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Hybrid Gamification and AI Tutoring Framework using Machine Learning and Adaptive Neuro-Fuzzy Inference System

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ABSTRACT

Although technology has significantly improved the teaching and learning process, it has not been able to increase students' self-motivation and engagement at the same level. The lack of self-motivation and intermittent engagement is currently one of the primary challenges faced by educators. This new approach to learning called the hybrid gamification framework uses a combination of artificial intelligence (AI), machine learning (ML), and the Adaptive Neuro-Fuzzy Inference System (ANFIS) to create a more engaging and personalized learning experience. By tracking students' interactions and performance, the system can allocate rewards based on their progress, which helps to increase their motivation and engagement. This technology makes it possible for educators to collect and analyse data related to students' engagement patterns, quiz scores, time spent on learning activities, participation in discussion forums, and much more. This data analysis enables educators to identify struggling students and high achievers, allowing them to provide tailored support and instruction to maximize student success. A pilot implementation of this system involving 200 computer science students successfully demonstrated the effectiveness of this technology. This research provides a comprehensive understanding of gamification's impact by combining quantitative data with qualitative insights.

1. Introduction

Education is constantly evolving with the integration of new technologies and innovative teaching approaches [1]. The digital era has brought about a new generation of learners with diverse learning preferences and needs. To address this, personalized and adaptive learning has emerged as a transformative approach, using Artificial Intelligence (AI), machine learning (ML), and advanced analytics to tailor educational experiences to each learner's individual needs [2]. This research delves into the creation of a comprehensive gamification framework that is not only a technological innovation but also a pivotal shift in how we think about education. By leveraging AI and ML, this framework aims to create a learning ecosystem that is engaging, motivating, and impactful. The

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fusion of technology and pedagogy presents an unprecedented opportunity to transcend the limitations of traditional education systems [3].

The proposed gamification framework combines the best of human instruction and technological prowess to usher in a new era of personalized and learner-centric educational experiences. The research takes a detailed approach to each facet of the framework's architecture, from the AI algorithms that power content generation to the analytical tools that dissect student behaviour patterns. Through a synthesis of theoretical constructs, empirical evidence, and technological ingenuity, the research explores the potential and possibilities that this gamification framework offers to the educational landscape. The future of education is exciting, and this research aims to unlock the capabilities of AI and ML to shape it positively.

This research takes a comprehensive approach by combining AI, ML, and advanced analytics in a gamification framework for education. It stands out by using Adaptive Neuro-Fuzzy Inference System (ANFIS) [4] to allocate dynamic rewards, creating a personalized content algorithm, and refining clustering techniques for learning analytics. The combination of these elements results in a new educational framework that has the potential to transform how personalized and engaging learning experiences are provided to students.

The objectives of this research are as follows:

i. Develop a gamification framework for personalized learning experiences using AI and ML techniques.
ii. Incorporate an ANFIS-based reward allocation system and a Personalized Learning Content Generation Algorithm.
iii. Enhance K-Means clustering algorithm and analyse behavioural patterns using ML techniques.
iv. Include dashboards and visualizations to showcase student progress and achievements transparently.
v. Analyse framework effectiveness in improving student engagement, motivation, and learning outcomes through empirical studies and data-driven evaluations.
vi. Evaluate the efficiency and accuracy of the reward allocation system and content generation algorithm through comparative analyses and case studies.
vii. Provide insights and recommendations for educators and administrators on implementation and optimization to improve the learning experience for diverse student populations.

2. Literature Review

In recent years, the integration of gamification into the field of education has garnered significant attention, offering innovative ways to enhance learning experiences. Educational games have been applied across various subjects, including mathematics, science, programming, literature, languages, and social sciences [5]. However, the adoption of gamification in cybersecurity education, particularly in relation to advanced concepts such as network security, remains relatively nascent. The Serious Game Design Assessment Framework (SGDA) has emerged as a standardized analytical approach to evaluate the design of educational games [6]. The framework identifies six essential components that influence game design, including purpose, content, aesthetics, mechanics, context, and narrative fiction. The alignment of these components contributes to the cohesiveness of the instructional design. The present study focuses on two dimensions, namely content and mechanics, as they are pivotal in driving the educational value of gamification [7]. Through this lens, cybersecurity themes relevant to games are explored, presenting a comprehensive overview of topics that contribute to the player's understanding of the subject matter.

