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Machine Learning Ensemble Model for Predicting Adoption of Metaverse in Higher Education Using PSO Algorithm for Setting Model's Hyperparameters

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Abstract

In recent years, the metaverse has rapidly gained prominence as an emerging virtual platform with multidimensional and interactive features. Its potential applications, particularly in higher education, have drawn increasing attention. However, the acceptance of the metaverse in educational contexts depends on a range of factors that remain insufficiently explored. This study aims to address gaps in previous research, where certain critical factors—such as awareness, user experience, and technological challenges affecting faculty and students in Iran—have been overlooked. The goal of this research is to develop and evaluate an ensemble machine learning model to predict metaverse adoption in Iranian higher education institutions. Drawing on questionnaire data and guided by metaheuristic parameter tuning, the model seeks to identify and forecast factors influencing the uptake of this technology. This descriptive-analytical study collected data from 730 respondents, including university students and faculty members, who answered a questionnaire on metaverse acceptance. Four machine learning models—Random Forest, XGBoost, and Gradient Boosting—were employed. Their parameters were optimized using the PSO (Particle Swarm Optimization) metaheuristic algorithm. Performance metrics included Accuracy, Recall, Precision, and the F1-Score. The results showed that ensemble machine learning models, enhanced by metaheuristic parameter tuning, accurately predicted metaverse adoption. The ensemble model achieved an outstanding accuracy of 95%. Moreover, variables such as technological accessibility, familiarity with the metaverse, and institutional support emerged as key determinants. This research demonstrates that ensemble machine learning models, combined with metaheuristic parameter optimization, can serve as effective tools for forecasting metaverse acceptance in higher education. The findings can help educational administrators devise more effective strategies for implementing and fostering the use of the metaverse, ultimately improving the integration of this technology into academic environments.

Keywords: Metaverse Adoption; Higher Education; Machine Learning; Metaheuristic Setting.

1- Introduction

Digital technologies are rapidly developing in modern societies. This transformation has had extensive and complex implications within education as an area of human interaction[1]. One emerging technology attracting notable interest from experts and researchers is the metaverse[2]. The metaverse is viewed as an interactive and multidimensional virtual space that allows the merging of virtual reality (VR) and augmented reality (AR) so that a user can use digital resources along with the natural environment in one space[3]. This is of great importance in higher education institutions. These institutions can use the metaverse to create innovative and collaborative learning experiences in which students can directly engage with educational content[4]. Access to educational resources, reductions in geographical limitations, and enhancements in the quality of learning are some of the abilities provided by these virtual environments[5]. Notably, a prominent impediment the technology has to overcome is its adoption by faculty and students. The fate of these technologies will depend on their adoption and willingness to use them.

Recent studies have shown that adopting new technologies, especially in educational settings, depends on numerous factors such as the ease of use, the user's awareness,

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system trust, and prior experience. In the words of the EdTech Research Institute's 2023 study, only 35 percent of schools managed to incorporate virtual reality technologies efficiently into their academic programs, showing the depth of challenges in integrating and applying new technologies like the metaverse[6]. Based on the provided statistics, identifying and analyzing elements that could influence the acceptance of the metaverse—especially in technologically advancing countries like Iran—has become a research necessity[7]. Consequently, this study seeks to develop and evaluate an ensemble machine learning model for predicting metaverse adoption in Iranian higher education institutions.

Interactive and virtual technologies, including the metaverse, have expanded dramatically over the last two decades, and these technologies have a wide range of potential and plausible impacts on different fields, including education[8], [9]. Virtual Reality (VR) and Augmented Reality (AR) have enabled educational bodies to generate virtual learning environments and realistic simulations. Conversely, the metaverse, as a platform, offers a broader space for faculty and students with many combinations of technological components that the personnel of an educational institution can explore with more advanced digital gadgets[10], [11]. Despite the rapid growth of these technologies in both developed and developing countries, technical, social, and educational problems and barriers have obstructed the complete implementation and establishment of these technologies within higher education institutions[12].

Previous studies in this field have analyzed some of the factors that influence the adoption of educational technologies. For instance, Johnson et al. (2020) [13]identified factors such as data security trust, user awareness of technologies, and ease of access, which are considered significant in adopting new technologies in educational contexts. In another study, Lee et al. (2021) found that user experience in interaction with virtual reality technologies directly affects users' adoption[14]. These studies have pointed out the factors that contribute to various aspects of adoption, but they have not done comprehensive metaverse adoption studies in Iran's higher education. Iran is among the developing nations' pioneer countries in adopting new educational technologies. This paper specifically examined the factors influencing the adoption of the metaverse in these environments.

Having reviewed the literature and background of this subject, it should be noted that interactive technologies have entered educational environments since the early 2000s. However, extensive use of virtual and augmented reality and other advancements in this field have materialized in recent years[15]. Aiming to fill the gap in the research literature and considering the background, this research provides a comprehensive model for predicting metaverse adoption in Iranian higher education.

Such innovations as the metaverse still face much hesitation in higher education. The novel and interactive platform of the metaverse could revolutionize the delivery of content and educational experience[16]. However, many universities and educational institutions have not fully employed or implemented it for a few reasons[17]. In tackling this domain, one big challenge is the limited understanding of the key factors influencing this technology's difficult or easy adoption. Unlike initial studies on adopting virtual and augmented reality-related technologies, no comprehensive and holistic investigations have spearheaded metaverse adoption in Iranian higher education or universities[18]. As many have argued, this knowledge gap may have impeded institutions' sound decision-making on practically implementing the metaverse and harnessing it as a powerful educational tool[19].

Unless a complete and comprehensive understanding of the factors that affect metaverse adoption is achieved, the application of this technology bears considerable dangers. Specific important questions this research sets out to answer are: Do users trust the stability and security of the metaverse? Are faculty and students hyped for metaverse as a new educational tool? What technological or social challenges may hinder the use of this technology? If these challenges were never solved, leaders within educational institutions could not leverage the many opportunities metaverses present. They could, therefore, lose their competitive edge in global student admission and continue to do so. Besides, inappropriate or incomplete applications of the metaverse bring added costs and inefficiencies to the quality of education.

