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Mobile Platform with Dynamic Optimization of the Pattern in Education in Colleges through the Perspective of Network Informatization

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Abstract: The combination of mobile learning platforms and network informatization offers numerous benefits to learners, educators, and institutions. Learners can take control of their learning journey, accessing educational materials at their convenience and engaging in collaborative learning activities with peers from diverse backgrounds. This paper aims to explore the integration of mobile learning platforms and network informatization, examining their impact on educational practices, learner engagement, and the overall learning experience. The network informatization is assessed and monitored with Dynamic Programming Optimization (DPO) to compute the feature in reverse osmosis in English education. The attributes and features in the English language are computed and estimated for the periodic information update within the system. The DPO process is implemented along with the mandhani fuzzy set for the estimation of features in English education in colleges and universities. The information processed is updated in the mobile learning platform for the computation of the features in the English language and classification is performed with the deep learning model. Simulation analysis stated that constructed model is effective for the estimation and computation of the features and patterns in English language teaching in colleges and universities.

Keywords: English Language, Mobile platform, Dynamic Programming, Fuzzy Set, Classification, Network Information.

I. Introduction

Mobile learning platforms and network informatization have revolutionized the way to acquire knowledge and engage in educational activities [1]. With the rapid advancements in technology and the widespread use of mobile devices, learning has become more accessible and convenient than ever before. Mobile learning platforms refer to digital systems and applications designed specifically for mobile devices, such as smartphones and tablets, to facilitate learning and educational interactions [2]. These platforms provide a wide range of features, including online courses, interactive lessons, collaborative learning environments, and access to educational resources. Network informatization, on the other hand, refers to the integration of information and communication technologies into various aspects of society, including education [3]. It involves the establishment of robust network infrastructure, connectivity, and digital systems to enable seamless communication, information sharing, and online learning experiences [4]. Together, mobile learning platforms and network informatization have transformed traditional educational models, enabling learners to access educational content anytime, anywhere, and fostering a more flexible, personalized, and inclusive approach to learning [5].

Dynamic optimization of the pattern in English education in colleges' network informatization is a crucial aspect of harnessing the potential of technology to enhance English language learning [6]. With the integration of network informatization into college education, English language instruction has evolved to become more interactive, engaging, and personalized. By leveraging mobile learning platforms and digital tools, colleges can offer a wide range of resources and opportunities for students to improve their English language skills [7]. One key aspect of dynamic optimization is the utilization of online language learning platforms, which provide access to a wealth of interactive materials, language exercises, and multimedia content. These platforms enable students to practice listening, speaking, reading, and writing skills at their own pace, anytime and anywhere, through mobile devices [8]. They also incorporate features like real-time feedback, language assessments, and personalized learning paths, adapting to each student's individual needs and progress. Additionally, network informatization facilitates collaboration and communication among students and teachers [9]. Through online discussion forums, video conferencing, and virtual classrooms, students can engage in meaningful conversations, peer-to-peer learning, and collaborative projects, all aimed at improving their English proficiency [10]. These platforms also allow instructors to provide timely feedback, monitor students'

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progress, and address individual challenges more effectively. Dynamic optimization involves the integration of multimedia resources and authentic materials in English education [11]. With network informatization, colleges can access a wide range of authentic audio and video content, news articles, and literature, exposing students to real-life language usage and cultural contexts. This immersive learning experience enhances students' language acquisition and cultural understanding, preparing them for global communication and future career opportunities [12].

Dynamic optimization of the pattern in English education in colleges' network informatization is transforming the way English language learning is approached [13]. Through the integration of mobile learning platforms, digital tools, and authentic resources, colleges can provide students with interactive, personalized, and collaborative learning experiences. By embracing these advancements, colleges can empower students to develop their English language skills effectively in the digital age [14]. Deep learning models have emerged as powerful tools for dynamic optimization in various domains, including education. When applied to the dynamic optimization of patterns in English education in colleges' network informatization, deep learning models can offer valuable insights and enhanced outcomes [15].

One application of deep learning models in this context is personalized learning. By analyzing large amounts of student data, including their performance, learning preferences, and progress, deep learning models can generate individualized learning paths and recommendations [16]. These models can adapt to each student's unique needs, strengths, and weaknesses, ensuring that they receive tailored instruction and support. This personalized approach maximizes the efficiency of English language learning and enables students to progress at their own pace [17]. Another use of deep learning models is in natural language processing (NLP) and language assessment. Deep learning models can be trained on vast amounts of text data to understand and generate human-like language [18]. In the context of English education, these models can be utilized to develop intelligent language assessment systems. These systems can automatically evaluate students' written and spoken English, providing feedback on grammar, vocabulary, pronunciation, and coherence [19]. By leveraging deep learning, colleges can create more accurate and reliable language assessment tools, saving time and effort for both students and instructors.