The diversity of game mechanics, including trivial games, puzzle games, and adventure games, correspond to established learning theories such as Behaviourism, Cognitivism, and Constructivism [8]. The integration of these mechanics with learning theories highlights the significance of thoughtful game design to foster engaging and effective learning experiences [9]. This relationship also emphasizes the importance of tailoring game mechanics to specific learning theories to achieve desired educational outcomes [10]. However, the integration of educational principles within game design remains a challenge, with various frameworks proposed to bridge this gap. The absence of a standardized methodology for educational game development necessitates deeper exploration in this area. Furthermore, the effectiveness of gamification in improving learning outcomes requires thorough investigation. The correlation between learner engagement, contextualization, and motivation underlines the complexity of this relationship and demands a nuanced approach to gauging the success of gamification in education [11].

Among the challenges faced in the deployment of gamification within educational contexts, limited technological infrastructure, budget constraints, and pedagogical readiness of educators emerge as crucial issues [12]. The utilization of non-digital gamification presents a potential solution to these challenges, as observed in some studies. However, further exploration of the effectiveness of non-digital gamification is warranted, considering both traditional and novel game design elements. The landscape of educational gamification is evolving, guided by a comprehensive understanding of learning theories, engagement mechanics, and the intricacies of student perception [13]. By examining the efficacy of gamification across both digital and non-digital platforms, researchers seek to unlock the potential of gamification in fostering effective and engaging learning experiences [14]. As the fields of education and technology continue to converge, the need for robust and adaptable gamification frameworks becomes increasingly evident.

The challenges addressed by this research are:

i. Low student engagement, reduced motivation, and limited learning outcomes are often observed in traditional educational approaches [15].
ii. Difficulty in creating a learning environment that captures and sustains students' interest, leading to increased attendance and active participation.
iii. Ensuring the seamless integration of technology and education, as well as developing a user-friendly interface that facilitates meaningful interaction with personalized content and rewards.
iv. Scalability and generalizability by designing a framework that can be applied across different courses, programs, and educational institutions while maintaining its effectiveness.
v. Providing timely and valuable feedback to students while guiding them through their learning journey.

3. Proposed Work

The proposed gamification framework aims to leverage the power of AI, ML, and ANFIS to create an adaptive and engaging learning environment. By dynamically allocating rewards based on students' performance and interactions, the framework enhances motivation, engagement, and learning outcomes. Figure 1 provides the architecture of the proposed framework.

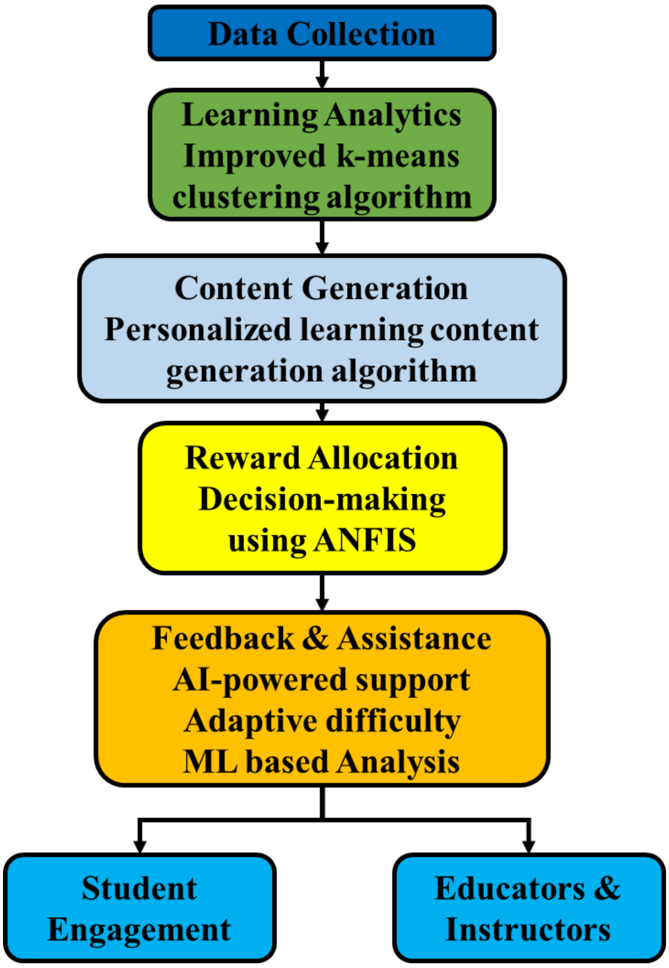

Fig. 1. Proposed Architecture

The proposed system is designed to capture, analyse, and interpret a plethora of data points related to students' interactions, achievements, and progress within the learning environment. By seamlessly integrating technology and education, this platform empowers educators with actionable insights that foster personalized learning experiences and optimize educational outcomes. The pilot implementation involved 200 students learning computer science. Data is gathered on students' interactions, achievements, and progress within the learning platform. The engagement patterns, quiz scores, and other relevant metrics, such as time spent on learning activities, assignment completion rate, participation in discussion forums, assessment progression, resource utilization, and learning pathways, are monitored. By analysing data on a granular level, educators can identify struggling students, high-performers, and trends in engagement. Armed with this knowledge, they can implement targeted interventions, provide additional support, and refine instructional strategies, fostering an environment conducive to student success.