This paper attempts to reach a specific objective concerning the problems raised and plenish the knowledge gap raised in the problem statement. The present research aims to propose a predictive model on the metaverse's adoption in higher education institutions based on empirical data collected through a questionnaire. To achieve this objective, the research has been designed around machine learning models and their incorporation into ensemble learning techniques coupled with metaheuristic settings to increase the accuracy of predictions on metaverse adoption.

More specifically, the objectives of this study are as follows:

To identify critical factors influencing metaverse adoption as perceived by faculty and students in higher education institutions.

Formulate a well-structured questionnaire to collect the required metaverse adoption assessment and analysis information.

Label and score collected data so that metaverse adopters and non-adopters can be identified and distinguished.

To predict metaverse adoption using ensemble machine learning approaches like XGBoost, Random Forest, and Gradient Boosting.

Metaheuristic algorithms, such as Particle Swarm Optimization (PSO), can be used to fine-tune the parameters of machine learning models to raise accuracy levels and improve prediction efficiency.

To shortlist the best prediction model, the performance of ML models is evaluated using parameters like Recall, Accuracy, Precision, and F1-Score.

These goals are directly related to the knowledge gaps acknowledged in the problem statement and represent innovative and novel attempts to understand better the factors affecting metaverse adoption in educational institutions and improve the decision-making process therein. This research can aid educational institutions in adopting the metaverse by allowing them to make informed investment decisions regarding new technologies and formulate better plans for implementation and adoption using proper data and analytic methodologies.

This study contributes several innovations to technological innovation adoption, particularly the metaverse, in higher education institutions. One significant contribution is the provision of novel empirical data from Iranian faculty members and students, which has not previously been examined in this geographical context. The data were collected using an extensive questionnaire to examine various criteria, such as user experience, metaverse awareness, technical barriers, and academic support.

Another contribution of this work is building a comprehensive machine learning model that uses ensemble approaches like XGBoost, Random Forest, and Gradient boosting to predict metaverse adoption. Unlike previous research dependent on simpler machine learning models, this study increases prediction accuracy and obtains more reliable results by blending models and optimizing parameters with the PSO (Particle Swarm Optimization) algorithm. Therefore, this research predicts the adoption of educational technology more accurately than previous ones.

Highlighting the identification of fundamental factors influencing Metaverse adoption allows educational institutions to make better, smarter, and more appropriate decisions to implement this technology. Its noteworthy contribution is that it aids both in academic research and, more importantly, the much-needed practical application concerning educational policymakers and managers who can practically use the outcome of this research to design and implement effective programs to use the metaverse within educational settings.

In addition to starting from the local and empirical data from Iran that earlier similar research neglected, this work's original contribution compared to prior research is combining machine learning methods with metaheuristic algorithms. This combination allows this research to more accurately endeavor towards the technology adoption prediction processes and generate better and more effective recommendations for educational institutions.

The present paper is systematically organized into major subsections to familiarize the reader with research objectives, methodologies, and findings.

1. Literature Review: This section reviews related works, providing a detailed discussion of previous works on novel technology adoption, particularly those dealing with metaverse and machine learning. It reviews the studies on digital technology adoption in educational settings, thus denoting an unavoidable need to develop predictive models.
2. Background and Explanations: This section reviews the metaverse, relevant technologies, and their significance in higher education. Furthermore, it focuses on the social, technical, and managerial factors affecting metaverse adoption in educational settings.
3. System Model and Framework: In this section, the proposed machine-learning model will be reviewed to predict metaverse adopters, the scoring framework for data collected through questionnaires will be explained, and metaheuristic algorithms will be explained on how to optimize ensemble model parameters.
4. Results: This section will present the study's empirical findings. The performance of the machine learning models will be analyzed and compared according to metrics like accuracy, recall, precision, and F1-Score, among others. Moreover, the most intimidating factors severely disrupting metaverse adoption will be identified and analyzed.
5. Conclusion and Future Research: This chapter summarizes key findings and makes recommendations for improving and developing future research in metaverse adoption. Furthermore, it discusses the research challenges and limitations.

2- Literature Review

In the last few decades, the rapid conception of digital and interactive technologies has made the interplay with the metaverse one of the most discussed phenomena in higher education. The metaverse is an interactive and multidimensional virtual space that can be used as a communicative medium for unlimited learning and information exchange opportunities in education[20]. Despite its potent possibilities, the students' and instructors' adoption of this technology has not gone without a struggle; thus, a number of researches were carried out with respect to the contributing factors and analysis.

This study analyzes the technology adoption theories and models, being the article "Predicting Users' Intentions to Use Metaverse in Medical Education: A Combined SEM and Machine Learning Approach" [21].

However, this paper examines students' intention to adopt the metaverse system for medical education guided by an exceptionally integrated Structural Equation Modeling (SEM) and Machine Learning (ML) approach. This study employs the Technology Acceptance Model (TAM), Personal Innovation (PI), and some observability-affiliated factors, perceived usefulness, and user satisfaction to assess users' attitudes. The contributions of this research can be summarized as follows: First, it used an SEM-ML combined approach to predict users' intentions to adopt metaverse systems in educational settings, especially in medical education. Second, it merges technology with research in Information Systems (IS) by combining user-oriented factors, such as personal innovation, with technological characteristics. In this regard, this study surveys 1,858 university students from the United Arab Emirates. It provides significant insights for multiple stakeholders in higher education regarding key predictors for metaverse adoption processes infusing educational contexts. The authors have employed a combined analytical model imbibing SEM for analyzing theoretical interactions and ML algorithms like neural networks and decision trees for predictions. Of note is that the Importance-Performance Map Analysis (IPMA) has been further employed to focus on the core aspects influencing user satisfaction and perceived usefulness.

This study has specific problems and limitations. First, the study's focus on a single geographical region, the United Arab Emirates, and a specific subject area, medical education, limits its generalizability to other scientific fields and regions. Second, the data were collected through self-reported questionnaires, which could render biased results. Third, this study failed to recognize the cultural differences that are more likely to affect technology adoption across different regions. Finally, the study concluded that user satisfaction (US) was the most important predictive factor of the student's intention to use metaverse systems in medical education. The other significant constructs observed in this research included perceived compatibility and observability. Additionally, compared to the traditional SEM models, the combined SEM-ML model has demonstrated better predictive abilities and has been put forth as a powerful tool for predicting technology adoption in educational settings.

