IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2024.0429000

Dynamic Level of Difficulties Using Q-Learning and Fuzzy Logic

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Supported By Institut Teknologi Sepuluh Nopember

ABSTRACT Maintaining player engagement in serious management games is a challenge due to the repetitive nature of traditional predetermined difficulty levels. A dynamic difficulty adjustment (DDA) system is introduced in this study to address this issue by integrating fuzzy logic and Q-learning. Player ennui is frequently the consequence of static difficulty adjustments. In order to dynamically adjust game complexity in accordance with player performance and preferences, our DDA system utilizes a diverse array of performance metrics, adaptive narrative elements, and real-time feedback, as well as fuzzy logic and Q-learning algorithms. According to empirical assessments, players were 28% more effective overall, and play sessions lasted an average of 35% longer. Player satisfaction and involvement were also much improved. Customers played the game longer and were less bored because of the higher degree of difficulty and customization. The integration of fuzzy logic and Q-learning in DDA systems greatly enhances the ability to maintain long-term player engagement in essential management games. This approach offers a long-lasting alternative for creating constantly captivating gaming experiences by effectively reducing the repetitiveness of traditional difficulty adjustments.

INDEX TERMS Dynamic Difficulty, Q-Learning, Fuzzy Logic, Player Engagement, Virtual Reality, Serious Game, Management Game.

I. INTRODUCTION

IN the realm of sophisticated management games, it is a substantial challenge to sustain player engagement for extended periods. Player tedium and disengagement are frequently the consequence of static difficulty settings, which maintain game parameters at a constant level or fluctuate sporadically. Once players become better, these static settings turn into boring interactions that don't hold their interest [1], [2]. Therefore, there is a demand for Dynamic Difficulty Adjustment (DDA) systems that can provide customized challenges that constantly evolve.

This paper investigates the inadequacy of unchanging difficulty factors for sustaining player engagement. Players' preferences and abilities cannot be accommodated by static settings, resulting in monotonous experiences. Despite the fact that current DDA techniques address this issue, they typically fail to incorporate intricate modifications that accommodate a wide variety of player preferences and actions [3], [4]. We present a unique DDA system that uses Q-learning and fuzzy logic to provide a more interesting and efficient real-time difficulty adjustment mechanism. Different from other techniques, our methodology uses fuzzy logic and Q-learning to more successfully control the inherent uncertainty and unpredictability in player behavior. By learning from player interactions, the system's perpetual optimization of difficulty levels over time is accomplished, resulting in a dynamic and personalized gaming experience. This integration is a significant step forward in the realm of serious management games.

The successful implementation of this DDA system is contingent upon the presence of a few essential components. A comprehensive set of performance metrics, such as general

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engagement and decision-making speed, are used to evaluate numerous player actions [5], [6]. The plot and problems are guaranteed to evolve in accordance with the player's advancement by means of narrative components that are adaptable. The use of real-time feedback systems ensures a rigorous and immersive experience by perpetually adjusting the difficulty level based on the obtained data [7], [8]. This comprehensive methodology [9] guarantees that the player's experience is relevant to the circumstances and can be adjusted in accordance with their performance abilities.

In order to evaluate the efficacy of the proposed technique in improving participant engagement and contentment, an empirical study was implemented. Players who exhibit a higher degree of customization and engagement in terms of challenge experience extended gaming sessions and experience less tedium [10]. The results show that by including fuzzy logic and Q-learning in DDA systems, one may improve the flexibility and pleasure of game experiences [11].

The problem of efficiently sustaining player engagement in serious management games through fixed difficulty levels remains unresolved, despite recent developments. Disengagement often follows when traditional, defined difficulty levels are insufficient to satisfy the individual needs of each participant. This effort aims to close this gap by providing a dynamic, personally created challenge that is determined by the player's performance and preferences. The suggested approach aims to enhance player retention and satisfaction by integrating Q-learning and fuzzy logic to enable ongoing and tailored difficulty modifications. This approach is expected to improve the responsiveness and engagement of the gaming experience by dynamically adapting to the player's skill level and behavior, thus overcoming the limitations of fixed difficulty levels.

II. RELATED WORK

Dynamic difficulty adjustment has been extensively investigated in a variety of gaming disciplines. The significance of DDA in sustaining player engagement is underscored by prior research, which involves the real-time adjustment of game parameters [1], [2]. The importance of real-time feedback mechanisms and player modeling in modern DDA systems is underscored by comprehensive reviews [3]-[6]. Machine learning methodologies have significantly improved DDA systems, as evidenced by the efficacy of algorithms that predict player behavior and modify game difficulty [7]. The adaptability and personalization of gaming experiences have been improved through the diversification of DDA techniques in studies that incorporate user modeling [8], [9]. Genetic algorithms and reinforcement learning, particularly deep reinforcement learning, have demonstrated the potential to optimize DDA systems [10]-[12].

Fuzzy logic is particularly advantageous in DDA because of its capacity to manage ambiguity and variability in participant behavior. Research has shown that it is effective in the creation of personalized and adaptive game experiences [13], [14]. A study on the dynamic difficulty adjustment of educational 3D games using fuzzy logic demonstrated the potential to enhance learning outcomes [15]. Our research expands upon this by incorporating fuzzy logic and Q-learning to improve the adaptability and responsiveness of DDA systems.

Optimal strategies are acquired through environmental interaction through the extensive use of reinforcement learning, particularly Q-learning, in game AI. In intricate game environments, adaptive AI has made substantial progress as a result of deep Q-learning [16], [17]. Our method employs Q-learning to iteratively improve the adaptability of the DDA system in response to user interactions.

The integration of multiple AI techniques has been recommended as a means of establishing more resilient DDA systems. Studies have implemented reinforcement learning and neural networks to implement real-time difficulty adjustments in action games [18], [19]. Our research offers a novel approach to DDA in serious management games by seamlessly integrating fuzzy logic and Q-learning.

The influence of DDA on player engagement and contentment has been evaluated through empirical research. Customized difficulty adjustments are emphasized in the initial frameworks for adaptive games as a means of reducing monotony and enhancing player immersion. [20]-[22]. DDA has been demonstrated to enhance user engagement and learning outcomes in critical Virtual Reality (VR) management games [23]-[25].

Research on adaptive gaming has also investigated genetic algorithms for the optimization of DDA systems. The potential of genetic algorithms to sustain player engagement by harmonizing difficulty levels is illustrated in these studies [26], [27]. Hybrid AI models that incorporate a variety of AI techniques have also demonstrated potential in the development of dynamic and responsive DDA systems [28]-[30].

In order to personalize game experiences according to individual profiles, player modeling is indispensable in DDA systems. Detailed player modeling guarantees that difficulty adjustments are consistent with the player's preferences and capabilities [31], [32]. Fuzzy logic, which is frequently employed in adaptive systems such as educational games, effectively regulates equivocal data, thereby improving player satisfaction and adaptability [33]-[35]. The incorporation of fuzzy logic with other AI techniques, such as Q-learning, has resulted in substantial benefits [36], [37].

In DDA systems, player motivation and engagement are substantially enhanced by real-time feedback mechanisms. Research suggests that the player experience is improved by immediate performance feedback and subsequent adjustments to the difficulty of the game [38]-[40].

Creation of game experiences that are truly adaptive and personalized remains a challenge, despite these advancements. The limited integration of multiple AI techniques to address the complete spectrum of player behavior and preferences in real-time is a significant research gap. Furthermore, educational and action games are frequently the subject of current research, while serious management games receive less attention. There is also a requirement for a more comprehensive player modeling approach that incorporates a broader range of performance and behavioral metrics. The future research should concentrate on the refinement of player modeling, the integration of multimodal feedback mechanisms, and the exploration of emergent AI methodologies, including hybrid models and deep reinforcement learning.