3.1 Learning Analytics

An improved K-Means clustering algorithm for learning analytics is proposed to group students based on their interactions, achievements, and progress within the learning platform. This improved version will address some of the challenges that are commonly faced when applying the conventional K-Means algorithm to educational data.

Algorithm 1: Improved K-Means Clustering Algorithm for Learning Analytics

1. Initialization:
Initialize centroids using the chosen method (e.g., K-Means++).
centroids= initial centroids
2. Main Loop:
For iteration=1 to max_iterations:
Assign each sample to the nearest centroid:
clusters[i]=$\text{argmin}_j \|X[i]-\text{centroids}[j]\|^2$
Update centroids:
For j=1 to K:
assigned_samples={i|clusters[i]=j}
If assigned_samples is not empty:
$$\text{centroids[j]} = \frac{1}{\text{assigned\_samples}} \sum\nolimits_{i \in \text{assigned\_samples}} X[i]$$
Else:
Randomly reinitialize centroids[j]
Calculate the change in centroids:
$$\text{delta}_{\text{centroids}} = \sum_{j=1}^{K} \left|\left|\text{centroids[j]} - \text{old}_{\text{centroids[j]}}\right|\right|^2$$
If delta_centroids<tolerance, break
3. Assigning Clusters:
Return clusters containing cluster assignments for each sample.
4. Final Centroids:
Return centroids - the final cluster centroids.

The K-Means algorithm is sensitive to the initial cluster centroids. However, robust initialization techniques like K-Means++ help select the initial centroids based on a probability distribution for better convergence. Choosing the right number of clusters (K) is crucial, and the Elbow Method helps determine an optimal K by looking for the "elbow point" where the within-cluster sum of squares (WCSS) starts to slow down, avoiding both underfitting and overfitting. Feature scaling using z-score normalization ensures that all student metrics contribute equally to the clustering process and prevent dominance by metrics with larger ranges. Assessing the quality of clusters helps in validating results. The Silhouette Score enables measuring the compactness and separation between clusters. For scalability with large datasets, Mini-Batch K-Means is used by utilizing random subsets (mini-batches) of data for each iteration. Outliers distort cluster assignments, but robust K-Means algorithms like K-Medians and K-Medoids help to handle outliers. To enhance the quality of clusters, domain-specific feature engineering is applied to create new features that capture meaningful aspects of student behaviour, such as engagement ratios or progress gradients. Utilizing a small labelled dataset guides the clustering process for more meaningful cluster assignments by incorporating domain knowledge. Visualization helps educators interpret and validate clusters, and interactive tools allow them to explore clusters based on different metrics for informed decisions. The clustering process is iterative, allowing educators to refine the algorithm by excluding irrelevant metrics or modifying clustering parameters based on their expertise.

3.2 Content Generation

Personalized challenges, quizzes, and activities aligned with individual students' learning styles and preferences are generated with a Personalized Learning Content Generation Algorithm. This algorithm helps identify optimal content based on past performance.

Algorithm 2: Personalized Learning Content Generation Algorithm

1. Learning Style and Preference Identification:
For each student $s \in S$:
Identify the learning style ls and preference lp based on their profile.
2. Learning Content Ranking:
For each challenge, quiz, or activity $c \in C$:
Calculate a ranking score $score_c$ based on the alignment with the student's learning style and preference, as well as past performance:
$$\mathrm{score_c} = \mathrm{w_1} \cdot \mathrm{alignment_{score_{ls}}(c)} + \mathrm{w_2} \cdot \mathrm{alignment_{score_{lp}}(c)} + \mathrm{w_3} \cdot \mathrm{past\_performance(s, c)}$$
Where w_1, w_2, and w_3 are weight factors.
3. Personalized Content Generation:
For each student $s \in S$:
Sort the challenges, quizzes, and activities in descending order of $score_c$ calculated for that student.
Select the top n challenges, quizzes, and activities with the highest $score_c$ as personalized content for the student.
4. Feedback Loop:
After students engage with the generated content:
Update past performance matrix based on their performance.