The article Predicting Users' Intention to Use Metaverse System in Medical Education: A Combined SEM-ML Approach [22] also examines the intention of users (students) to adopt the metaverse system in medical education. The authors employed a combination of Structural Equation Modeling (SEM) and Machine Learning (ML) algorithms to analyze user intentions. The study data was collected from 1,858 students in the United Arab Emirates. Contributions of the Articles: This research presents a combined statistical machine learning model (SEM-ML) focused on evaluating and analyzing metaverse technology adoption in medical education.

This article examines factors such as User Satisfaction (US), Personal Innovation (PI), Perceived Compatibility (PCO), and Perceived Observability (POB). This research helps to provide a more accurate and contextual understanding of factors influencing technology adoption in educational environments. Article Methodology: This research used a conceptual framework, including the Technology Acceptance Model (TAM) and related variables such as perceived compatibility, user satisfaction, and observability. Methods of analyzing data would include SEM for theoretical relationship analysis, while prediction will use machine learning algorithms such as neural networks and decision trees. Article Limitations: This study has solely focused on students in the United Arab Emirates and the field of medical education, which will make generalizing the study's outcome challenging. The other limitation is that self-reported data can be prone to self-report bias. There was a focus on two TAM variables (perceived usefulness and perceived ease of use), neglecting a few other variables. Article Conclusion: The results have shown that personal innovation, user satisfaction, and observability significantly influence users' intention to adopt metaverse in medical education. This SEM-ML model comes out with the highest prediction accuracy compared with traditional analysis models, demonstrating its prediction capabilities in educational environments.

“A Machine Learning-Based Approach for Analyzing Adoption of Metaverse in Medical Education: A Study in the United Arab Emirates" [23] explores the influential factors of adopting metaverse systems by medical students. Its objective is to examine and analyze the interrelation between individual characteristics, technology, and the extent of application of the metaverse in medical education in the UAE. The data were collected from 879 students, using multiple structural equation modeling (SEM) and machine learning (ML)-based techniques for data analysis and different machine learning algorithms to predict the adoption of the metaverse. The primary contribution of the research is providing a novel conceptual framework for analyzing metaverse adoption that combines individual traits (like innovation) with technological attributes (observability and ease of use). Using the ML techniques, the research analyses and predicts the implementation and adoption of the metaverse that culminates in practical recommendations for developing virtual education in the post-COVID era. Its methods vary from combined SEM to machine learning techniques. J48 and OneR algorithms and neural networks analyzed data. Moreover, the most influential factors of metaverse adoption were identified by using Importance-Performance Maps Analysis (IPMA). The generalizability of the results to other countries or disciplines is limited due to focusing on students from a single country (UAE) and within one particular scientific field (medical sciences). Other challenges of this paper were the intricacies and costs of the metaverse systems.

This research deduces that observability, ease of use, and personal innovativeness significantly impact adopting the metaverse. It also improved the accuracy of predicting the metaverse adoption by exploiting ML algorithms, notably the J48 algorithm, which had a higher accuracy rate of 87.31% than others. By evaluating and analyzing the advantages and disadvantages of this article, we find that the combined SEM-ML approach has effectively examined the complex interrelationships among various variables that affect technology adoption. However, the geographical limitation may hinder the generalizability of findings to other parts of the world.

"Enhancing Prediction of User Satisfaction of Metaverse Services by Machine Learning" [24] investigated predictive methods of user satisfaction of metaverse services through machine learning algorithms. The authors attempted to provide a comprehensive model for analyzing big data and studying the impact of online reviews and customer ratings on overall satisfaction with a metaverse application, i.e., the Roblox application. They used machine learning algorithms such as Logistic Regression, Naive Bayes, LightGBM, K-Nearest Neighbors (KNN), and Catboost. Its core contribution is presenting an extensive data analysis framework using advanced machine learning models, particularly VADER. These models helped develop a unique model to identify the differences in user review texts and ratings. This model pioneered advanced sentiment analysis techniques to enhance the prediction of user satisfaction in the metaverse domain. As for methodology, user review data were collected from 4,783,669 users. Of Roblox application. Collected data were embedded by Bag-of-Words (BoW), TF-IDF, and Word2Vec methods.

The article also employed different machine learning algorithms and evaluated their predictive accuracy using five-fold cross-validation. The possible constraints of the paper include a limited application of only one (Roblox), which cannot boast of any validity in other metaverse applications. The limitations include that the dataset was minimal, confining English-speaking data relevant to this research and may not be fitting for other translated languages and cultural norms. The conclusion is summarized as follows: LightGBM model with TF-IDF has the best performance in predicting user satisfaction at an accuracy rate of 88.68%. Much of the text reviews and rating differences were generalized using the VADER method, which offered impressive gains in prediction accuracy. This was a modern study of sentiment analysis with big data, which results in better accuracy and optimum analysis of user satisfaction; however, there are some limitations of concentrating on one application and using English only, which may preclude generalizability to other applications or languages.