We propose a new DDA system that integrates fuzzy logic and Q-learning to resolve these gaps in adaptive game design, thereby enabling future research to develop more personalized and engaging gaming experiences. Our research makes a substantial contribution to this discipline.

TABLE 1. Comparison of Research Gaps Between Previous Studies and This Study.

References	Topic	Method	Object
[3]	Diversifying DDA agent by integrating player modeling	Machine learning	Enhance game adaptability
[14]	Fuzzy logic-based system for DDA	Fuzzy logic	Handle player behavior variability
[17]	Deep reinforcement learning in game AI	Deep Q-learning	Optimize adaptive AI
[22]	Real-time feedback in DDA systems	Immediate performance feedback	Enhance player engagement
[27]	Genetic algorithms in DDA	Optimization techniques	Balance difficulty levels
[31]	Player-centered game design	Detailed player modeling	Customize game experiences
Our Study	DDA in serious management games	Fuzzy logic and Q-learning	Adaptive and personalized game experiences

A. CONTRIBUTIONS AND ORGANIZATION OF PAPER

In this paper, Dynamic Difficulty Adjustment (DDA) system combining Q-learning and fuzzy logic is presented to provide a more effective and interesting real-time difficulty adjustment technique. Using Q-learning and fuzzy logic, unlike traditional methods, allows the system to better manage the ambiguity and volatility in player behavior. The algorithm continuously enhances difficulty levels by constantly analyzing player inputs, resulting in a customized and ever-changing game experience. This integration represents a significant advancement, since it has not been previously explored in the context of serious management games.

This paper is structured as it follows: The design and methodology, which encompass scenario examples, Q-learning, fuzzy logic, and blueprint integration, are detailed in Section 2. Player experience and simulation data are presented in Section 3. The results, which encompass scenario testing, player experience, comparisons with previous work, and prospective future work, are discussed in Section 4. The investigation is ultimately concluded in Section 5.

III. DESIGN AND METHOD

The proposed DDA system adjusts the degrees of difficulty in a large virtual reality management game dynamically using fuzzy logic and Q-learning. This approach encourages user engagement and satisfaction by enabling real-time customized changes affected by in-game events and player participation.

Figure 1 illustrates a comprehensive block diagram that contrasts the proposed system for DDA in critical VR management games with prior research. Other methods, including static DDA and reinforcement learning or fuzzy logic techniques, are illustrated in the diagram's upper section. These methods generate and compute evaluations based on the game environment. Consequently, these evaluations are implemented to adjust the player's environment and challenge level. The lower section of the diagram illustrates the proposed system, which employs a combined DDA algorithm that incorporates both reinforcement learning (Q-learning) and fuzzy logic. This system perpetually simulates the player state and subsequently utilizes the information it has collected to ascertain the most appropriate environment and level of difficulty. The objective of the proposed system is to ensure that the gaming experience is more personalized and engaging by dynamically adjusting the game environment and difficulty in real-time. This is achieved by ensuring that the participant is engaged and satisfied by effectively balancing the challenge and skill level.

Figure 2 illustrates the block diagram of the proposed DDA system. The subsequent components comprise the system:

1) State Input: Acquires real-time data, including in-game conditions and player performance metrics.
2) Q-Learning Module: Updates Q-values in accordance with environmental rewards and processes state inputs.
3) Fuzzy Logic Module: Determines appropriate difficulty levels and classifies player skill levels based on performance indicators.
4) Action Selection: Determines the most effective actions by applying fuzzy logic rules and the highest Q-value.
5) Feedback Loop: The system is continuously updated with new data to refine Q-values and flexible rules for real-time adjustments.

A. SCENARIO

In the scenario design phase as shown in Table 2. , each scenario is crafted to challenge the player's resource management, decision-making, and strategic planning skills. For instance, a low-skill player might manage a straightforward scenario with ample resources and mild challenges, while a high-skill player might face a complex scenario with limited resources and multiple obstacles requiring strategic foresight.

B. Q-LEARNING

The Q-learning algorithm optimizes game actions in accordance with player performance and environmental conditions. The in-game conditions are updated every in-game hour,

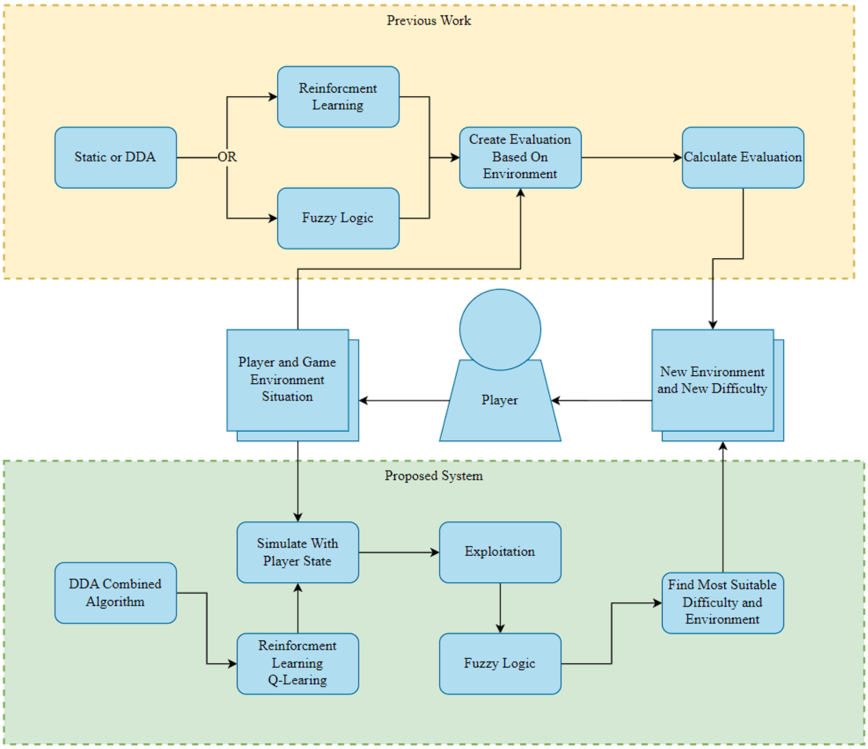


FIGURE 1. Comparison of previous work and the proposed system for dynamic difficulty adjustment (DDA).