The algorithm analyses the learning style and preference of each student in the set. This information helps the algorithm understand how each student prefers to learn. The second step involves evaluating available challenges, quizzes, or activities to determine how well they align with the student's learning style, preference, and past performance. It calculates a ranking score for each learning content based on three components, each with a weight factor. It then sorts the available learning content, selects the top n challenges, quizzes, and activities with the highest score, and offers personalized learning content for the student. The fourth step involves monitoring the performance and interactions of students as they engage with the generated personalized content. The feedback loop is crucial for the algorithm to adapt and fine-tune its content recommendations over time, ensuring that the learning experiences continue to evolve and improve. The primary goal of the algorithm is to provide personalized learning experiences that align with each student's learning style and preference, promoting areas where students need improvement. It enhances student engagement and motivation by providing content that matches their interests and learning preferences. It also supports a variety of learning content types, catering to diverse learning preferences. Its personalized approach reduces cognitive load on students by presenting content that resonates with their individual learning styles.

3.3 Reward Allocation Decision-Making

The ANFIS tool uses fuzzy logic to address the uncertainties and complexities of human behaviour and preferences. When it comes to dynamic reward allocation, ANFIS considers multiple factors simultaneously, including achievement, effort, and progress. To assess achievement, ANFIS considers various factors, such as quiz scores, challenges completed, and learning objectives achieved. It also evaluates the effort put in by the student, which can be determined by analysing the time spent on tasks, engagement levels, and active participation. Additionally, ANFIS evaluates the progress made by the student over time by comparing their current performance with past achievements.

To improve the accuracy of reward allocation decisions, ANFIS models utilize historical data. By analysing the student's previous interactions, achievements, and answers, the models develop a comprehensive understanding of the student's learning trajectory. This historical context enables ANFIS to identify patterns, trends, and areas where the student has made progress or faced challenges. Based on the input data, fuzzy logic considerations, and historical context, the ANFIS model generates a dynamic reward allocation decision. This decision is not a one-size-fits-all approach but is personalized for each student. ANFIS adjusts the allocation of rewards in real-time, reflecting the changing needs, progress, and effort of the student.

Regular attendance is an important aspect of the current education system, as it has a positive impact on classroom learning. In this gamified framework, students earn points for attending lectures. Each student receives 4000 points for attending 40 lectures. However, if a student is absent, 100 points are deducted from their total earned points. If a student is on duty leave, they receive 100 points per lecture. The faculty should encourage classroom discussion to promote interactive teaching and enhance speaking skills. To increase student engagement, those who actively participate will be awarded points and badges on a weekly basis. The faculty will receive 100 points per lecture, which they can allocate to students who answer verbal questions related to previous or current topics during the lecture. Each question will be worth 10 points, and correct answers will earn 10 points. Students can also ask questions, and those who challenge their peers will receive points. Participation in international conferences, hackathons, and events will earn 500 points, national events 300 points, interuniversity participation 200 points, and organizing college or class events 100 points. Students involved in innovative projects, such as developing research-based applications or improving existing algorithms, will be highly appreciated, and awarded. This gamified framework aims to promote attendance, classroom participation, and student engagement while recognizing their talents and achievements.

3.4 Feedback and Assistance

The proposed comprehensive personalized learning model offers students real-time feedback and invaluable assistance throughout their challenges, with the integration of AI-powered support. This AI assistance provides tailored hints, thorough explanations, and relevant references, bolstering their learning journey. Through the implementation of a sophisticated ML algorithm, an adaptive difficulty level for challenges is achieved successfully. This algorithm dynamically adjusts the difficulty of tasks based on individual students' proficiency and progress, striking an optimal balance between engagement and effective learning. It incorporates the prediction of student proficiency, adjustment of challenge difficulty, and continuous refinement based on performance metrics.

Algorithm 3: Adaptive Difficulty Level Algorithm

1. Initialization
- Define initial difficulty levels for each challenge/task: $D_{initial}$
- Gather baseline data on each student's proficiency and performance.

2. Data Collection
- Continuously collect data on each student's performance, progress, and interactions with challenges/tasks.
- Update the proficiency metrics based on performance.

