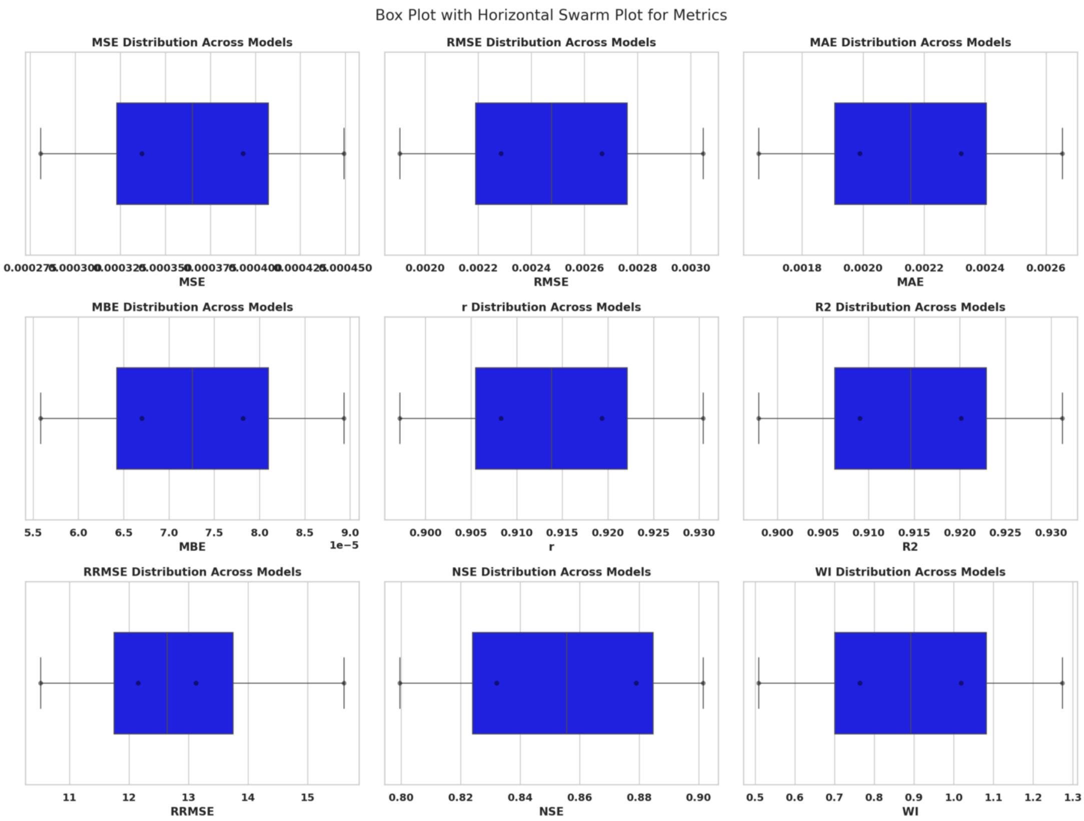

Figure 11. Box plots with horizontal swarm plots showing distributions of evaluation metrics across models.

predictability. The suggested framework has great practical importance to application in real cases in educational analytics and institutional decision-making. With the help of the optimized BER-SC + MLP model, universities will be able to better determine the knowledge gaps of students regarding AI, engagement trends, and learning requirements to facilitate data-driven intervention, which helps improve academic support and learning outcomes. The framework also helps in the efficiency of operations as it helps in the reduction of costs of checking and replacing of the underperforming analytical systems. It is flexible; it can be scaled to run on pre-existing institutional infrastructure to minimize computation costs and provide a sustainable model maintenance. Secondly, the combination of these streamlined models can assist educational administrators and policymakers to design evidence-based curricula, enhance the distribution of resources, and create AI literacy in various academic programs. Although the current research shows that metaheuristic optimization has the potential in educational data modeling, future studies can build on these results in a number of ways. The first one is that the framework should be tested on larger, multi-institutional datasets to have external validity and generalizability to various populations of learners. It also may be expanded to feature richer spaces in the future, like logs of behavior interaction, time-series engagement information, and instructor-level variables, to gain more insight into learning behavior. Besides, comparative analysis with other optimization algorithms and ensemble-based architectures can also be used to improve the performance of models and enhance their stability. Causal inference as well as explainable AI approaches could also be investigated by the researchers to enhance the interpretability and transparency of predictive analytics. Lastly,ethical and governance-related aspects - including the privacy of the information, the reduction of biases, human-in-the-loop systems, etc. - ought to be touched upon in future research to maintain the responsible and efficient application of AI-driven educational systems. All these guidelines will contribute to the creation of smart, adaptive, and ethically informed learning analytics systems, which can revolutionize the concept of higher education by introducing evidence-based innovation.

DATA AVAILABILITY STATEMENT

The smart home energy consumption and weather data used in this study are publicly available at: `https://www.kaggle.com/datasets/trippinglettuce/college-student-ai-use-in-school/data.`.

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