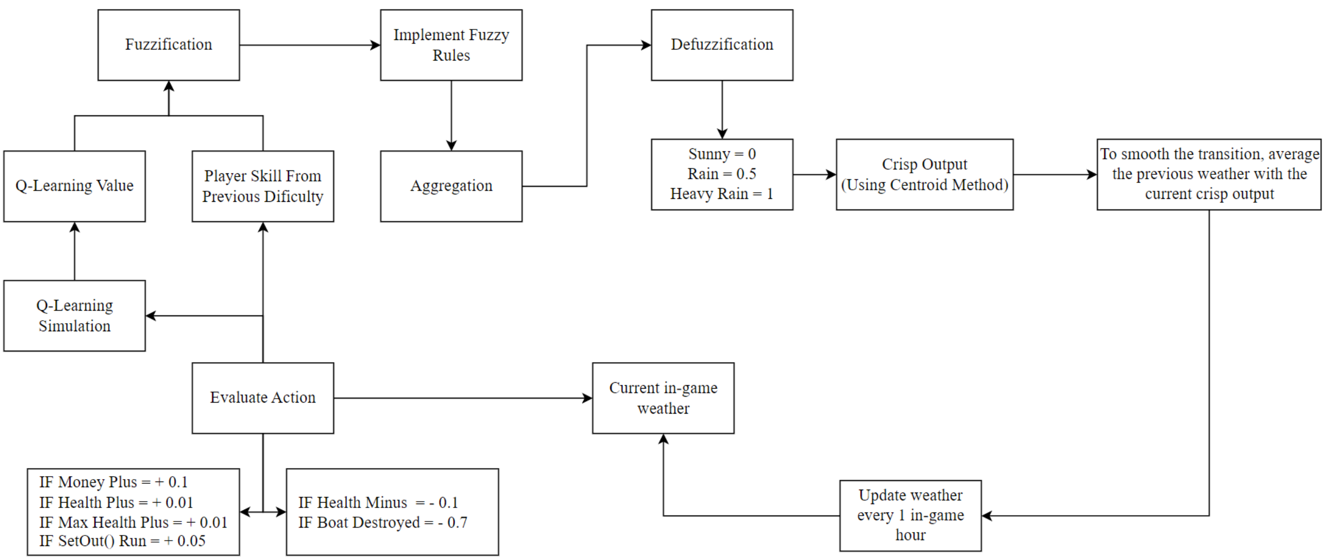


FIGURE 2. Flowchart of the proposed DDA system integrating Q-learning and fuzzy logic for in-game weather adjustment.

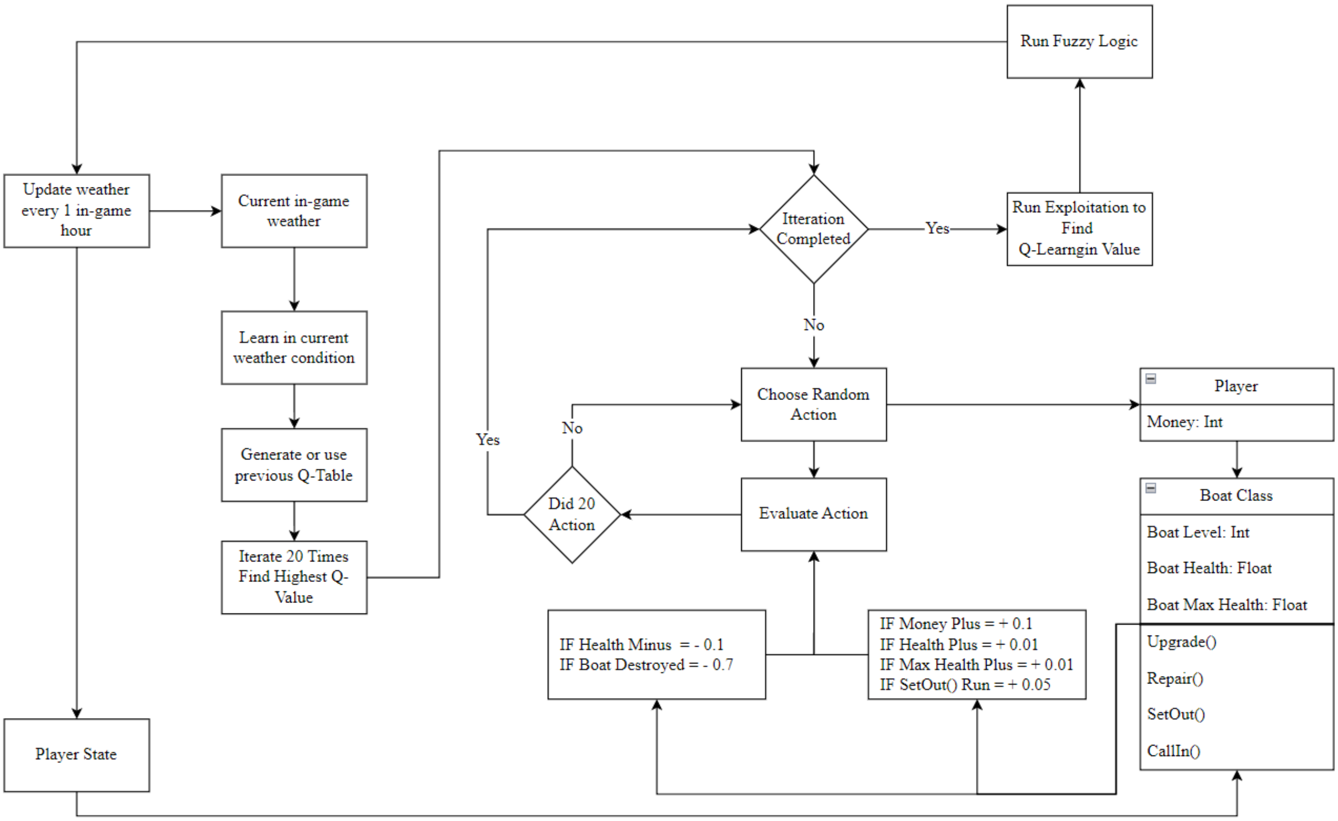


FIGURE 3. Flowchart illustrating the Q-learning process for dynamic difficulty adjustment in the proposed system.

TABLE 2. Skill Level, Performance Indicators, Weather Condition, and Challenge Level.

Skill Level	Performance Indicators	Weather Condition	Challenge Level
Low	Poor resource management, slow decision-making	Sunny	Easy
Middle	Average resource management, moderate speed	Rain	Moderate
High	Efficient resource management, quick decisions	Heavy Rain	Hard

which is a critical state input, to initiate the process. The current state is used to optimize actions, such as initiating specified tasks, performing maintenance, or upgrading equipment, by modifying Q-values. The selection of optimal actions is guaranteed by the iterative improvement of Q-values for a variety of state-action pairs in the Q-table.

Figure 3 shows Q-table is composed of Q-values for a diverse array of state-action pairings and is either generated from inception or retrieved from previous game sessions. By iterating 20 times, the algorithm identifies the highest Q-value for the current state, thereby guaranteeing the selection of optimal actions, including the initiation of specific tasks, the performance of maintenance, or the upgrading of equipment. The algorithm indiscriminately selects and evaluates actions to enhance learning if the maximum number of iterations is not reached. As a result, the selected actions are indicative of dynamic changes that are influenced by the results of Q-learning. These changes are reflected in the revisions to player resources and the overall game state.

The Q-learning process is collectively guided by these equations, which iteratively enhance the Q-values in response to observed rewards and errors. The Q-values are updated by the Bellman Equation, which considers the instantaneous reward and the maximum expected future rewards, weighted by the discount factor γ. The TD Error quantifies the discrepancy between the observed and anticipated Q-values, which indicates the extent to which the current estimate is inaccurate. The update rule subsequently modifies the Q-values by utilizing the TD Error and the learning rate α to ensure that the system progressively refines its action choices to optimize performance.

$$Q(S_n, \text{Action})_{\text{observed}} = R(S_{n+1}) + \gamma \max_a Q(S_2, a) \quad (1)$$

$$\text{TD Error} = Q(S_n, \text{Action})_{\text{observed}} - Q(S_n, \text{Action})_{\text{expected}} \quad (2)$$

$$Q(S_n, \text{Action}) = Q(S_n, \text{Action}) + \alpha \times \text{TD Error} \quad (3)$$

The observed Q-value update is represented by the formula in (1). The Q-value associated with taking a specific action in state S_n is denoted by $Q(S_n, \text{Action})$ in this context. The immediate recompense received upon transitioning to the subsequent state S_{n+1} is denoted by the term $R(S_{n+1})$. The importance of future rewards in comparison to imminent rewards is determined by the discount factor γ, which encompasses the range of 0 to 1. The expression $\max_a Q(S_2, a)$ denotes the utmost Q-value for the subsequent state S_2, taking into account all potential actions a. In order to effectively balance short-term gains with long-term potential, this formula combines the immediate reward and the best possible future rewards to provide a comprehensive update to the Q-value for the present state-action pair.