3. Feature Extraction

Extract relevant features from the collected data: F(student, challenge) = $[f_1, f_2, ..., f_n]$

4. Model Training

Train machine learning models, such as decision trees, random forests, or neural networks, using the extracted features and the historical performance data: Model = $Train_{Model}$(Data)

5. Prediction and Adjustment

For each challenge/task c attempted by student s:
- Predict the student's proficiency using the trained model: p_{prof} = Model(Predict, F(s, c))
- Compare the predicted proficiency with the predefined challenge difficulty: $p_{diff} = F(c) - p_{prof}$
- Adjust the challenge's difficulty level based on the prediction:
  - If $p_{diff} > 0$, increase the challenge's difficulty: $D_{new} = D_{initial} + \alpha \times p_{diff}$
  - If $p_{diff} < 0$, decrease the challenge's difficulty: $D_{new} = D_{init} + \beta \times p_{diff}$

6. Dynamic Adjustment
7. Balancing Engagement and Learning
8. Feedback Loop
9. Iterative Improvement

To enhance transparency and motivation, intuitive dashboards that visually represent students' progress, achievements, and rewards are developed as shown in Figure 2. This clear visualization fosters a healthy sense of competition and inspires students to continually strive for improvement. Leveraging advanced ML techniques, the model conducts in-depth behavioural analysis and pattern recognition to unveil insightful trends in student engagement, motivation, and performance. These analyses serve as the foundation for our framework's adaptive strategies, ensuring a truly personalized and impactful educational experience.

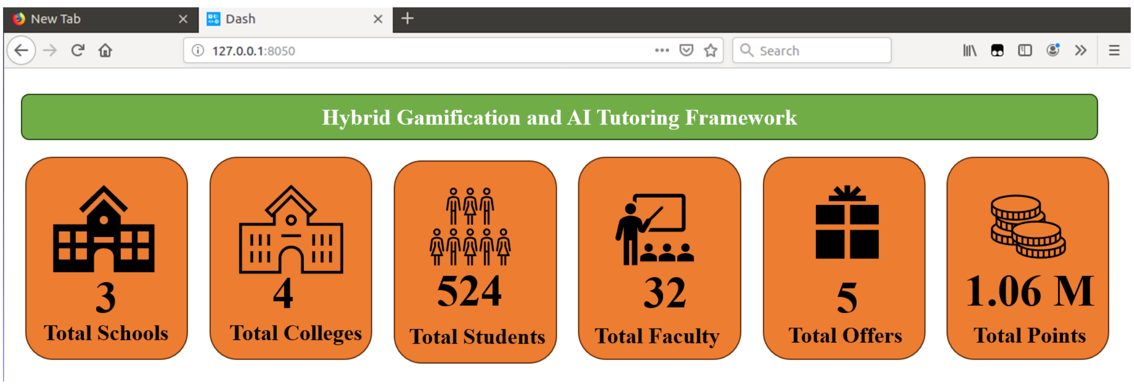

Fig. 2. Sample dashboard

During the dynamic adjustment phase, the algorithm remains responsive to the ever-changing learning landscape by incorporating new data, continually updating proficiency metrics, and closely monitoring students' performance and engagement trends over time. This ongoing monitoring allows for the quick identification of any shifts in proficiency and learning progress, enabling the algorithm to make timely and accurate adaptations. To achieve a balance between engagement and effective learning, the algorithm regularly assesses the equilibrium between keeping students engaged and ensuring meaningful learning outcomes. By using reinforcement learning techniques, the algorithm fine-tunes its parameters to achieve the desired balance, optimizing both engagement and learning impact. Using a feedback loop, the algorithm actively gathers students' perspectives on the perceived difficulty and engagement levels of challenges. This valuable feedback is used to refine the model's performance and fine-tune difficulty levels, resulting in a more tailored learning experience. Through continuous improvement, the algorithm is constantly evolving, leveraging fresh data, user input, and research insights to make continuous refinements.

4. Results and Discussions

Gamification involves using psychological factors to create engaging experiences that shape user engagement and creativity. This framework encompasses the core components of the research, providing a systematic approach to enhance student engagement and motivation through the integration of AI, ML, and gamification principles. It goes beyond simply giving students points and instead fosters collaboration, strategy, and immersion. To implement this approach, a versatile framework was developed and tested in multiple educational settings with 200 computer science students that belong to two educational institutions and 5 classes with a class strength of 40 each. In one institute where attendance was optional, the gamified approach led to increased attendance and engagement. However, for university-level students where attendance was mandatory, the framework did not have a significant impact. Further analysis and refinement of the framework was needed.

In both scenarios, students responded positively to the gamified approach, with increased engagement and participation in learning activities. The accumulation of points for performance and attendance also motivated students. The framework was designed to be adaptable to different courses and programs, emphasizing meaningful gamification that enhances educational experiences. This research shows the potential of technology-mediated gamification to improve teaching and learning approaches. The gamified system was introduced to encourage intrinsic motivation and attendance at an institute where students were not required to attend. This system included points-based attendance tracking, interactive learning, online quizzes, and verbal discussions. The results, presented in Figure 3, showed an increase in attendance across all six sections. While university students still needed to maintain 75% attendance, the implementation of the gamified framework resulted in a significant improvement compared to previous months without it.