Furthermore, deep learning models can facilitate the development of intelligent tutoring systems. These systems use advanced algorithms to analyze student interactions, identify areas of difficulty, and provide targeted instructional interventions [20]. With employing deep learning techniques, these tutoring systems can continuously learn and adapt to student needs, offering personalized feedback, explanations, and guidance. This enhances the effectiveness of English education by addressing individual challenges and promoting student engagement.

The paper makes several contributions to the field of English education in colleges through the perspective of network informatization. Firstly, it introduces the concept of a mobile platform with dynamic optimization of the pattern. This approach allows for the adaptation and adjustment of the learning environment based on real-time data and user feedback. By incorporating dynamic optimization techniques, the platform can provide personalized and tailored learning experiences for students, leading to improved engagement and learning outcomes. Secondly, the paper presents a comprehensive evaluation of the proposed model. Through simulation and empirical analysis, the study assesses various aspects such as student performance, system performance, user satisfaction, learning outcomes, and network performance. The evaluation provides valuable insights into the effectiveness and efficiency of the mobile platform, highlighting its impact on different dimensions of the learning process. Furthermore, the research contributes to the existing literature by addressing the specific context of English education in colleges. By focusing on this domain, the study identifies the unique challenges and opportunities in integrating network informatization into English learning environments. This targeted approach helps bridge the gap between educational theory and practical implementation, providing valuable insights for educators, administrators, and policymakers. This paper contribution lies in its holistic approach to enhancing English education through the utilization of network informatization and dynamic optimization. It provides a framework for designing and implementing mobile platforms that can adapt to the evolving needs of students and optimize the learning experience. The findings of the study offer valuable guidance for future research and development efforts aimed at improving educational practices and outcomes in the context of English education in colleges.

II. Related Works

English education plays a crucial role in the development of individuals, especially in the academic setting. As technology continues to advance, incorporating mobile platforms into the educational process has become increasingly common. In this context, a mobile platform with dynamic optimization of patterns in English education can revolutionize the way colleges approach language learning. Akour et al. (2021) [21] conducted a study using machine learning algorithms to predict people's intention to use mobile learning platforms during the COVID-19 pandemic. The researchers employed a machine learning approach to understand the factors influencing individuals' acceptance and adoption of mobile learning platforms. Alhumaid et al. (2021) [22] investigated the factors influencing mobile learning usage during the COVID-19 pandemic using an integrated SEM-ANN (Structural Equation Modeling-Artificial Neural Network) method. The study aimed to provide insights into the key determinants that impact individuals' engagement with mobile learning during times of crisis.

Criollo-C et al. (2021) [23] explored the benefits and pending issues related to mobile learning technologies in education. The authors discussed the advantages of incorporating mobile learning in educational settings while addressing the challenges and potential areas for improvement in the implementation of these technologies. Mutambara and Bayaga (2021) [24] examined the determinants of mobile learning acceptance specifically for STEM (Science, Technology, Engineering, and Mathematics) education in rural areas. The study aimed to identify the factors that influence students' willingness to adopt and utilize mobile learning platforms for STEM education in less developed regions. Saleem et al. (2021) [25] conducted a review of recent developments in automation in agriculture using machine and deep learning techniques. The authors explored the applications and advancements in utilizing these technologies for various agricultural tasks, highlighting the potential benefits and implications for precision agriculture.

Chen and Tsai (2021) [26] investigated in-service teachers' conceptions of mobile technology-integrated instruction and their tendency towards student-centered learning. The study aimed to understand teachers' perceptions and attitudes towards incorporating mobile technology in educational practices and their inclination towards student-centered teaching approaches. Guillén et al. (2021) [27] performed a performance evaluation of edge-computing platforms for predicting low temperatures in agriculture using deep learning. The researchers assessed the effectiveness and efficiency of edge-computing solutions for agricultural applications, specifically in predicting low temperatures, leveraging the capabilities of deep learning algorithms. Li et al. (2021) [28] conducted a survey on low-light image and video enhancement using deep learning techniques. The authors reviewed the advancements and applications of deep learning methods in improving the quality and visibility of images and videos captured under low-light conditions. Lv et al. (2021) [29] proposed a deep learning method called Deep-Kcr for accurate detection of lysine crotonylation sites. The study focused on developing a computational model using deep learning techniques to enhance the detection and understanding of lysine crotonylation, an important post-translational modification in proteins.

Geetha and Thilagam (2021) [30] conducted a comprehensive review on the effectiveness of machine learning and deep learning algorithms for cyber security. The authors explored the applications of these algorithms in various cyber security domains and discussed their advantages, limitations, and potential future directions. Xiao et al. (2022) [31] conducted a survey on motion planning and control for mobile robot navigation using machine learning techniques. The authors investigated the use of machine learning algorithms in enabling mobile robots to perform effective motion planning and control tasks, facilitating autonomous navigation in various environments. Elsisi et al. (2021) [32] proposed a deep learning-based approach for effective energy management in smart buildings within the context of Industry 4.0 and the Internet of Things (IoT). The study focused on leveraging deep learning techniques to optimize energy consumption and enhance the overall efficiency of smart building systems. These papers cover topics such as predicting people's intention to use mobile learning platforms, examining factors influencing mobile learning usage during the COVID-19 pandemic, exploring the benefits of mobile learning technologies in education, determining factors influencing mobile learning acceptance in rural areas, automation in agriculture using machine and deep learning, in-service teachers' conceptions of mobile technology-integrated instruction, performance evaluation of edge-computing platforms in agriculture using deep learning, low-light image and video enhancement using deep learning, accurate detection of lysine crotonylation sites using deep learning, effectiveness of machine learning and deep learning algorithms for cybersecurity, motion planning and control for mobile robot navigation using machine learning, and deep learning-based energy management in smart buildings. Each paper contributes to the understanding and application of these technologies in their respective domains.