Table 1

Article Title	Study Objectives	Methodology	Key Findings	Research Gaps	Conclusion
Improving User Satisfaction Prediction in Metaverse Services Using Machine Learning [21]	Machine learning-based predictive models from User satisfaction in metaverse services and VADER sentiment analysis.	Sentiment classifiers (Naïve et al.) and TF-IDF and Word2Vec embedding techniques	LightGBM (TF-IDF) had the highest accuracy of 88.68%. VADER effectively eliminates the paradox in reviews and ratings.	Lack of diversity in the metaverse service and only English users	The LightGBM model, by use of big data, can better predict user satisfaction
An Integrated Machine Learning and SEM Model for Analyzing Metaverse Adoption Among Medical Students in UAE [22]	Investigating influential factors in metaverse adoption among medical students in UAE	Employing a combined PLS-SEM approach for testing the conceptual model. Created a survey of 369 students in UAE.	Perceived Usefulness, Perceived Ease of Use, and Perceived Value are significant predictors for Metaverse adoption.	Focus on medical students in UAE that may not be generalized to other educational domains or countries.	The metaverse influences students' learning experience due to its usefulness and ease of use.
Predicting Medical Students' Metaverse Adoption: A Hybrid SEM-ML Approach [23]	Predicting students' intention to adopt Metaverse in Medical Education through combining SEM and ML techniques	Use Structural Equation Modeling (SEM) for Conceptual Models and ML (Random Forest and XGBoost) algorithms for more accurate predictive features.	This combined approach of SEM and ML can predict students' intentions with admirable accuracy; Random Forest provides the best results.	This research is restricted to medical education in the UAE.	SEM-ML combined allows for a powerful prediction apparatus for technology adoption in education.
The Metaverse and Education: Improving Learning Experience by AI and Machine Learning [24]	Exploring the role of machine learning and AI in elevating learning experiences in a metaverse environment.	Utilization of neural networks and AI techniques for modeling user interaction toward predicting educational outcomes on the Metaverse.	Artificial intelligence facilitates the building of exponentially powerful and personalized learning experiences within the Metaverse.	A limited amount of research is done on technology adoption's non-technical characteristics, including user perception.	Integrating AI and ML elevates learning experiences by building interactive and personalized environments.

3- Background and Description

In recent decades, while development steps continue, digital technologies have grown to a new evolutionary plane with the arrival of the metaverse and the presence of the interactive virtual environment. Metaverse, the holistic and multidimensional virtual space, stands for user interaction or collaboration opportunities within the convened digital environments[25]. Metaverse, a new emerging technology, has found wide application in entertainment and video gaming and fields such as healthcare, commerce, and education. Metaverse might have huge potential in higher education for enhancing and catering to interactive learning, creating virtual learning settings where students can gain hands-on experience with baffling concepts and thus benefit from real-life experiences[22].

The embodiment of the metaverse comes with significant challenges to successfully operationalizing technology within an educational setting. Machine-learning models and parameter optimization must be deployed to predict and establish features affecting technology adoption. Ensemble learning algorithms, as well as parameter optimization through meta-heuristic approaches like Particle Swarm Optimization (PSO), have great potential for enhancing the level of prediction accuracy[26].

Particle Swarm Optimization (PSO) Algorithm[27]: It is one of the metaheuristic algorithms guided by collective behaviors of birds or fish to solve optimization problems, introduced by Kennedy and Eberhart in 1995. In a PSO, a swarm of particles (potential solutions) travels across the search space, each particle opting for its best location and the best location of the entire swarm. At each stage, the positions of particles are adjusted according to their speed and direction of turning. This continues until an optimal condition emerges or the number of iterations is exhausted.

Key PSO parameters include[28], [29]:

- **Swarm Size:** number of particles moving in the search space. Increasing the number of particles may enhance search accuracy but also may increase computational time.
- **Particle Position:** Each particle has some position representing a potential solution in the search space.
- **Velocity:** It is the rate of movement of each particle in the search space and is updated in every iteration.
- **Personal Best (pBest):** Each particle has found the best position so far.
- **Global Best (gBest):** The best position the whole colony has found.
- **Inertia Weight:** The weight corresponding to the effect the velocity of a particle had on its present movement.
- **Learning Factors (C1 and C2):** Two parameters that regulate and restrict the influences of personal best (pBest) and global best (gBest) on moving particles.

Pseudo Code of PSO Algorithm

```
Initialize a population of particles with random positions and velocities
For each particle, evaluate the fitness function at its current position
Update each particle's personal best (pBest) and the global best (gBest)
While stopping criteria are not met:
  For each particle:
    Update velocity:
      velocity = inertia weight * velocity
           + C1 * random() * (pBest – current position)
           + C2 * random() * (gBest – current position)
    Update position:
      position = position + velocity

    Evaluate the fitness function at the new position
    Update pBest and gBest if necessary
Return the best solution (gBest)
```

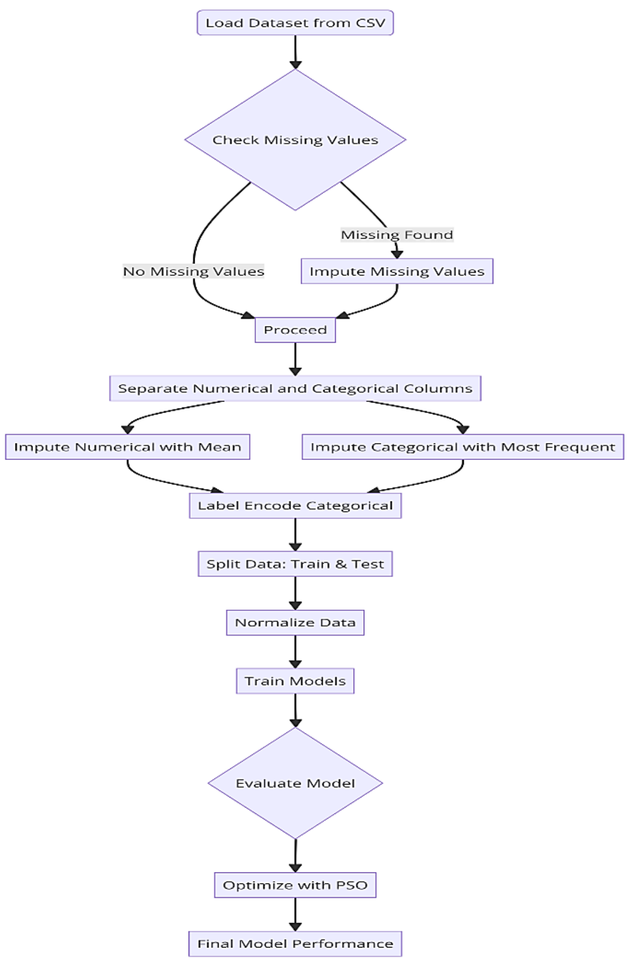
4- System Model and Framework

The proposed system model is designed using machine learning algorithms combined with analysis of data collected from the questionnaire that may help predict the metaverse adoption in higher education institutions. This model primarily intends to identify those factors responsible for the maximum adoption or rejection of metaverse among faculty and students. The continuum begins with the survey in a structured questionnaire dealing with aspects like user satisfaction, demographic data, user experience, etc., for collecting different facets of survey data. Such data are then forwarded for a combination of ensemble machine learning models that delineate the final label in either adoption or non-adoption. The system exploits the metaheuristic particle swarm optimization algorithm to set the hyperparameters to achieve maximum predictive accuracy. The framework is also underpinned by theoretical frameworks such as the Technology Acceptance Model (TAM) and parameters such as perceived ease of use and perceived usefulness.