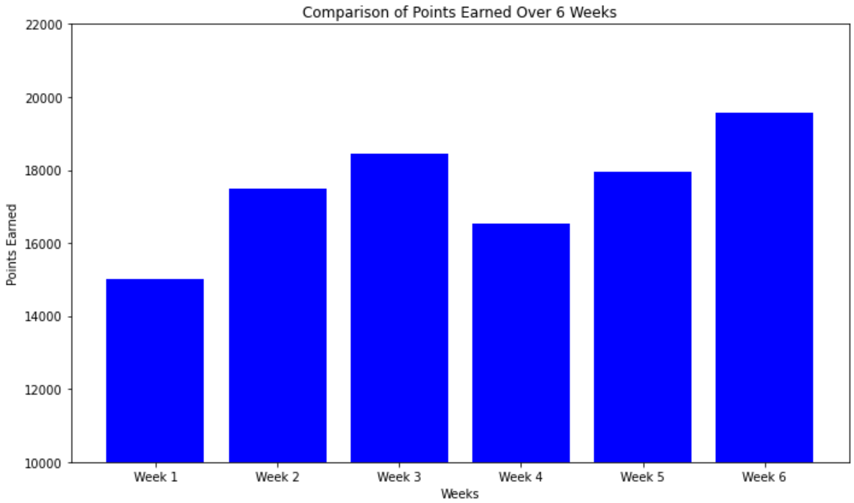

Fig. 3. Comparing Attendance Rates Between Gamified and Non-Gamified Classroom Learning

The students showed a high level of motivation during game-based learning sessions, striving to earn more points each week. Figure 4 demonstrates a steady increase in weekly points earned for three consecutive weeks, followed by a decrease. While this indicates improved student engagement, there may be room to incorporate more intrinsic learning methods.

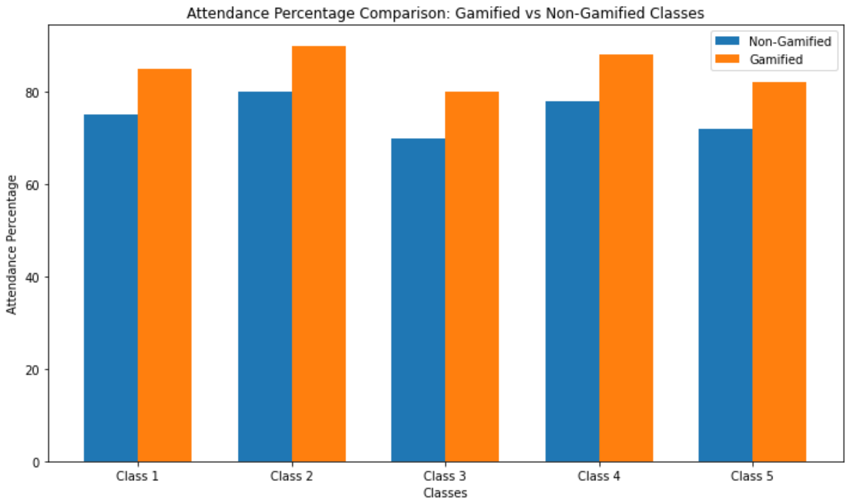

Fig. 4. Comparison of weekly performance of students

50 datasets were collected, comprising over 500 events focused on improving engagement, particularly attendance. 35 datasets were used for training, and 15 were evaluated to assess the system's performance. Table 1 details the evaluation of various machine learning decision-making models' training and testing performance. Sensitivity, accuracy, specificity, and F-measure were used to gauge system effectiveness. Error rates were also analysed, using metrics like root mean square error (RMSE), median absolute error (MEDAE), variance accounted for (VAF) and R-squared statistic (R^2). The proposed model outperformed the ANFIS model [16], Fuzzy System (FS) [17] and Artificial Neural Network (ANN) [18] in accuracy, specificity, sensitivity, and F-measure, making it the best choice for addressing intricate, nonlinear problems, particularly those rooted in multifactor-based relationship analysis.

Table 1
Comparison of testing and training performance

Performance parameters	Fuzzy System		ANN		ANFIS		Proposed	
	Train	Test	Train	Test	Train	Test	Train	Test
Accuracy	93.15%	89.57%	95.14%	91.35%	96.32%	93.57%	98.06%	94.91%
Specificity	93.76%	88.64%	96.46%	91.04%	96.93%	94.23%	98.12%	95.41%
Sensitivity	95.26%	91.35%	96.34%	93.20%	97.82%	94.45%	98.73%	96.34%
F1-Score	94.83%	90.27%	95.63%	92.12%	97.42%	93.35%	98.64%	94.63%

Table 2 shows closely aligned distribution values, distinguishing it from ANFIS, FS and ANN predictive outcomes. The R2 value demonstrated outstanding precision at 0.91, in contrast to ANN's 0.85 and FS's 0.83. Error metrics, including VAF, RMSE, and MEDAE, were notably lower in the proposed model. The findings highlight the proposed model's exceptional performance, positioning it as the optimal solution for effective reward system mechanisms.