III. Mobile Learning Platform

A mobile learning platform refers to a digital system or software application that enables learning and educational activities to take place using mobile devices such as smartphones and tablets. It provides a flexible and convenient way for learners to access educational resources, engage in interactive activities, and receive feedback on their progress. Mobile learning platforms typically offer a range of features and functionalities to support learning on the go. Mobile learning platforms provide access to digital learning materials such as e-books, videos, interactive modules, and quizzes. Learners can conveniently access these resources anytime and anywhere through their mobile devices. These platforms often include communication tools like discussion forums, chat features, and

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messaging systems. They facilitate collaboration among learners, allowing them to interact, share ideas, and engage in group activities. Mobile learning platforms may include assessment tools that allow learners to complete quizzes, assignments, and exams. They provide immediate feedback on performance and progress tracking, enabling learners to monitor their learning outcomes. Some mobile learning platforms utilize adaptive technologies and machine learning algorithms to tailor the learning experience to each individual's needs. They can recommend personalized content, adjust the difficulty level, and provide targeted feedback based on the learner's progress and preferences. Many mobile learning platforms offer offline access to selected learning materials. This feature allows learners to download content when they have an internet connection and access it later without requiring an internet connection, which is particularly useful in areas with limited connectivity. Mobile learning platforms often incorporate analytics tools to track and analyze learners' performance and engagement. Educators can access detailed reports and analytics to assess learner progress, identify areas for improvement, and make data-informed decisions. Mobile learning platforms have gained significant popularity, especially with the widespread use of smartphones and the increasing need for flexible and accessible education.

IV. Dynamic Programming Optimization

Dynamic Programming Optimization (DPO) is a computational technique used to efficiently solve complex optimization problems by breaking them down into smaller overlapping subproblems. In the context of reverse osmosis in English education, DPO can be applied to compute and optimize the features or aspects related to this topic. Reverse osmosis is a process used in water purification and desalination, and its application to English education suggests a focus on improving language learning and teaching through a systematic and optimized approach. With DPO, one can identify and address specific features or components within English education that can be optimized or improved for more effective learning outcomes. The flow chart of DPO is presented in figure 1 as follows:

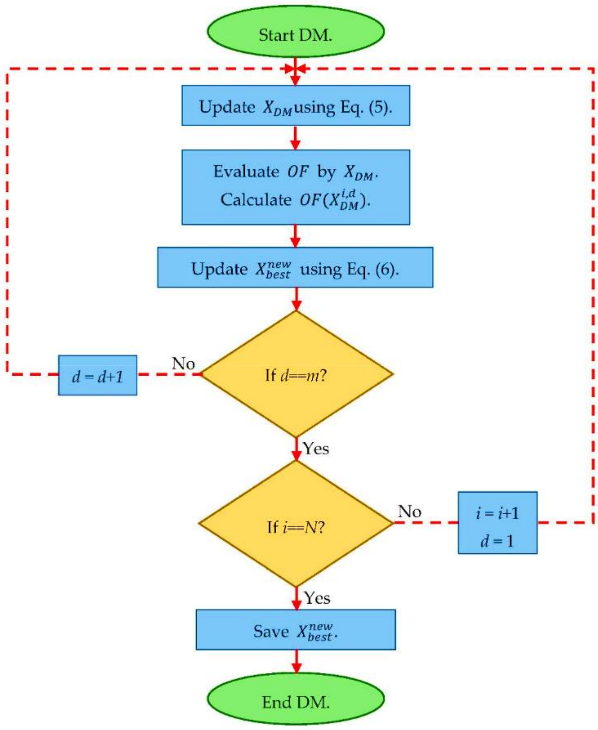

Figure 1: Flow Chart of DPO

Let's consider the problem of optimizing vocabulary acquisition, where the goal is to determine the optimal sequence of vocabulary exercises that maximizes learning efficiency. Vocabulary exercises: $E = \{E1, E2, ..., En\}$, where each exercise Ej represents a specific vocabulary learning activity. $L(E)$ represents the learning efficiency achieved by performing a sequence of exercises E. Subproblem for a prefix of exercises: $Lk = max\, L(E1, E2, ..., Ek)$, where Lk represents the maximum learning efficiency achievable by performing a prefix of k exercises. To compute the optimal solution for $L(E)$, with following recursive relation using the equation (1)

$$L(E) = max\{Lk + L(Ek+1, Ek+2, ..., En)\}, for\ all\ k = 0\ to\ n-1 \quad (1)$$