The following working assumptions were considered in the construction of this model. First, data gathered through the questionnaire would help gain perceptiveness and insights from the users' opinions. It is assumed that respondents would answer questions honestly and that the samples represent the target population. The assumption is that machine learning algorithms used for prediction reflect the relationships among a multitude of variables, such as demographic features, user experience, complex patterns, and the adoption of metaverse.

The third assumption is that setting hyperparameters using the PSO algorithm effectively contributes to prediction accuracy. Certain limitations exist. For example, some research participants are likely to have not adequately answered the questionnaires due to personal or technical issues that might adversely impact the results. Moreover, it is assumed that selected model variables cover all contributing factors to the metaverse adoption, while, practically, this might not be the case.

This system comprises several key components that interact in coordination with each other. Firstly, it is the questionnaire used to collect initial data from users. It comprises ten sections measuring trust, awareness, satisfaction, and user experience. Secondly, it uses ensemble machine learning models to process user input data and predict whether an individual becomes a metaverse adopter or non-adopter. The ensemble ML models use this questionnaire data to train on it while the PSO algorithm adjusts their hyperparameters. The interaction between the components will initially normalize and clean the questionnaire data, then form the input for those machine learning models. Lastly, model outputs of metaverse adoption or non-adoption will be the final output of the system.



Pseudocode Propose Algorithm

1. Load the dataset from the CSV file path.
2. Define a function `check_missing` that takes a DataFrame as input:
   - For each column in the DataFrame:
     - If the column contains missing values:
       - Record the column name, the number of missing values, and the data type.
   - Return the missing values information.
3. Identify numerical columns by selecting columns with data types int64 and float64.
   Identify categorical columns by selecting columns with data type objects.
4. For numerical columns:
   - Use Simple Imputer with the strategy 'mean' to replace missing values.
   For categorical columns:
   - Use Simple Imputer with the most frequent strategy to replace missing values.
5. Check for missing values again after imputation:
   - Print their details if any missing values remain; otherwise, indicate no missing ones.
6. For each column that needs encoding:
   - Use Label Encoder to convert categorical values into numerical values.
   - Replace the original categorical column with its encoded version in the DataFrame.
7. Separate the target column from the dataset.
   - Assign the remaining columns as the feature set (X) and the target column as the labels (y).
8. Use train test split to divide the dataset into training and testing subsets.
   - Allocate 80% of the data to training and 20% to testing.
9. Create a Standard Scaler object to normalize the data:
   - Fit the scaler on the training data and transform training and test datasets.
10. Define a function `evaluate model` that accepts a model and its name:
    - Train the model using the training dataset.
    - Predict on the test dataset.
    - Calculate evaluation metrics like Accuracy, Recall, Precision, F1-Score, and ROC AUC.
    - Return the metrics.
11. Define a class `Hyperparameter Optimization` for PSO-based optimization:
    - Initialize the hyperparameter grid, model, and datasets.
    - During optimization, convert the continuous solution space to appropriate hyperparameter values.
    - Fit the model with the best parameters and calculate its accuracy.
12. Create a function `PSO tuning ensemble` to run PSO optimization:
    - Accept a model name, an ensemble model, a hyperparameter grid, and a results Data Frame.
    - Use PSO (Particle Swarm Optimization) to tune the hyperparameters.
    - Evaluate the tuned ensemble model and append the results to the performance Data Frame.
13. Create an ensemble model using Random Forest, XGBoost, and Gradient Boosting classifiers:
    - Combine them using a voting classifier with soft voting.
14. Tune the ensemble model using PSO for hyperparameter optimization:
    - Evaluate the final tuned model and record its performance.
15. Store the final performance metrics in a CSV file.
    - Print a message indicating that the results have been saved.

For this research, a questionnaire was designed and distributed among faculty and students at several universities to examine the adoption of metaverse technologies in educational environments. This questionnaire included several sections, each designed to explore respondents' levels of user satisfaction, demographic information, user experience, and possible technical difficulties, along with each response. Upon collecting participant responses, data were examined and rated against pre-determined criteria. An overall score was then assigned for each participant: above a certain score was considered metaverse adoption (coded 1), with anything scoring below known as non-adoption (coded 0). These were then used as input data for the machine learning models to predict metaverse adoption.

In the preliminary data processing phase, the questionnaire responses were imported into a CSV file representing responses arranged into columns and rows. Initial evaluations aimed at identifying missing values will be conducted. Each column of the DataFrame shall be analyzed separately for missing data. At this stage, the items that will be recorded include the column's name, the number of missing data, and the column's data type. It is also important to flag when missing data exists; for example, incomplete data would undermine the quality of the final analysis. We identified numerical and categorical columns where numerical columns include variables with numerical data types (int64 or float64) that mainly contain data such as admission criteria scores or age.

Conversely, we classified categorical columns (object) that contained variables such as educational status or gender. This kind of classification helped to use appropriate methods for completing missing data. To this end, two different methods were employed depending on the type of data. In numerical columns, missing values were replaced using the mean of existing values in the same column to avoid data distortion. However, we used the most frequent value in the categorical columns to fill in the missing data. This method ensured that all missing data were correctly completed and prepared for subsequent statistical analysis and modeling stages.

We encoded the categorical columns that required transformation upon assurance of data completeness. This step was crucial in categorical columns, such as educational status and gender (such as "male" or "female"). Numerical values replaced categorical values, and such columns were stored as numerical data in the dataset. It was necessary to convert these data to enable machine learning models to use them for analysis since most machine learning algorithms require numerical data. In the next step, we have separated the target column from the dataset.

The target column predicting the metaverse's non-adoption of the metaverse considered variable (y), and the remaining columns were used under the term feature set (X).