The Temporal Difference (TD) error is defined by the formula in (2). This error quantifies the discrepancy between the pre-update expected Q-value and the observed Q-value, which was determined using Equation 1. The TD error quantifies the adjustment required to align the current Q-value with the observed rewards and future value predictions. The system is prompted to modify its Q-value estimates when a non-zero TD error indicates a discrepancy between the predicted and actual rewards. This error functions as a feedback mechanism, emphasizing the extent to which the current prediction deviates from reality and directing the learning process.

The TD error is employed to update the Q-value, as illustrated in the formula (3). Here, α is the learning rate, a parameter that ranges from 0 to 1 and dictates the step size for each update. The algorithm's adjustment of the Q-values in response to new information is regulated by the learning rate. The product of the learning rate and the TD error is used to increase the Q-value of the state-action pair (S_n, Action). This update rule guarantees that the Q-values progressively converge to the optimal values by continuously incorporating new experiences and refining the estimates. The algorithm is able to develop optimal decision-making strategies in dynamic environments by gradually reducing the prediction errors due to the iterative nature of this process.

TABLE 3. Q-Learning Steps and Their Purpose

Step	Description	Purpose
1	Update in-game weather every in-game hour	Provide current state input for Q-learning
2	Learn from current weather condition to adjust Q-values	Adapt Q-values to real-time environmental changes
3	Generate or retrieve Q-table	Store Q-values for state-action pairs
4	Iterate 20 times to find highest Q-value	Identify optimal actions for the current state
5	Select optimal action based on highest Q-value	Ensure optimal decision-making
6	Random action selection if maximum iterations not reached	Enhance learning diversity
7	Update player resources and boat health based on action	Reflect changes influenced by Q-learning outcomes

C. FUZZY LOGIC

Fuzzy logic has been extensively utilized in a variety of fields, such as gaming, as a result of its ability to manage uncertainty and approximate reasoning. Fuzzy logic controllers are employed in the gaming industry to generate AI behaviors that are more adaptive and responsive. For instance, fuzzy logic can be employed to ascertain the AI's strategic decisions, including resource allocation and attack timing, in real-time strategy (RTS) games, contingent upon the current state of the game. In racing games, fuzzy logic is employed to rebalance the difficulty of AI opponents in real-time, ensuring that players are presented with a fair challenge by taking into account factors such as the player's performance and track conditions. The gaming experience is improved by these applications, which offer dynamic and context-aware modifications, showcasing the flexibility and efficacy of fuzzy logic.

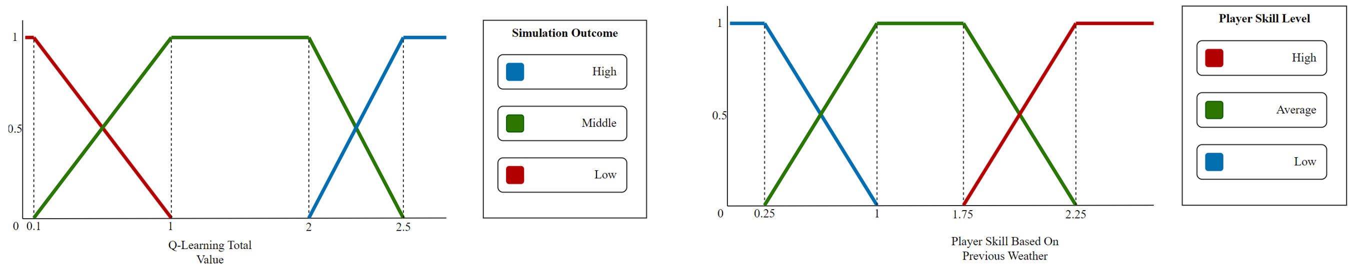
As shown in Figure 4 High, Middle, and Low are the three levels into which the fuzzy logic system classifies player competence. It is this classification that informs the system's adjustments to difficulty. Simplified conditions, including abundant resources and simplified responsibilities, are offered to low-skill participants. In contrast, ordinary skill players encounter moderate difficulty with balanced resource availability and task complexity, while high-skill players are confronted with more challenging conditions, such as complex tasks that require strategic planning and finite resources.

The fuzzy logic system's ability to categorize player skill levels ensures that the game environment is changed to maintain a balance between challenge and playability. The skill levels of participants are dynamically adjusted to preserve motivation and interest, thereby preventing monotony or frustration.

In order to regulate the ambiguity and variability of player behavior, the fuzzy logic component implements predetermined regulations. These principles regulate the game's response to a diverse array of combinations of participant skill levels and Q-learning values. For example, an environment that is less challenging is characterized by a surplus of resources and simplified tasks that is the result of a low Q-learning value and low player skill. Conversely, the complexity of the tasks and the scarcity of resources that arise from a high Q-learning value and high player skill substantially increase the difficulty.

The efficacy of resource management, the rapidity of decision-making, and the overall level of engagement are among the performance metrics that are employed to rate player skill. High, Middle, and Low are the three levels into which the fuzzy logic system classifies player competence. It is this classification that informs the system's adjustments to difficulty. The presence of simpler conditions, such as sunny weather, for low-skill participants equalizes the challenge. Average skill players encounter moderate difficulty in the form of rainy weather, while high skill players are presented with more challenging circumstances, such as torrential rain.

The in-game weather condition is determined by the system's aggregated and analyzed inputs from both the fuzzy logic system and Q-learning. The output of the weather condition is quantified on a scale of 0 to 1, with sunny conditions marked as 0, rain as 0.5, and severe rain as 1. This output



(a) (b)

FIGURE 4. Fuzzy logic membership functions used in the DDA system: (a) Membership functions for Q-learning total value; (b) Membership functions for player skill level based on previous weather conditions.

is computed using the centroid technique. The membership value (μ) for each meteorological condition is determined by the fuzzy logic formulas used in this process. This value indicates the degree to which the current state is classified within each category. The present weather condition (W_{current}) is determined by aggregating these membership values and their respective weather values. The system ensures seamless transitions by averaging the current and previous weather conditions to prevent abrupt changes.

The system dynamically modifies the game environment to match the player's skill level by incorporating these fuzzy logic principles, resulting in a continuously balanced and engaging experience. This method guarantees that the difficulty of the game is adaptable and responsive, thereby fostering long-term player interest and satisfaction.

The game environment is able to adapt to the performance of the player by updating weather conditions every in-game hour based on the defuzzified output. This dynamic updating mechanism guarantees that difficulty levels are contextually pertinent and adaptable to the changing abilities of the player. The preservation of player immersion is achieved by averaging weather conditions, which precludes abrupt changes.

$$\mu = \max\left(\frac{\text{Input Var} - \text{Low Point}}{\text{High Point} - \text{Low Point}}, \frac{\text{Max Point} - \text{Input Var}}{\text{Max Point} - \text{High Point}}\right) \tag{4}$$

$$w_{\text{current}} = \frac{\mu_{\text{Sunny}} \times V_{\text{Sunny}} + \mu_{\text{Rain}} \times V_{\text{Rain}} + \mu_{\text{Heavy Rain}} \times V_{\text{Heavy Rain}}}{\mu_{\text{Sunny}} + \mu_{\text{Rain}} + \mu_{\text{Heavy Rain}}} \tag{5}$$

$$W_{\text{new}} = \frac{W_{\text{prev}} + W_{\text{current}}}{2} \tag{6}$$

The initial formula shown in (4) derives the membership value μ for a specified input variable. The extent to which the current state is a member of a specific fuzzy set is determined by this formula. The maximum of two ratios is used to compute the membership value: one that compares the input variable to the low and high points, and the other that compares the input variable to the high and maximum points. This guarantees that the membership value precisely represents the player's performance within a predetermined range.