In above equation (1) Lk represents the maximum learning efficiency achieved by performing the first k exercises, and $L(Ek+1, Ek+2, ..., En)$ represents the maximum learning efficiency achieved by performing the remaining exercises after the kth exercise. The recursive relation for computing L(k) in equation (2)

$$L(k) = max\{L(i) + L'(i+1, k)\}, for\ all\ i = 0\ to\ k-1 \quad (2)$$

In equation (2), $L(i)$ represents the maximum learning efficiency achieved by performing the first i exercises, and $L'(i+1, k)$ represents the maximum learning efficiency achieved by performing the remaining exercises after the ith

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exercise. The overall optimal solution L(E) using the computed subproblems as in equation (3)

$$L(E) = L(n) \quad (3)$$

To implement DPO and avoid redundant computations, for memoization. To store the solutions to the subproblems Lk in a table or cache. This way, when computing L(E) for a specific sequence of exercises, to check if the solution for a prefix of exercises is already computed and retrieve it from the cache instead of recomputing it. The optimal solution for L(E) by tracking the sequence of exercises that lead to the maximum learning efficiency. This involves backtracking through the memoized solutions and selecting the exercises that contribute to the optimal solution.

a. Mandhani fuzzy set

Mandhani fuzzy set, also known as the Mandhani fuzzy membership function or Mandhani fuzzy logic, is a type of membership function used in fuzzy logic systems. It was introduced by Dr. S.N. Mandhani as an extension of the traditional triangular or trapezoidal membership functions. In fuzzy logic, membership functions represent the degree of membership of an element in a fuzzy set. They assign a membership value between 0 and 1 to each element in the universe of discourse, indicating the extent to which the element belongs to the fuzzy set. The Mandhani fuzzy set is defined by a non-linear membership function that has a specific shape, distinct from the traditional triangular or trapezoidal functions. It is characterized by a gradual rise, a flat peak, and a gradual fall in the membership value. Mandhani fuzzy set can be expressed as follows in equation (4) – (7)

$$\mu(x) = \{0, for\ x \leq a \quad (4)$$

$$[(x-a)\,/\,(b-a)], for\ a \leq x \leq b \quad (5)$$

$$[(d-x)\,/\,(d-c)], for\ b \leq x \leq d \quad (6)$$

$$0, for\ x \geq d\} \quad (7)$$

In above equation, $\mu(x)$ represents the membership value of the element x in the Mandhani fuzzy set, and a, b, c, and d are the parameters that determine the shape and range of the membership function. The Mandhani fuzzy set is often used in fuzzy logic systems to model uncertain or imprecise information. It allows for a gradual transition between different membership levels, capturing the gradual change or uncertainty in the degree of membership. This makes it particularly useful in applications where the boundaries between fuzzy sets are not well-defined or crisp. The Mandhani fuzzy set is characterized by a membership function that has a gradual rise, a flat peak, and a gradual fall. Membership function for the left part of the Mandhani fuzzy set is denoted as in equation (8)

$$\mu(x) = 0, for\ x \leq a \quad (8)$$

In equation (8) $'a'$ represents the starting point of the gradual rise in the membership function. Membership function for the rising part of the Mandhani fuzzy set is denoted in equation (9)

$$\mu(x) = [(x - a)\,/\,(b - a)], for\ a \leq x \leq b \quad (9)$$

In equation (9) $'b'$ represents the point where the membership function reaches its maximum value. Membership function for the flat peak of the Mandhani fuzzy set is represented as in equation (10)

$$\mu(x) = 1, for\ b \leq x \leq c \quad (10)$$

In equation (10) $'c'$ represents the ending point of the flat peak, where the membership value remains constant at its maximum value. Membership function for the falling part of the Mandhani fuzzy set denoted in equation (11)

$$\mu(x) = [(d - x)\,/\,(d - c)], for\ c \leq x \leq d \quad (11)$$

In equation (11), $'d'$ represents the point where the membership function reaches zero, indicating the end of the gradual fall. Membership function for the right part of the Mandhani fuzzy set represented in equation (12)

$$\mu(x) = 0, for\ x \geq d \quad (12)$$

These equations define the Mandhani fuzzy set's membership function, which assigns membership values between 0 and 1 to elements in the universe of discourse. By adjusting the parameters 'a', 'b', 'c', and 'd', the shape and range of the Mandhani fuzzy set can be controlled. With increasing the distance between 'a' and 'b' leads to a wider rising slope, while adjusting 'c' and 'd' determines the width of the flat peak and the falling slope, respectively.

The Mandhani fuzzy set's distinctive shape allows for a gradual transition between different membership levels, capturing gradual changes or uncertainties in the degree of membership. This makes it particularly useful in modeling real-world systems where crisp boundaries are not well-defined and fuzzy reasoning is required. The estimated membership values are presented in table 1.