Table 2
Comparison of statistical criteria and conditions

Error parameters	Fuzzy System		ANN		ANFIS		Proposed	
	Train	Test	Train	Test	Train	Test	Train	Test
MEDAE	1.87	1.45	2.34	1.20	1.62	1.20	1.58	1.18
VAF (%)	90.02	81.53	87.34	78.93	92.47	89.34	94.52	90.02
R2	0.88%	0.82%	0.87%	0.83%	0.91%	0.89%	0.93%	0.91%
RMSE	4.12%	3.74%	2.63%	1.78%	1.85%	1.41%	1.70%	1.25%

4.1 Discussion

The use of ANFIS in this gamification framework ensures that reward allocation can adapt to changing student behaviour and engagement patterns over time. Additionally, AI and ML personalize challenges, content, and support based on individual student preferences and learning trajectories. This combination of technologies also provides adaptive difficulty levels and dynamic rewards to sustain students' engagement by providing challenges aligned with their learning abilities.

Transparency is also a key feature of the framework, with the visualization of achievements and rewards fostering healthy competition and motivation among students. Behavioural pattern recognition and AI-driven analysis provide insights that enable continuous improvement of the framework's effectiveness. By utilizing AI, ML, and ANFIS, this gamification framework offers a multifaceted approach to improving student engagement and motivation. The challenges, rewards, and support mechanisms are dynamically adapted to create an enriched learning experience tailored to each student's unique journey.

To further understand the impact of gamification on student engagement and motivation, a longitudinal study is conducted over an extended period. Additionally, different AI and ML models are analysed and compared to determine the most effective approach for reward allocation, considering factors such as adaptability and transparency. Behavioural analysis is also performed to understand how gamification elements influence students' engagement patterns and identify trends in their interactions. Finally, advanced ML techniques are utilized to enhance personalization within the gamification framework, tailoring challenges, and support to individual student preferences.

5. Conclusion and Future Work

The proposed hybrid gamification framework integrates AI, ML, and ANFIS to enhance education. Students receive rewards based on their progress, achievements, and interactions, leading to increased engagement, motivation, and learning outcomes. This technology-education combination allows for personalized teaching strategies and valuable insights into students' learning experiences. The pilot implementation involved 200 computer science students in multiple settings, demonstrating the framework's potential to positively impact student engagement and attendance. The model brings new approaches to learning analytics, content generation, reward allocation, and feedback assistance. It outperformed existing methods in accuracy, specificity, sensitivity, and overall performance. This work signifies the significant potential of technology-mediated gamification in reshaping the educational landscape. The gamification framework offers exciting opportunities for research and development in education and technology. Future directions include advanced AI and ML techniques, long-term impact analysis, natural language processing, adaptive learning pathways, ethical considerations, cross-disciplinary applications, user-centred design, lifelong learning and professional development, integration of AR and VR, and international and cultural adaptations.

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References
[1] Escueta, Maya, Andre Joshua Nickow, Philip Oreopoulos, and Vincent Quan. "Upgrading education with technology: Insights from experimental research." *Journal of Economic Literature* 58, no. 4 (2020): 897-996. https://doi.org/10.1257/jel.20191507

[2] Haleem, Abid, Mohd Javaid, Mohd Asim Qadri, and Rajiv Suman. "Understanding the role of digital technologies in education: A review." *Sustainable Operations and Computers* 3 (2022): 275-285. https://doi.org/10.1016/j.susoc.2022.05.004

[3] Abdunabievich, Fazliddin Abdurazaqov, Fazliddin Odinaboboev Baxriddin Ugli, and Nozimakhon Donaeva Norbutaevna. "Types of Pedagogical Technologies That Correspond to the Specifics of Moral and Aesthetic Education and Teaching of Students." *European Scholar Journal* 3, no. 3 (2022): 68-74.