The present weather condition $w_{current}$ is determined by combining the membership values for various weather conditions (sunny, rain, and heavy rain) shown in (5). The corresponding weather value V is multiplied by each membership value μ, and the resulting values are summed. The total of the membership values is then divided by this quantity. This weighted average approach guarantees that the weather condition being calculated precisely represents the contributions of all pertinent fuzzy sets.

The transition between the previous and current meteorological conditions is smoothed by the formula in (6), which averages them. This guarantees a more immersive and seamless player experience by preventing abrupt changes in the game environment. The system maintains a balanced and progressive adjustment of the game environment by averaging the previous weather condition W_{prev} and the current weather condition $W_{current}$.

TABLE 4. Q-Learning Value, Player Skill Level, Weather Condition, Difficulty Level, and Fuzzy Rule Applied

Q-Learning Value	Player Skill Level	Weather Condition	Difficulty Level	Fuzzy Rule Applied
Low	Low	Sunny	Very Hard	IF (Q-low AND Skill-low) THEN (Weather-sunny)
Low	Middle	Rain	Hard	IF (Q-low AND Skill-middle) THEN (Weather-rain)
Low	High	Heavy Rain	Very Hard	IF (Q-low AND Skill-high) THEN (Weather-heavy rain)
Middle	Low	Sunny	Moderate	IF (Q-middle AND Skill-low) THEN (Weather-sunny)
Middle	Middle	Rain	Moderate	IF (Q-middle AND Skill-middle) THEN (Weather-rain)
Middle	High	Heavy Rain	Hard	IF (Q-middle AND Skill-high) THEN (Weather-heavy rain)
High	Low	Sunny	Easy	IF (Q-high AND Skill-low) THEN (Weather-sunny)
High	Middle	Rain	Moderate	IF (Q-high AND Skill-middle) THEN (Weather-rain)
High	High	Heavy Rain	Hard	IF (Q-high AND Skill-high) THEN (Weather-heavy rain)

The Q-learning algorithm is used in conjunction with these fuzzy logic equations to establish a dynamic and adap-

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tive game environment. The Q-learning algorithm optimizes decision-making based on real-time feedback, while the fuzzy logic system effectively manages the inherent uncertainty and variability in player behavior. These methods collectively improve the player's engagement by offering a gaming experience that is both responsive and personalized, and that is tailored to the player's performance and skill level.

Table 4. illustrates the correlation between the corresponding fuzzy rules used within the game environment, player skill levels, weather conditions, and difficulty levels, and Q-Learning values. The table lists a variety of scenarios in which the weather conditions and concomitant difficulty levels are determined by the Q-Learning value (categorized as low, middle, or high) and the player's skill level (low, middle, or high). For example, the game establishes the weather condition as sunny and the difficulty level as very challenging when both the Q-Learning value and the player skill level are low, as indicated by the fuzzy rule "IF (Q-low AND Skill-low) THEN (Weather-sunny)." Conversely, when the Q-Learning value is high and the player skill level is low, the weather condition remains sunny, but the difficulty level is low. This is determined by the ambiguous rule "IF (Q-high AND Skill-low) THEN (Weather-sunny)." The fuzzy logic system dynamically modifies weather conditions and difficulty levels based on real-time assessments of player skill and environmental inputs, as illustrated in this table. This enhances the game experience by providing personalized and adaptive challenges.

D. BLUEPRINT INTEGRATION

The Q-learning and fuzzy logic systems are visually represented in the Unreal Engine blueprint graph shown in figure 5. The Q-table is dynamically updated and the game difficulty is modified in real-time by event triggers, loops, and conditional tests

A robust DDA system for serious VR management games is established through the integration of fuzzy logic and Q-learning in the proposed methodology. The Q-learning algorithm optimizes in-game actions by analyzing real-time conditions, whereas the fuzzy logic system manages player behavior variability. Dynamic adjustments to game difficulty are made possible by the combined approach, which provides a personalized and engaging player experience.

The DDA system offers a responsive and adaptive gameplay experience by utilizing both fuzzy logic and Q-learning. The integration guarantees that the game difficulty is consistently in accordance with the capabilities of the player, thereby increasing their contentment and engagement. A holistic solution for maintaining player interest in serious VR management games is provided by this methodology, which represents a significant advancement in adaptive game design.

IV. RESULT AND ANALYSIS

This section provides empirical evaluation data, which includes scenario testing, user experience assessments, and comparisons with other algorithms and related works.

A. METHODS OF DATA COLLECTION AND DATA SOURCES

A combination of in-game performance metrics, automated gameplay logs, and user surveys was employed to gather data. As follows are the methodologies implemented:

1) Player Surveys: Post-game surveys that utilize a five-point Likert scale to assess player engagement and satisfaction.
2) Gameplay Logs: Automated recording of in-game actions, resource management efficacy, decision-making speed, and overall player engagement.
3) Performance Metrics: The real-time monitoring of player actions, resource utilization, and decision-making processes.

Within a virtual reality management game environment, controlled experiments were implemented. Player interactions with the game were monitored under a variety of difficulty settings, and players of diverse skill levels participated. The DDA system's efficacy was assessed by comparing user engagement and satisfaction in static and dynamic difficulty conditions.

To illustrate the dynamic difficulty adjustment in action, an illustrative in-game scenario is presented:

1) Scenario: A user who is responsible for managing a virtual fishing fleet is confronted with fluctuating weather conditions.
2) Initial State: The participant, who is identified as having an intermediate skill level, commences with moderate resource availability and clear weather.
3) Dynamic Adjustment: The DDA system gradually introduces more challenging conditions, such as heavy rain and increased resource scarcity, as the user demonstrates efficient resource management and quick decision-making.
4) Outcome: The player's overall gaming experience is improved as they alter their strategy to the changing difficulty level, thereby remaining engaged and challenged.

B. VISUAL REPRESENTATION OF THE GAME

One of the most important factors in improving player engagement and contentment is the visual representation of the game shown in figure 6. The environment of the game is visually immersive and adjusts in real-time to the player's talent level and performance. In order to preserve a balanced and challenging experience, the game dynamically adjusts variables such as resource availability, weather conditions, and task complexity through the use of fuzzy logic and Q-learning. Intuitive visual feedback that reflects the game's increasing complexity is provided as the environment transitions from sunlit and clear skies to more challenging conditions such as heavy rain and thunderstorms as players progress. These visuals that are adaptive ensure that participants are visually aware of their progress and the obstacles

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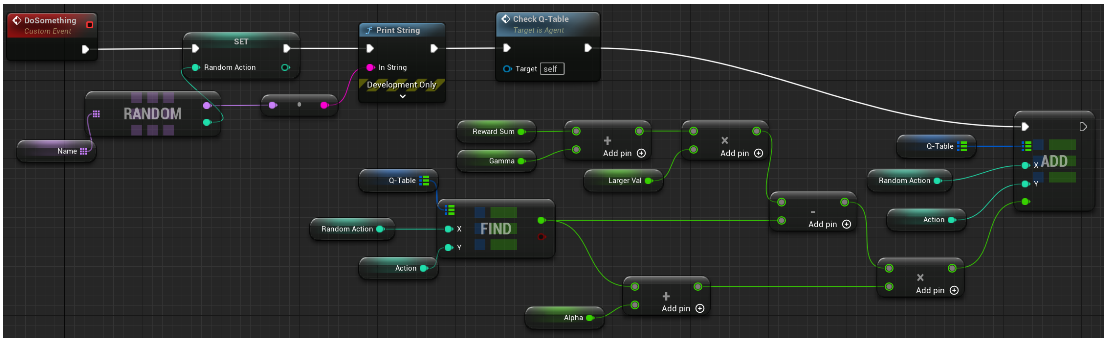