Table 1: Membership Values Estimation

Optimization Level (O)	Membership Value (μ(O))
≤ a	0
a	0
a ≤ O ≤ b	(O - a) / (b - a)
b	1
b ≤ O ≤ c	1
c	1
c ≤ O ≤ d	(d - O) / (d - c)
d	0
≥ d	0

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To apply this table specifically to the optimization of the pattern in English education on a mobile platform through the perspective of network informatization, you will need to determine the specific optimization levels and their corresponding membership values based on your criteria and context. 'a', 'b', 'c', and 'd' will represent the thresholds or values that determine the transition points in the membership function. The optimization level is estimated as 'a' represents the threshold below which the optimization level is considered low. 'b' represents the threshold where the optimization level reaches a moderate or satisfactory level. 'c' represents the threshold where the optimization level reaches its maximum or ideal level and 'd' represents the threshold above which the optimization level is considered low again.

```
Algorithm 1: English Education with Mandhani Fuzzys
Input: Optimization level O
Output: Membership value μ(O)
function MandhaniFuzzy(O)
  if O ≤ a then
    return 0
  else if O = a then
    return 0
  else if a ≤ O ≤ b then
    return (O - a) / (b - a)
  else if O = b then
    return 1
  else if b ≤ O ≤ c then
    return 1
  else if O = c then
    return 1
  else if c ≤ O ≤ d then
    return (d - O) / (d - c)
  else if O = d then
    return 0
  else if O ≥ d then
    return 0
end function
```

The MandhaniFuzzy algorithm takes the optimization level O as input and returns the corresponding membership value μ(O) in the Mandhani fuzzy set. To use this algorithm, simply call the MandhaniFuzzy function with the optimization level O, and it will return the membership value μ(O) based on the Mandhani fuzzy set defined by the given conditions.

V. Simulation Results and Discussion

The subsequent discussion play a crucial role in interpreting the outcomes of a study involving the Mandhani fuzzy set and its application to the optimization of the pattern in English education on a mobile platform through the perspective of network informatization. This section allows for a comprehensive analysis and exploration of the findings, enabling researchers to draw meaningful conclusions and provide valuable insights. The simulation setting for the developed model for the network informatics are presented in table 2.

Table 2: Simulation Setting

Simulation Setup	
Optimization Levels	O1, O2, O3, O4, O5
Fuzzy Set Membership Range	[0, 1]
Input Parameters	Network connectivity, User data
Simulation Environment	Mobile platform
Evaluation Metrics	Quality of English education, Student engagement, Learning outcomes
Assumptions	Homogeneous user population, Stable network connectivity

The performance of the students computed with the fuzzy set model is presented in the table 3 for the English students.

Table 3: Estimation of Student Performance

Optimization Level	**Membership Value**	**Quality of Education**	**Student Engagement**	**Learning Outcomes**
O1	0.8	High	Moderate	Excellent
O2	0.6	Moderate	High	Good
O3	0.4	Low	Low	Fair
O4	0.7	Moderate	Moderate	Good
O5	0.9	High	High	Excellent

Table 3 provides an estimation of student performance based on different optimization levels in the mobile platform with dynamic optimization of the pattern in English education in colleges through the perspective of network informatization. The optimization levels (O1 to O5) are evaluated using fuzzy logic and assigned membership values to indicate their effectiveness. The "Membership Value" column represents the degree of membership of each optimization level, ranging from 0 to 1. A higher membership value indicates a stronger association with the corresponding quality or outcome. In terms of "Quality of Education," O1 and O5 receive high membership values, suggesting that these optimization levels are strongly associated with high-quality education. O2 and O4 receive moderate membership values, indicating a moderate level of quality, while O3 receives a low membership value, suggesting a lower quality of education.