[4] Méndez, Juana Isabel, Pedro Ponce, Othoniel Miranda, Citlaly Pérez, Ana Paula Cruz, Therese Peffer, Alan Meier, Troy McDaniel, and Arturo Molina. "Designing a consumer framework for social products within a gamified smart home context." In *International Conference on Human-Computer Interaction*, pp. 429-443. Cham: Springer International Publishing, 2021. https://doi.org/10.1007/978-3-030-78092-0_29

[5] Manzano-León, Ana, Pablo Camacho-Lazarraga, Miguel A. Guerrero, Laura Guerrero-Puerta, José M. Aguilar-Parra, Rubén Trigueros, and Antonio Alias. "Between level up and game over: A systematic literature review of gamification in education." *Sustainability* 13, no. 4 (2021): 2247. https://doi.org/10.3390/su13042247

[6] Geerts, David, Marije Nouwen, Evert Van Beek, Karin Slegers, Fernanda Chocron Miranda, and Lizzy Bleumers. "Using the SGDA framework to design and evaluate research games." *Simulation & Gaming* 50, no. 3 (2019): 272-301. https://doi.org/10.1177/1046878118808826

[7] Baigi, Seyyedeh Fatemeh Mousavi, Reyhaneh Norouzi Aval, Masoumeh Sarbaz, and Khalil Kimiafar. "Evaluation tools for digital educational games: A systematic review." *Acta Medica Iranica* (2022).

[8] Toda, Armando M., Ana CT Klock, Wilk Oliveira, Paula T. Palomino, Luiz Rodrigues, Lei Shi, Ig Bittencourt, Isabela Gasparini, Seiji Isotani, and Alexandra I. Cristea. "Analysing gamification elements in educational environments using an existing Gamification taxonomy." *Smart Learning Environments* 6, no. 1 (2019): 1-14. https://doi.org/10.1186/s40561-019-0106-1

[9] Kalogiannakis, Michail, Stamatios Papadakis, and Alkinoos-Ioannis Zourmpakis. "Gamification in science education. A systematic review of the literature." *Education Sciences* 11, no. 1 (2021): 22. https://doi.org/10.3390/educsci11010022

[10] Huang, Rui, Albert D. Ritzhaupt, Max Sommer, Jiawen Zhu, Anita Stephen, Natercia Valle, John Hampton, and Jingwei Li. "The impact of gamification in educational settings on student learning outcomes: A meta-analysis." *Educational Technology Research and Development* 68 (2020): 1875-1901. https://doi.org/10.1007/s11423-020-09807-z

[11] Hakak, Saqib, Nurul Fazmidar Mohd Noor, Mohamad Nizam Ayub, Hannyzurra Affal, Nornazlita Hussin, and Muhammad Imran. "Cloud-assisted gamification for education and learning–Recent advances and challenges." *Computers & Electrical Engineering* 74 (2019): 22-34. https://doi.org/10.1016/j.compeleceng.2019.01.002

[12] Legaki, Nikoletta-Zampeta, Nannan Xi, Juho Hamari, Kostas Karpouzis, and Vassilios Assimakopoulos. "The effect of challenge-based gamification on learning: An experiment in the context of statistics education." *International journal of human-computer studies* 144 (2020): 102496. https://doi.org/10.1016/j.ijhcs.2020.102496

[13] Kim, Jihoon, and Darla M. Castelli. "Effects of gamification on behavioral change in education: A meta-analysis." *International Journal of Environmental Research and Public Health* 18, no. 7 (2021): 3550. https://doi.org/10.3390/ijerph18073550

[14] Kalogiannakis, Michail, Stamatios Papadakis, and Alkinoos-Ioannis Zourmpakis. "Gamification in science education. A systematic review of the literature." *Education Sciences* 11, no. 1 (2021): 22. https://doi.org/10.3390/educsci11010022

[15] Pektaş, Murat, and İbrahim Kepceoğlu. "What do prospective teachers think about educational gamification?." *Science education international* 30, no. 1 (2019). https://doi.org/10.33828/sei.v30.i1.8

[16] Méndez, Juana Isabel, Omar Mata, Pedro Ponce, Alan Meier, Therese Peffer, and Arturo Molina. "Multi-sensor system, gamification, and artificial intelligence for benefit elderly people." *Challenges and trends in multimodal fall detection for healthcare* (2020): 207-235. https://doi.org/10.1007/978-3-030-38748-8_9

[17] Khairy, Ghada, Abeer M. Saad, Salem Alkhalaf, and Mohamed A. Amasha. "A Proposed Gamification Framework Using Sentiment Analysis and Fuzzy Logic In Higher Education." *Journal of Theoretical and Applied Information Technology* 101, No. 2 (2023).

[18] Pal, Rituparna, and Satyajit Chakrabarti. "A Gamification Architecture for Online Learning Platform Using Neural Network." In *International Conference on Data Management, Analytics & Innovation*, pp. 363-372. Singapore: Springer Nature Singapore, 2022. https://doi.org/10.1007/978-981-19-2600-6_26