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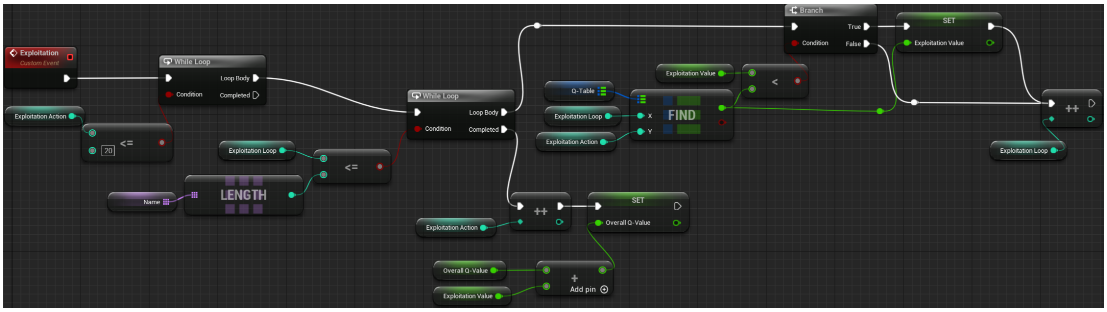

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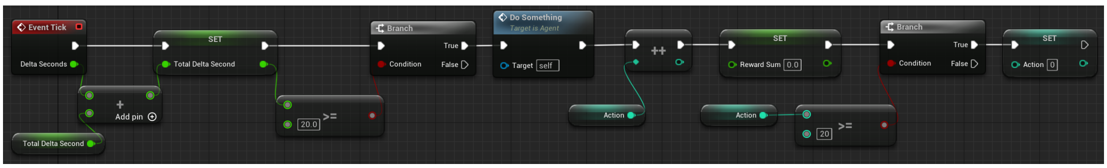
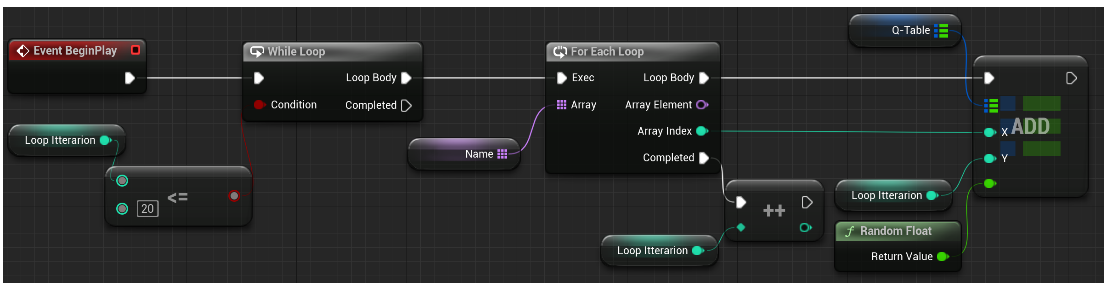


(c)



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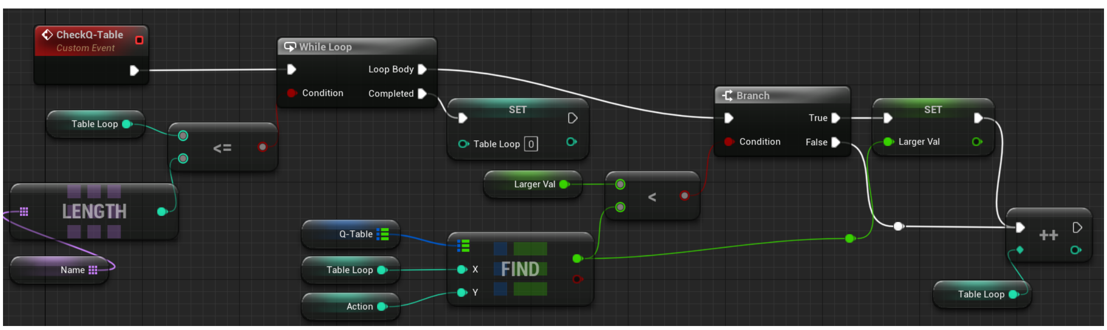

(e)

FIGURE 5. Blueprint implementation in Unreal Engine for the proposed DDA system: (a) Initialization of Q-learning variables; (b) Action selection and reward calculation; (c) Fuzzy logic evaluation; (d) Update of Q-values and fuzzy rules; (e) Integration and execution of combined DDA algorithms.

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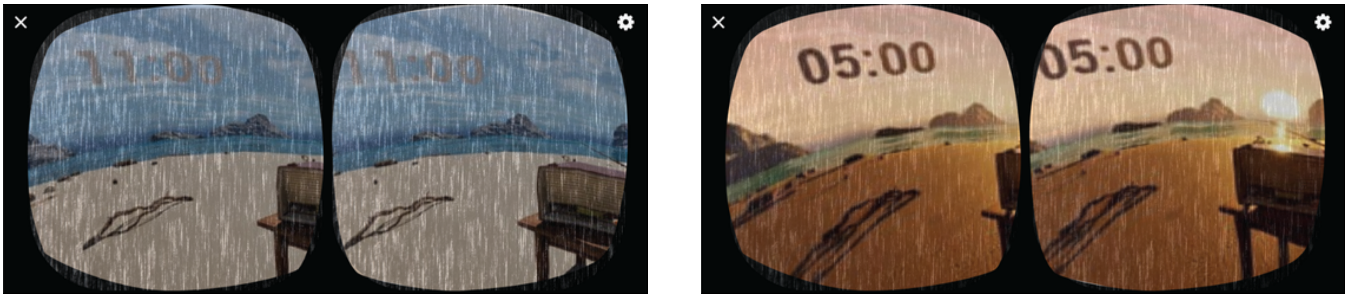

(a) (b)

FIGURE 6. Visual representation of the game environments at varying difficulty levels: (a) Game environment under rainy conditions, showcasing a day with low visibility; (b) Game environment under stormy conditions, illustrating a sunset scene with heavy rain and increased difficulty in resource management.

they surmount, thereby maintaining their engagement and motivation.

C. SCENARIO TESTING

The DDA system's robustness was evaluated in a variety of scenarios, and the following are the primary findings shown in figure 7:

1) Low Skill Dynamic Environment: Players with low skill levels experienced increased engagement and decreased frustration as a result of the simpler difficulty settings.
2) High Skill Dynamic Environment: High-skill participants faced more difficult obstacles, but they maintained a high level of engagement and interest.
3) Adaptive Challenge Over Time: Players were presented with a balanced challenge that was customized to their advancing skill levels, which led to a sustained level of interest and engagement.

The integration of fuzzy logic and Q-learning demonstrated a substantial improvement in the field of adaptive game design. The system's continuous development was guaranteed by Q-learning, which learned from player interactions, while fuzzy logic effectively managed the uncertainty and variability in player behavior. This synergy resulted in a more customized and responsive gaming experience.

1) Contributions of Fuzzy Logic: The system was able to manage ambiguous and imprecise player performance data as a result of fuzzy logic, which ensured that difficulty adjustments were contextually appropriate and seamless.
2) Q-Learning Contributions: Q-learning enabled the game to evolve dynamically in accordance with the player's skill level and preferences by optimizing game actions based on real-time conditions.
3) Combined Advantages: The combined approach enabled the continuous adjustment of game difficulty, which led to a balanced challenge that captivated players and encouraged the development of their skills.

Various scenarios were evaluated to assess the functionality of the DDA system in order to guarantee its robustness. Ten significant scenarios and their respective outcomes are summarized in the table 5.