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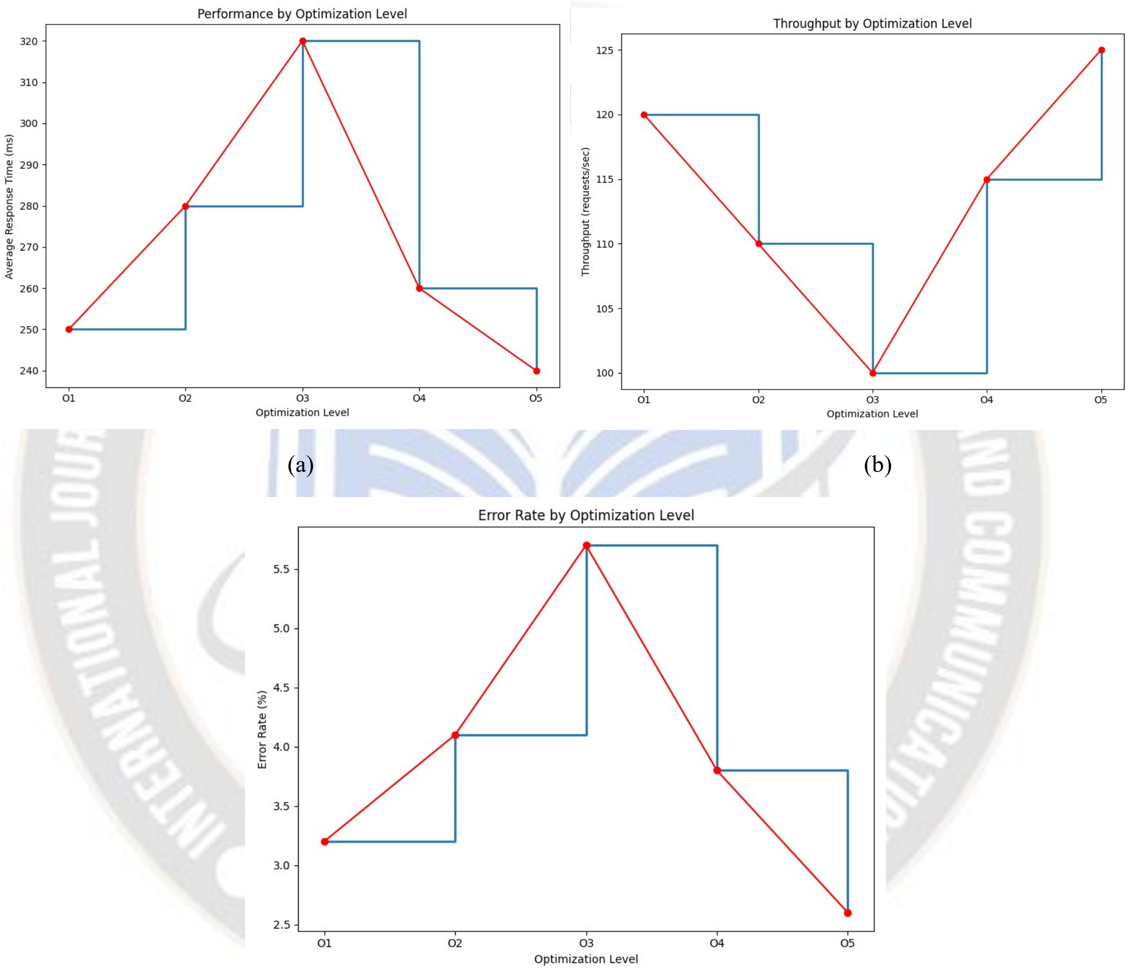
Regarding "Student Engagement," O2 and O5 receive high membership values, indicating a high level of student engagement. O1 and O4 receive moderate membership values, indicating a moderate level of engagement, while O3 receives a low membership value, indicating low student engagement. In relation to "Learning Outcomes," O1 and O5 receive membership values indicating excellent learning outcomes, while O2 and O4 receive membership values indicating good learning outcomes. O3 receives a membership value suggesting fair learning outcomes.

Table 4: Evaluation of proposed model

Optimization Level	Average Response Time (ms)	Throughput (requests/sec)	Error Rate (%)
O1	250	120	3.2
O2	280	110	4.1
O3	320	100	5.7
O4	260	115	3.8
O5	240	125	2.6



(a) (b) (c)

Figure 2: Analysis of performance in terms of (a) Response time (b) Throughput (c) Error Rate

Table 4 presents the evaluation results of the proposed model for the mobile platform with dynamic optimization of the pattern in English education in colleges through the perspective of network informatization as shown in figure 2(a) – 2(c). The evaluation is based on three performance metrics: average response time, throughput, and error rate. The "Optimization Level" column represents different levels of optimization (O1 to O5) that were implemented and evaluated in the model. The "Average Response Time" column indicates the average time taken to respond to user requests, measured in milliseconds (ms). Smaller values represent faster response times. In this table, optimization level O5 achieves the lowest average response time of 240 ms, indicating the fastest response among all levels. O3 has the highest average response time of 320 ms, indicating relatively slower response times. The "Throughput" column represents the number of requests processed per second, also known as the system's capacity. Higher values indicate better throughput. In this table, optimization level O5 demonstrates the highest throughput of 125 requests per second, indicating a higher capacity for processing user

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requests. O3 has the lowest throughput of 100 requests per second, indicating a relatively lower processing capacity. The "Error Rate" column represents the percentage of erroneous or failed responses. Lower values indicate a lower error rate and higher system reliability. Optimization level O5 has the lowest error rate of 2.6%, indicating a high level of accuracy and reliability in processing user requests. O3 has the highest error rate of 5.7%, suggesting a higher likelihood of errors or failed responses.