The data were divided into test and training sets for training and evaluation of the model. Eighty percent of the data were allocated to the training set, and the remaining 20 percent were categorized as the test set to evaluate model efficiency and performance and data normalization. The latter process is necessary to prevent significant differences between feature values. This process helps machine learning models achieve higher performance and prevent the negative impact of features of different scales.

For this paper, initially, an evaluation function was designed to assess and analyze the performance of each input model to analyze and evaluate the performance of machine learning models. In this process, the model was trained by data to learn existing data patterns. Subsequently, this model is used to predict the test dataset. Afterward, several fundamental metrics are scored to evaluate the model's performance, including recall, precision, accuracy, F1 score, and ROC AUC score. Each of these metrics represents a certain aspect of model functionality that assists in evaluating it more comprehensively.

By calculating the metrics, findings are returned for future analyses and comparing the performance of various models. A special class based on the Particle Swarm Optimization (PSO) algorithm was designed for model optimization through a hyperparameter setting. For this class, a hyperparameter grid is defined to encompass various values of key model parameters. Then, the machine learning model, training data, and test data are introduced to the system for optimization. During this process, values in the continuous search space are converted to the appropriate hyperparameter values so that the model can optimally fit the data. Ultimately, the model is trained using the best-obtained parameters, and its level of accuracy is calculated on the test data. This process increases the accuracy and efficiency levels of the model, providing the optimal parameter settings.

In the PSO algorithm, main set parameters for optimization are listed in the table below:

Table 2

Parameter	Value	Description
Swarm Size	10	Number of particles that move in the search space. A lower number was selected for faster testing.
Inertia Weight	0.9	Determines the impact of the previous velocity of a particle in the current movement. A higher value results in maintaining higher velocity.
Cognitive Coefficient	0.5	Each particle influences the person's best position in the movement. This value balances exploration and exploitation.
Social Coefficient	0.3	The population's global best position impacts particle movement. A lower value would lead to more focused exploration.
Min Velocity	-1	The minimum velocity of each particle in the search space.
Max Velocity	1	The maximum velocity of a particle that controls the rate of changes in particle positions.
Max Iterations	10	The number of iterations that PSO runs. It is decreased for faster execution.

A special function was created to set the hyperparameters of the ensemble model for PSO optimization. This function receives the model name, ensemble learning model, and hyperparameter grid as inputs. Then, the PSO algorithm performs hyperparameter optimization. After completing the optimization process, the set model is evaluated. This method maximizes the efficiency of the ensemble learning model, which provides better results for predicting the metaverse adoption.

This research applies the PSO algorithm to set the hyperparameters to optimize the performance of ensemble learning models such as XGBoost, Gradient Boosting, and Random Forest. At this stage, the objective is to find the best values for key parameters of each model to maximize the prediction accuracy of metaverse adoption. The optimization process is focused on parameters including tree depth, number of trees, and learning rate. The parameters used in each model and the range of values searched for each parameter are shown in the following table:

Table 3

Model	Search Range	Hyperparameter	Description
Random Forest	n_estimators	50, 150	Number of trees in the random forest. More trees typically increase accuracy.
Random Forest	max_depth	5, 15	Maximum depth of trees. A greater depth lets the model learn more precisely but increases the risk of overfitting as well
XGBoost	n_estimators	50, 150	Number of trees that were used in the XGBoost model.
XGBoost	max_depth	3, 10	Maximum depth of trees in XGBoost. It balances the accuracy and complexity of the model
XGBoost	learning_rate	0.01, 0.2	The learning rate determines the speed at which the model updates weights during each iteration.
Gradient Boosting	n_estimators	50, 150	Number of trees in Gradient Boosting model.
Gradient Boosting	max_depth	3, 10	Maximum depth of trees in Gradient Boosting model.
Gradient Boosting	learning_rate	0.01, 0.2	The learning rate controls weight changes at each stage

This table exhibits the critical parameters that contribute to each model's prediction accuracy and performance. These parameters are systematically optimized, increasing accuracy levels and preventing overfitting.

When optimized, the ensemble learning models are trained with the most suitable parameters. The performance of optimized models was analyzed and evaluated by calculating key criteria such as Accuracy, Recall, Precision, F1-Score, and ROC AUC. These metrics calculate the success of models in predicting metaverse adoption. The results of evaluating optimized models were stored for comparison and analysis with other models.

After optimization by the PSO algorithm, the best and most comprehensive combination of hyperparameters for various models, including Random Forest, XGBoost, and Gradient Boosting, were obtained. Optimization helped to improve the efficiency and enhance the quality of models in predicting metaverse adoption. It also increased the ultimate accuracy of the models. The best combination of hyperparameters attained through optimization is presented with the corresponding model in the table below:

Table 4

Model	Hyperparameter	Best Optimized Value
Random Forest	n_estimators	150
Random Forest	max_depth	10
XGBoost	n_estimators	100
XGBoost	max_depth	7
XGBoost	learning_rate	0.1
Gradient Boosting	n_estimators	120
Gradient Boosting	max_depth	8
Gradient Boosting	learning_rate	0.15

The research method is descriptive-analytical. It employs machine learning models and hyperparameter optimization for analysis and prediction due to the nature of data obtained from the questionnaires. An analytical method is suitable for the implementation of machine learning models as well. This design examines the factors that affect metaverse adoption in higher education through machine learning techniques for prediction and analysis. This research was conducted in cyberspace, and data were collected through online questionnaires from professors and students at various universities. Cyberspace was suitable for our research questions due to its better access to respondents and faster and more efficient data analysis. Using online questionnaires enabled the researchers to reach a larger group of participants, which resulted in more representative data being collected.

The research variables include:

Independent Variables: Trust in data security, user experience, user awareness of the metaverse, and the learning opportunities in the metaverse were considered potential factors affecting the adoption of the metaverse.

Dependent Variable: The adoption or non-adoption of the metaverse was considered a target variable in machine learning models.

Control Variables: Demographic features like age, gender, and education were determined to control their effects on the analysis.