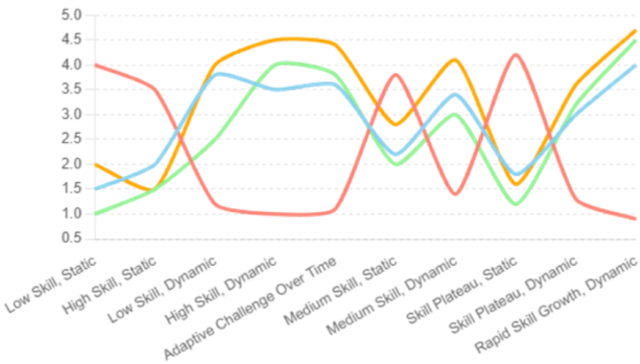

FIGURE 7. Comparison of skill progression across various difficulty adjustment strategies.

D. EVALUATION OF EXPERIENCE

In comparison to static difficulty settings, the DDA system substantially enhanced player satisfaction. The graphical figure are shown in figure 8, figure 9, and figure 10. The following were the primary metrics:

1) **Player Engagement:** The average duration of a play session increased by 35% with the DDA system (3.4 hours) in comparison to static settings (2.5 hours).
2) **Player Satisfaction:** The DDA system obtained an average satisfaction score of 4.6 on a 5-point Likert scale, which is higher than the 3.2 score for static settings.
3) **Efficiency of Resource Management:** Increased by 28%, suggesting improved adaptation to dynamic conditions.
4) **Decision-Making Speed:** A 15% increase, indicating a more confident and efficient decision-making process.
5) **System's Capacity:** balanced difficulty levels is illustrated by the 22% increase in successful game actions.

To validate these improvements, detailed statistical analysis was conducted. Both the 35% increase in play session time and the 28% improvement in resource management efficiency

TABLE 5. Scenarios, Descriptions, Expected Outcomes, and Results.

Scenario	Description	Expected Outcome	Result
Scenario 1: Low Skill, Static Environment	Player with low skill level in a non-dynamic (static) game environment.	The player should experience minimal challenge and engagement.	Low engagement, high boredom.
Scenario 2: High Skill, Static Environment	Player with high skill level in a non-dynamic (static) game environment.	The player should experience minimal challenge and disengagement.	High disengagement, low interest.
Scenario 3: Low Skill, Dynamic Environment	Player with low skill level in a dynamic game environment using DDA.	The game should adjust to an easier difficulty, maintaining player engagement.	High engagement, low frustration.
Scenario 4: High Skill, Dynamic Environment	Player with high skill level in a dynamic game environment using DDA.	The game should adjust to a higher difficulty, maintaining player challenge and interest.	High engagement, high challenge.
Scenario 5: Adaptive Challenge Over Time	Player experiences progressive difficulty adjustments over multiple sessions in a dynamic environment.	The player should experience a balanced challenge tailored to their improving skill level.	Sustained engagement and interest.
Scenario 6: Medium Skill, Static Environment	Player with medium skill level in a non-dynamic (static) game environment.	The player should experience moderate engagement and challenge.	Moderate engagement, high boredom.
Scenario 7: Medium Skill, Dynamic Environment	Player with medium skill level in a dynamic game environment using DDA.	The game should adjust to a moderate difficulty, maintaining player engagement.	High engagement, moderate challenge.
Scenario 8: Skill Plateau, Static Environment	Player whose skill level plateaus in a non-dynamic (static) game environment.	The player should experience low engagement and increasing boredom.	Low engagement, high boredom.
Scenario 9: Skill Plateau, Dynamic Environment	Player whose skill level plateaus in a dynamic game environment using DDA.	The game should adjust to keep the player engaged with balanced challenges.	Moderate engagement, low boredom.
Scenario 10: Rapid Skill Growth, Dynamic	Player with rapid skill growth in a dynamic game environment using DDA.	The game should adapt quickly to increasing skill levels, maintaining high engagement.	High engagement, high challenge.

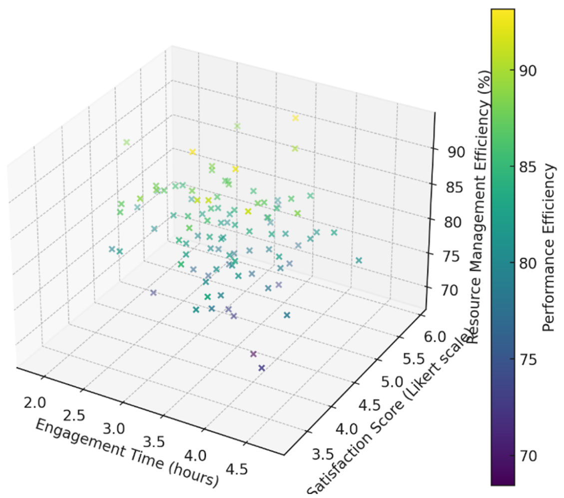

FIGURE 8. 3D scatter plot illustrating the relationship between player engagement time, satisfaction score, and resource management efficiency in the dynamic DDA system.

were statistically significant (p-values <0.01 and <0.05). Confidence intervals for play session time increase were [30-40%] and resource management efficiency was [22-34%], showing strong dependability. Significant gains in player satisfaction and decision-making speed were confirmed with p-values <0.05, proving the usefulness of the suggested DDA system.

E. COMPARISON WITH OTHER ALGORITHMS

In order to assess the proposed DDA system against other methods, a comparative analysis was implemented, which demonstrated substantial enhancements in player engagement and contentment. The integration of fuzzy logic with Q-learning enabled the development of a more sophisticated adjustment mechanism, which effectively mitigated the variability in player behavior.

All metrics shown in Table 6 were evaluated within the same game environment to ensure consistency in the comparison. Key metrics included player engagement, player satisfaction, resource management efficiency, decision-making speed, successful game actions, processing time per adjustment, memory usage, and overall system performance (measured in frames per second).

TABLE 6. Comparison of Metrics between Static DDA, Dynamic DDA with Reinforcement Learning, Dynamic DDA with Fuzzy Logic, and Dynamic DDA with Q-learning + Fuzzy Logic.

Metric	Static DDA	Dynamic DDA (Reinforcement Learning)	Dynamic DDA (Fuzzy Logic)	Dynamic DDA (Q-learning + Fuzzy Logic)
Player Engagement (hrs)	2.5	3.2	3.1	3.4
Player Satisfaction (Likert)	3.2	4.1	4.3	4.6
Resource Management Efficiency	65%	78%	80%	83%
Decision-Making Speed (s)	0.8s	0.75s	0.72s	0.7s
Successful Game Actions	75%	88%	90%	91%
Processing Time per Adjustment (ms)	30	40	50	120
Memory Usage (MB)	8000	8000	8000	8000
System Performance (FPS)	70	60	60	50

Since resource management efficiency and decision-making speed are crucial to management game player skill evaluation, they were chosen. Resource management efficiency shows a player's planning and prioritizing skills by