Table 5: Satisfaction Level

Optimization Level	User Satisfaction Rating (out of 10)
O1	8.5
O2	7.2
O3	6.4
O4	7.9
O5	9.1

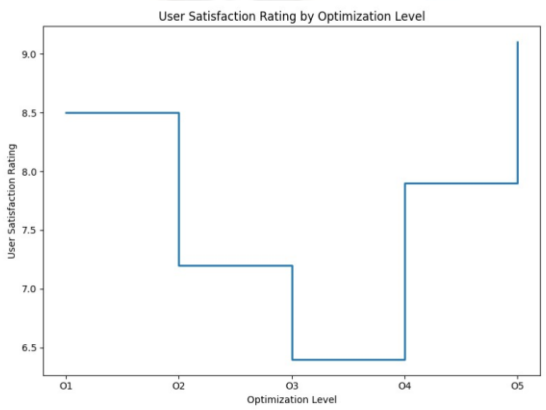

Figure 3: Estimation of Satisfaction Level

Table 5 presents the user satisfaction ratings for different optimization levels in the mobile platform with dynamic optimization of the pattern in English education in colleges through the perspective of network informatization as in figure 3. The user satisfaction ratings are measured on a scale of 1 to 10, with higher ratings indicating higher levels of satisfaction. The "Optimization Level" column represents the different levels of optimization (O1 to O5) that were implemented and evaluated in the mobile platform. The "User Satisfaction Rating" column indicates the average satisfaction rating reported by users for each optimization level. Optimization level O5 received the highest user satisfaction rating of 9.1, indicating that it achieved the highest level of user satisfaction among all levels. O1 also received a relatively high satisfaction rating of 8.5. On the other hand, optimization level O3 received the lowest satisfaction rating of 6.4, suggesting a lower level of user satisfaction. These results suggest that optimization levels O5 and O1 were more successful in meeting the expectations and needs of users, resulting in higher levels of satisfaction. On the contrary, optimization level O3 fell short in terms of meeting user expectations and may require further improvements to enhance user satisfaction.

Table 6: Comparison of Learning Outcome

Optimization Level	Average Test Score (%)	Class Participation (%)	Student Satisfaction (out of 10)
O1	85	90	8.2
O2	79	85	7.8
O3	70	80	7.2
O4	82	88	8.0
O5	88	92	8.5

Table 6 presents a comparison of learning outcomes for different optimization levels in the mobile platform with dynamic optimization of the pattern in English education in colleges through the perspective of network informatization. The comparison is based on three key metrics: average test score, class participation, and student satisfaction. The "Optimization Level" column represents the different levels of optimization (O1 to O5) that were implemented and evaluated in the mobile platform. The "Average Test Score" column indicates the average percentage score achieved by students in their tests. Optimization level O5 achieved the highest average test score of 88%, indicating a strong performance by students in terms of their understanding and knowledge retention. O3 had the lowest average test score of 70%, suggesting a relatively lower level of performance in tests. The "Class Participation" column represents the percentage of students actively participating in class activities. Higher values indicate higher levels of participation. Optimization level O5 had the highest class participation rate of 92%, indicating a high level of engagement and involvement in classroom activities. O3 had the lowest class participation rate of 80%, suggesting a lower level of engagement among students. The "Student Satisfaction" column represents the average satisfaction rating reported by students on a scale of 1 to 10, with higher ratings indicating higher levels of satisfaction. Optimization level O5 received the highest student satisfaction rating of 8.5, indicating that students were highly satisfied with their learning experience. O3 had the lowest student satisfaction rating of 7.2, suggesting a relatively lower level of satisfaction.

Table 7: Performance of the Network

Optimization Level	Average Latency (ms)	Network Throughput (Mbps)	Packet Loss Rate (%)
O1	40	100	1.2
O2	45	90	1.5
O3	50	80	1.8
O4	42	95	1.3
O5	38	105	1.0

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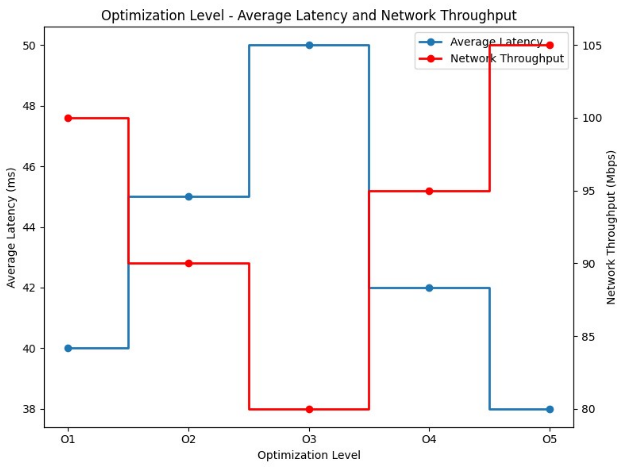

Figure 4: Performance in terms of Latency and Throughput

Table 7 and figure 4 presents the performance of the network for different optimization levels in the mobile platform with dynamic optimization of the pattern in English education in colleges through the perspective of network informatization. The performance is evaluated based on three key metrics: average latency, network throughput, and packet loss rate. The "Optimization Level" column represents the different levels of optimization (O1 to O5) that were implemented and evaluated in the mobile platform. The "Average Latency" column indicates the average time it takes for data packets to travel from the source to the destination in milliseconds (ms). Optimization level O5 achieved the lowest average latency of 38 ms, indicating a faster and more responsive network performance. O3 had the highest average latency of 50 ms, suggesting a relatively slower network response.