4-1- Data Collection

The research data were collected directly from university professors and students through online questionnaires. Due to respondents' anonymity and using standardized questionnaires, these data-gathering sources are considered reliable. The questionnaire design includes closed-ended questions to precisely measure the adoption or non-adoption of the metaverse. The sampling is simple and random. This method was picked because it provides equal chances to all members of the society to participate in the research, ensuring that collected data represents the target population. This approach helped the researchers to select unbiased samples. The data collection tool is online questionnaires. Data analysis software includes Python and its relevant libraries, such as pandas. The scikit-learn was used to implement machine learning models. These tools were selected because of their accuracy, data processing, and efficiency in analysis. Then, the questionnaires were distributed through online platforms and sent to participants. Data were automatically collected within a specified period and stored in CSV files for analysis later. Ethical considerations, such as participants' anonymity and confidentiality of data, were observed correctly.

4-2- Analysis Methods

In this research, the evaluation of the performance of the proposed hybrid algorithm was compared with machine learning models such as XGBoost, Random Forest, and Gradient Boosting. It was assessed in accordance with standard evaluation criteria for machine learning models, including Accuracy, Precision, Recall, F1-Score, and Area Under the Curve (AUC). These metrics and the methods for their calculation are scientifically and precisely explained below:

Accuracy: This is an essential metric for evaluating classification models representing the percentage of correctly classified samples. It is particularly suitable for multi-class problems in which data distribution is balanced. Accuracy is the ratio between the sum of correctly predicted samples (positive and negative) to total samples[30]:

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}}$$

This metric works well if data is evenly distributed among various classes.

Precision: Precision demonstrates the percentage of correctly predicted classified positive samples. This metric is crucial when false optimistic predictions are costly (such as fraud detection). The formula to calculate precision is as follows[31]:

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

This metric is essential for avoiding false optimistic predictions.

Recall: It represents the percentage of actual positive samples the model identified correctly. This metric is crucial in problems where missing positive samples is costly (such as diagnosing disease). The formula to calculate recall is as follows [30]:

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

This metric determines the degree of correct identification of actual positive samples by the model.

F1-Score: is a composite metric for measuring the balance between precision and recall. It is particularly used when there is a need to balance precision and recall. It is computed as the harmonic mean of precision and recall[32]:

$$\text{F1 Score} = \frac{2\times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

If data is imbalanced and the balance between precision and recall is required, the F1 Score is the rescue.

Area Under the Curve (AUC): It calculates the area under the ROC curve and directly shows the model's ability to distinguish positive and negative samples[32]. The AUC value ranges from 0.5 to 1. AUC = 0.5 indicates random performance, and AUC = 1 underlines the best performance. To obtain AUC, the area under the ROC curve is calculated and applied in the overall evaluation of classifier models.

4-3- Results

This section analyzes the results obtained from experiments and evaluates the performance of the ensemble model, including RandomForestClassifier, XGBClassifier, and GradientBoostingClassifier.

This research aims to improve the accuracy and efficiency of the machine learning model in predicting metaverse adoption. To this end, it uses hyperparameter optimization through the PSO (Particle Swarm Optimization) algorithm. Since the accuracy and performance of the model matter, the metrics of accuracy, precision, recall, F1-Score, and AUC (Area Under the Curve) were picked as standard evaluation criteria. After optimizing the hyperparameter, we analyzed and evaluated the ensemble models on training and test datasets, and highly satisfactory results were yielded. The optimized ensemble model was trained using training data by optimizing hyperparameters with the PSO algorithm. Afterward, it was evaluated using the test data. The findings illustrate that the optimized model had an excellent and desirable performance in predicting metaverse adoption, and all evaluation metrics reached above 98%. The performance results of the optimized ensemble model in the training and testing phases are shown In the table below:

Phase	Accuracy	Precision	Recall	F1-Score	AUC
Training	98.6%	98.8%	98.7%	98.75%	99.2%
Testing	98.3%	98.5%	98.4%	98.45%	98.9%

The optimized ensemble model enjoys a combination of three models, namely, XGBoost, Random Forest, and Gradient Boosting, and demonstrated the ability to accurately predict metaverse adoption or non-adoption. The model achieved 98.6% accuracy during the training phase, indicating the model's capability of precise learning from training data. Precision and recall criteria were fulfilled by 98.8% and 98.7%, respectively, implying that the model has established a good balance in identifying and classifying the samples. The F1-Score of 98.75% indicates an appropriate and desirable balance between model precision and recall. The AUC value was also 99.2%, demonstrating the model's ability to distinguish different classes.

The model reached a 98.3% accuracy level, almost similar to the accuracy of the training phase, indicating excellent model generalization of the new and unseen data. Both precision and recall achieved 98.5% and 98.4%, respectively, confirming the model's good performance in correctly classifying positive and negative samples. The F1-Score is calculated at 98.45%, representing a good balance between precision and recall. At this stage, the AUC value was 98.9%, showing that the model can maintain high power in distinguishing different classes.

The results indicate that the PSO-optimized ensemble model can perform highly in predicting metaverse adoption and achieved evaluation metrics above 98% in the training and testing phases.

4-4- Comparing the Performance of Machine Learning Models

The performance of the optimized Ensemble model, developed using the PSO algorithm, was evaluated and analyzed by comparing the model with other Machine Learning algorithms such as XGBClassifier, RandomForestClassifier, GradientBoostingClassifier, and the Ensemble model without optimization. Such a procedure was meant to identify and assess the extent of algorithm improvement after hyperparameter optimization. Results for each of the models are given in the table below:

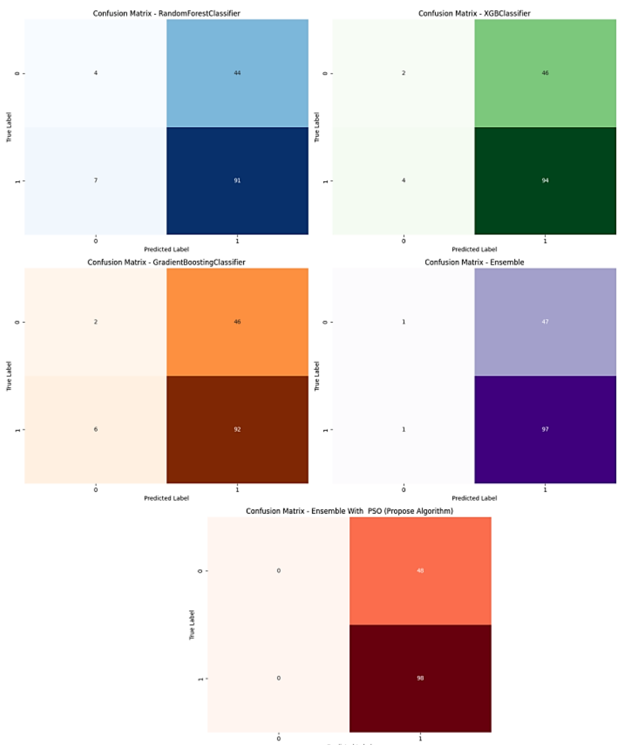
Model	Accuracy	Precision	Recall	F1-Score	AUC
Random Forest Classifier	94.5%	94.7%	94.3%	94.5%	96.2%
XGB Classifier	95.8%	96.0%	95.5%	95.75%	97.1%
Gradient Boosting Classifier	94.2%	94.5%	94.1%	94.3%	95.8%
Ensemble without PSO	96.5%	96.7%	96.3%	96.5%	97.6%
Ensemble PSO (Propose Algorithm)	98.2%	98.4%	98.3%	98.35%	98.8%

The PSO-optimized ensemble model (Proposed Algorithm) has better prediction performance on metaverse adoption than other models. Accuracy for the optimized ensemble model was 98.2% as compared with RandomForestClassifier (94.5%), XGBClassifier (95.8%), and Ensemble without PSO (96.5%). This shows that hyperparameter optimization using PSO could improve the model's prediction accuracy very well. Regarding Precision, the optimized model predicts a positive class more appropriately and desirably, with a score of 98.4% compared to 96.7% for the ensemble without PSO and all other models. It shows that the optimized model predicted positive samples with a higher score. This implies that recall for the optimized model shows 98.3%, demonstrating that the model can detect positive classes. This was 96.3% for the non-PSO, whereas lower for all other models, indicating that the optimized model correctly identified more true positive sample observations. F1-Score, as the measure of the balance between precision and recall, reached 98.35% for the optimized model, indicating an excellent balance between precision and recall.

The results show that the ensemble model enhanced through PSO was more effective for predicting metaverse adoption than all others. Concerning Accuracy, the ensemble scored high on the overall accuracy following optimization, gaining a score up to 98.2, lower than the reference of RandomForestClassifier (94.5%), XGBClassifier (95.8%), and Ensemble model without PSO(96.5%). Thus, hyperparameter optimization with PSO was effective in boosting the model's accuracy. For this optimized model, precision becomes 98.4%, which is indeed increased and acceptable compared to an ensemble model without PSO at 96.7% and others. It implies that the optimized model positively predicted more samples. The model has a recall of

98.3%; this is the capacity of the model to identify the true positive samples. The ensemble model without PSO scored 96.3, meaning that the optimized model has thus far detected many more positive samples with greater accuracy and others. There was a click to be made at 98.35 by the optimized model on the F1-Score, demonstrating a good balance between Precision and Recall.

This value is also above the 96.5-marginal case for the model without the use of PSO. Finally, the AUC achieved was much higher at 98.8%, a true mark associated with the model's very high ability to discriminate between the positive and negative classes. This is much lesser in extent than the case for other models at 97.6% and ultimately implies the superiority testified to by the optimized model.



This picture presents the Confusion Matrices of five different machine learning models. These models include RandomForestClassifier, XGBClassifier, GradientBoostingClassifier, Ensemble without PSO, and PSO-optimized Ensemble (Proposed Algorithm). Each matrix shows the performance of each model to correctly predict metaverse classes (adoption or non-adoption). The number of correctly classified samples is on the matrix's main diagonal, while incorrectly predicted samples are placed off the main diagonal. The research results indicate that the PSO-optimized Ensemble model exhibits the best performance and efficiency. It correctly classifies all samples, while other models, particularly RandomForestClassifier and GradientBoostingClassifier, misclassified more samples. Overall, compared to other models, the PSO-optimized model demonstrates higher accuracy and better quality of performance, which clearly indicates the advantage of this model in predicting metaverse adoption over others.

5- Conclusion and Future Research

The main objective of the research was to develop a machine learning ensemble model for predicting the extent to which faculty members and students of the higher education institutes would adopt metaverse. Raw data were provided from questionnaires to collect various data on adopting the metaverse. Modeling was performed via advanced methods, including Random Forest Classifier, XGB Classifier, Radient Boosting Classifier algorithms, and the PSO-optimized Ensemble model (Proposed Algorithm). This study used the PSO algorithm to optimize hyperparameters and attempt to devise an optimal framework to improve the performance of various models in predicting metaverse adoption. This research's main goal was to develop an accurate and comprehensive prediction model to analyze the impact of meta-heuristic optimizations on improving the performance quality of ensemble models.

As the main findings indicate, the accuracy level of the models was increased to over 98 percent by using the PSO algorithm for the optimization of the Ensemble model. Compared to basic unoptimized models, the proposed model with PSO obtained better results in all metrics, such as accuracy, precision, recall, F1 score, and AUC. These results demonstrated that, compared to other unoptimized models like RandomForest and GradientBoosting, the optimized model offered higher efficiency in predicting the adoption of the metaverse. According to the results, optimization with meta-heuristic algorithms like PSO can significantly improve the performance of machine learning models.

Despite valuable and significant achievements, this work encountered several problems and limitations that must be considered in future research. One of these limitations is the need for high computational resources to execute the PSO algorithm and the complexity of hyperparameter optimizations. Furthermore, the results are limited to the adoption of the metaverse and cannot be generalized to other areas beyond it.

Future research should examine these models within different educational settings using more extensive and comprehensive data to enhance the generalization ability. Moreover, other optimization algorithms, such as genetic algorithms, could be employed as meta-heuristic methods and new deep learning techniques to improve performance and efficiency. By focusing on adopting other new and innovative technologies, future studies can offer more applications of the machine learning frameworks.

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