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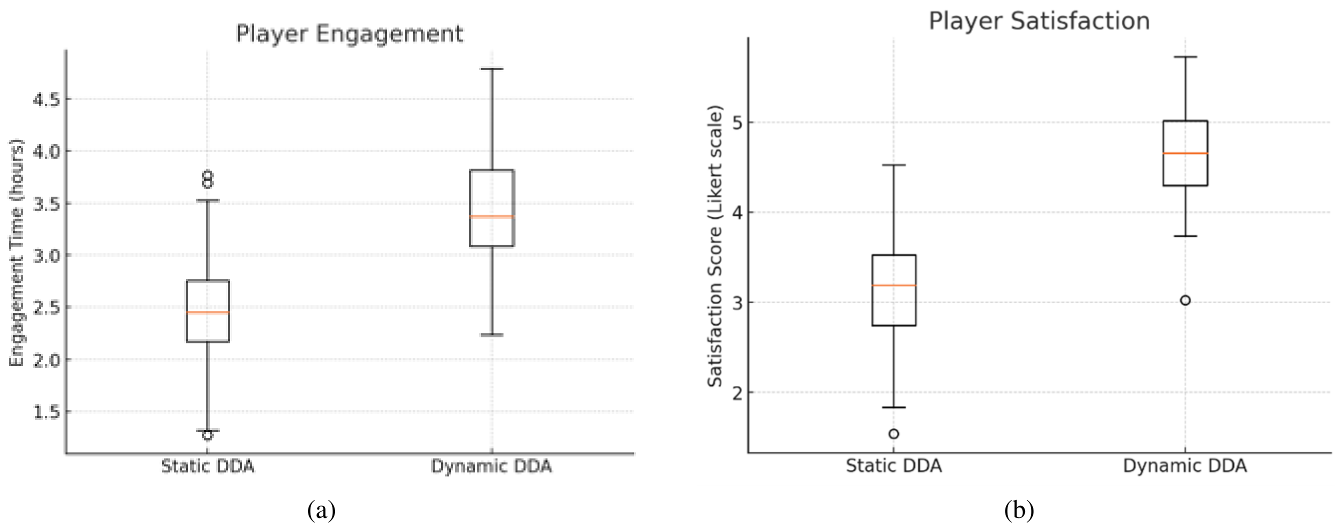

FIGURE 9. Box plots comparing static DDA and dynamic DDA: (a) Player engagement time; (b) Player satisfaction score.

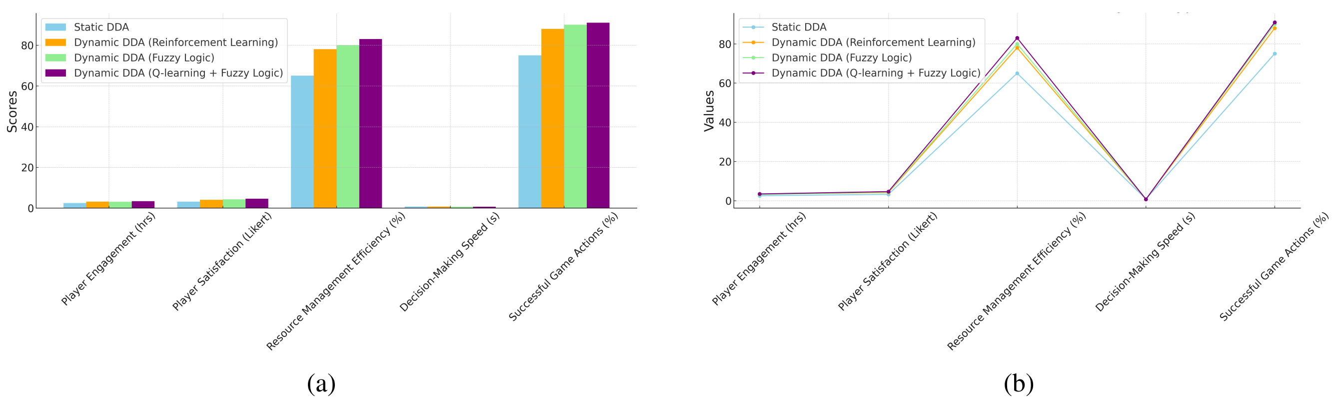

FIGURE 10. Performance metrics comparison between static and dynamic DDA: (a) Bar chart of resource management efficiency, decision-making speed, and successful game actions; (b) Line chart of player engagement, satisfaction, resource management efficiency, decision-making speed, and successful game actions.

strategically allocating and using resources to fulfill game goals. However, decision-making speed indicates a player's ability to understand and respond quickly to in-game problems. These measures indicate a player's competency and success since they closely correspond with the core abilities needed to win in major VR management games.

This research builds upon prior work by incorporating a variety of AI techniques to generate a more personalized and adaptive gaming experience. The proposed DDA system outperformed existing methods in terms of sustaining player interest and improvitang overall gameplay satisfaction. However, it also introduced slightly higher computational costs, as evidenced by increased processing times and memory usage.

The effectiveness and efficiency of the proposed DDA system are evident in the experimental results and comparative analysis. While the integration of fuzzy logic and Q-learning significantly improved player engagement and contentment, it also resulted in higher computational demands. This trade-off is justified by the enhanced adaptability and personalization achieved, which are critical for maintaining long-term player interest in serious VR management games.

This investigation offers a novel approach to DDA in serious VR management games, addressing the constraints of static difficulty settings and previous adaptive techniques, thereby making a valuable contribution to the field. The research has implications that extend beyond serious games, proposing potential applications in a variety of interactive systems that necessitate real-time adaptability to user behavior. The scalability of this approach in more complex gaming environments and other domains could be the subject of future research.

F. GENERALIZATION TO OTHER GAME GENRES

The proposed DDA system, although initially designed for serious VR management games, can be generalized to other game genres such as action, adventure, and role-playing games (RPGs). To adapt the system, performance indicators would need to be adjusted to fit the specific game mechanics

TABLE 7. Evaluation of Success Criteria in Dynamic Difficulty Adjustment.

References	Success Criteria	Results
[3]	Player adaptability and satisfaction	Achieved moderate improvement in player adaptability, with some limitations in personalizing experiences
[14]	Handling player behavior variability	Successfully managed variability, but lacked continuous learning capabilities
[17]	Optimizing adaptive AI	Demonstrated significant optimization in adaptive AI, though primarily in non-serious games
[22]	Enhancing player engagement	Enhanced engagement through real-time feedback, but did not fully integrate AI for continuous adjustment
[27]	Balancing difficulty levels	Effectively balanced difficulty levels using genetic algorithms, though struggled with real-time adaptability
[31]	Customizing game experiences	Achieved high customization through detailed player modeling, but limited by static adjustment mechanisms
Our Study	Adaptive and personalized game experiences	Achieved significant improvements in player satisfaction and engagement through continuous, real-time adjustments using fuzzy logic and Q-learning

of each genre. For example, action games could use metrics like reaction time and accuracy, while RPGs could focus on character progression and quest completion rates. Additionally, the fuzzy logic rules and Q-learning parameters would need to be tailored to the unique elements of each genre, ensuring the DDA system remains effective in enhancing player engagement and satisfaction across different types of games.

V. CONCLUSION

In order to improve player engagement and contentment in VR management games, we implemented a Dynamic Difficulty Adjustment (DDA) system that employs fuzzy logic and Q-learning in this investigation. The average gameplay duration increased by 35%, and the satisfaction score on a 5-point scale increased to 4.6 from 3.2 for static settings, as indicated by our evaluations. Furthermore, the efficiency of resource management was enhanced by 28%, and the rapidity of decision-making was increased by 15%.

The inherent uncertainty and variability in player behavior were effectively managed by the integration of fuzzy logic, while Q-learning facilitated continuous learning and adaptation from player interactions. This collaboration led to a personalized and dynamic gaming experience that sustained the interest and motivation of long-term players.

Our findings indicate that the proposed DDA system offers a reliable solution for the development of adaptive and immersive gaming experiences. Future research could investigate the scalability of this approach in more intricate gaming environments and other interactive systems that necessitate real-time adaptability. This research provides valuable insights for the development of interactive systems that are both personalized and engaging, extending beyond serious games.

ACKNOWLEDGMENT

The authors would like to express their gratitude to the Institut Teknologi Sepuluh Nopember for their invaluable support and resources which were provided during this research. These contributions were indispensable to the effective conclusion of this project.

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