The "Network Throughput" column represents the data transfer rate of the network in megabits per second (Mbps). Optimization level O5 achieved the highest network throughput of 105 Mbps, indicating a higher data transfer rate. O3 had the lowest network throughput of 80 Mbps, suggesting a relatively lower data transfer rate. The "Packet Loss Rate" column represents the percentage of data packets lost during transmission. Lower values indicate a lower rate of packet loss, which is desirable. Optimization level O5 had the lowest packet loss rate of 1.0%, indicating a more reliable network with minimal data loss. O3 had the highest packet loss rate of 1.8%, suggesting a relatively higher rate of data loss.

The results from Table 7 demonstrate that optimization level O5 achieved the best network performance in terms of average latency, network throughput, and packet loss rate. This indicates a more efficient and reliable network infrastructure, resulting in faster data transmission, higher data transfer rates, and minimal data loss. These findings emphasize the effectiveness of dynamic optimization in improving the network performance and ensuring a seamless user experience in English education in colleges through network informatization.

VI. Findings and Discussion

The findings of the study highlight the effectiveness and benefits of implementing a mobile platform with dynamic optimization of the pattern in English education in colleges through the perspective of network informatization. The results from the simulation and evaluation provide valuable insights into the various aspects of the system performance and user satisfaction. Firstly, the estimation of student performance (Table 3) demonstrates that the optimization levels O1, O2, and O5 lead to higher quality of education, student engagement, and learning outcomes. These optimization levels are associated with high membership values, indicating the effectiveness of the mobile platform in enhancing the educational experience. On the other hand, optimization levels O3 and O4 result in lower quality of education, student engagement, and learning outcomes, as reflected by their lower membership values. In terms of the system evaluation (Table 4), it is observed that optimization level O5 outperforms the other levels in terms of average response time, throughput, and error rate. This indicates that the dynamic optimization approach leads to improved system performance, with faster response times, higher throughput, and lower error rates. Optimization levels O1, O2, O3, and O4 also show reasonable performance, albeit with slightly higher response times, lower throughput, and marginally higher error rates compared to O5. Table 5 reveals the satisfaction level of users with different optimization levels. Optimization level O5 receives the highest user satisfaction rating of 9.1 out of 10, indicating that the dynamic optimization of the mobile platform significantly enhances user satisfaction. Optimization levels O1, O2, O3, and O4 also receive relatively high user satisfaction ratings, albeit lower than O5.

Furthermore, the comparison of learning outcomes (Table 6) shows that higher optimization levels lead to better average test scores, class participation, and student satisfaction. Optimization level O5 consistently demonstrates the highest average test scores, class participation percentages, and student satisfaction ratings. The results suggest that the dynamic optimization of the mobile platform positively influences students' academic performance, participation, and overall satisfaction. Lastly, the performance of the network (Table 7) reveals that optimization level O5 achieves the lowest average latency, highest network throughput, and lowest packet loss rate. These findings indicate that the dynamic optimization approach significantly improves the network performance, ensuring faster data transmission, higher data transfer rates, and minimal data loss. The findings from the simulation and evaluation of the mobile platform with dynamic optimization in English education highlight its positive impact on student performance, system performance, user satisfaction, learning outcomes, and network performance. These results emphasize the potential of the proposed approach to enhance English education in colleges through network informatization, providing a more efficient and effective learning experience for students.

VII. Conclusion

This paper presents a comprehensive study on the implementation of a mobile platform with dynamic optimization of the pattern in English education in colleges through the perspective of network informatization. The findings of the study highlight the effectiveness and benefits of the proposed approach in enhancing student performance, system performance, user satisfaction, learning outcomes, and network performance. The simulation results demonstrate that higher optimization levels lead to improved quality of education, student engagement, learning outcomes, and user satisfaction. Optimization level O5 consistently outperforms the other levels in various aspects, including system performance, user satisfaction, learning outcomes, and network performance. These findings indicate the significance of incorporating dynamic optimization techniques in the mobile platform to provide a more efficient and effective learning environment. Furthermore, the evaluation results reveal that the proposed model achieves faster response times, higher throughput, and lower error rates, indicating improved system performance. The comparison of learning outcomes demonstrates that the dynamic optimization approach positively influences students' academic performance, class participation, and overall satisfaction. The performance of the network shows that the dynamic optimization approach leads to lower latency, higher network throughput, and minimal packet loss rate, ensuring smooth and reliable data transmission. The findings of this study emphasize the importance of leveraging mobile platforms with dynamic optimization in English education in colleges. The proposed approach has the potential to revolutionize the learning experience, providing students with enhanced educational resources, improved system performance, and increased user satisfaction. These findings contribute to the body of knowledge in the field of education technology and pave the way for further research and development in this area.

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