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A Personalised Optimising Level Adaptation (OLA) Difficulty Algorithm for Scenario Simulations in Professional VR Simulators

Spersonalizowany algorytm poziomu trudności Optimising Level Adaptation (OLA) do symulacji scenariuszy w profesjonalnych symulatorach VR

ABSTRACT

Purpose: This study introduces the Optimising Level Adaptation (OLA) algorithm, designed to enhance scenario simulations for professional VR training by dynamically adjusting difficulty levels to match user performance, thereby supporting personalised learning and readiness for high-stakes situations such as firefighting and emergency response.

Project and methods: The OLA algorithm divides scenario activities into blocks and adjusts their difficulty based on user performance in comparison to a reference group of AI-controlled agents. The algorithm's efficacy was tested across three proprietary VR simulators covering diverse professional scenarios: public speaking, hydrogen electrolysis and mechanical technician operations. Each scenario was divided into ten blocks of varying difficulty (easy, medium, difficult), dynamically adjusted based on the user's performance. This structure enables rapid adaptation, making it particularly beneficial for fire and rescue training, where realistic, yet scalable, scenario complexity is critical to preparing for unpredictable conditions in the field.

Results: Testing with 30 participants per simulator revealed an average final score of approximately 75%, closely aligning with the target success rate of 70%. The average number of difficulty level switches (between 0.8 and 1.16 across scenarios) demonstrated the algorithm's effective adaptation to user performance, thus ensuring optimal engagement. The OLA algorithm's capacity to tailor training difficulty in real time reflects its potential to enhance skill retention and readiness in emergency response settings, where maintaining user engagement at appropriate challenge levels is essential for preparedness in life-threatening situations.

Conclusions: The OLA algorithm provides significant advancements in personalised VR training, particularly within fire- and rescue-related applications, by maintaining optimal engagement and adaptive challenge levels. The adaptability demonstrated across multiple scenarios indicates its versatility and potential for use in diverse high-risk training applications. Future research could enhance the OLA algorithm's effectiveness by refining scenario block determination, therefore contributing to improved response times, decision-making and operational efficiency in the emergency services.

Keywords: VR training, personalised learning, adaptive difficulty, fire and rescue training, scenario simulation, professional development, Optimising Level Adaptation (OLA), emergency response preparedness

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ABSTRAKT

Cel: W niniejszym badaniu przedstawiono algorytm Optimizing Level Adaptation (OLA), który ma na celu ulepszenie symulacji scenariuszy na potrzeby profesjonalnych szkoleń VR poprzez dynamiczne dostosowywanie poziomów trudności do wydajności użytkownika, wspierając w ten sposób spersonalizowane nauczanie i gotowość do radzenia sobie w sytuacjach wysokiego ryzyka, takich jak gaszenie pożarów i reagowanie na sytuacje awaryjne.

Projekt i metody: Algorytm OLA dzieli działania scenariusza na bloki i dostosowuje ich trudność na podstawie wyników użytkownika w porównaniu do grupy referencyjnej agentów kontrolowanych przez AI. Skuteczność algorytmu została przetestowana w trzech zastrzeżonych symulatorach VR obejmujących różne scenariusze zawodowe: wystąpienia publiczne, elektrolizę wodoru i operacje technika mechanicznego. Każdy scenariusz został podzielony na dziesięć bloków o różnym stopniu trudności (łatwy, średni, trudny), dynamicznie dostosowywanych na podstawie wyników użytkownika.

Taka struktura umożliwia szybką adaptację, co czyni ją szczególnie korzystną w przypadku szkoleń strażaków i ratowników, gdzie realistyczna, ale skalowalna złożoność scenariusza ma kluczowe znaczenie dla przygotowania się na nieprzewidywalne warunki w terenie.
Wyniki: Testowanie z udziałem 30 uczestników na symulatorze wykazało średni wynik końcowy wynoszący około 75%, co ściśle odpowiada docelowemu wskaźnikowi sukcesu wynoszącemu 70%. Średnia liczba zmian poziomu trudności (od 0,8 do 1,16 w różnych scenariuszach) wykazała skuteczną adaptację algorytmu do wydajności użytkownika. Zdolność algorytmu OLA do dostosowywania poziomu trudności szkolenia w czasie rzeczywistym odzwierciedla jego potencjał do poprawy retencji umiejętności i gotowości w sytuacjach reagowania kryzysowego.
Wnioski: Algorytm wpływa znacząco na zmiany w zakresie spersonalizowanych szkoleń VR, szczególnie w przypadku zastosowania ich w straży pożarnej i ratownictwie, ze względu na optymalne zaangażowanie i dostosowanie poziomów wyzwań. Zdolność adaptacji wykazana w wielu scenariuszach wskazuje na jego wszechstronność i potencjał w przypadku różnorodnych zastosowań szkoleniowych wysokiego ryzyka. Przyszłe badania mogą zwiększyć skuteczność algorytmu OLA poprzez udoskonalenie określania bloków scenariuszy. Przyczyni się to do skrócenia czasu reakcji, podejmowania decyzji i zwiększenia wydajności operacyjnej w służbach ratunkowych.
Słowa kluczowe: szkolenie VR, scenariusz symulacji, optymalizacja poziomu adaptacji (OLA), przygotowanie do sytuacji krytycznych, szkolenie ratowniczo-gaśnicze
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Introduction

Numerous professions, including those in the fire service, military, police and medical sectors, require their personnel to be adept at making informed decisions in situations characterised by risk and pressure. To achieve proficiency in these areas, individuals need to engage in training that involves critical and illustrative scenarios pertinent to their profession. However, acquiring such experience through direct on-the-job training in high-stakes environments is impractical, as misjudgements could potentially result in dire consequences that endanger lives. Scenario-based training (SBT) is considered an effective and suitable method for training in these contexts [1–2]. SBT allows participants to engage in interactive role-playing exercises, often with live actors, within made-up scenarios that mimic real-life challenges. These exercises traditionally take place in physically simulated settings, providing a secure and controlled context wherein learners can witness the outcomes of their decisions. Nonetheless, SBT is hampered by significant logistical and organisational requirements, such as setting up locations, developing complex scenario narratives, training role players and ensuring the simultaneous availability of everyone involved (actors, trainees, instructors). A further limitation is the difficulty of modifying scenarios on the fly to tailor the training experience, as well as challenges in monitoring and systematically analysing scenario events, which becomes particularly complex in large-scale scenarios spread across multiple locations. The adoption of modern technologies that utilise educational games within VR/AR/XR could address these issues by transferring SBT into a virtual gaming environment, where aspects of the training are managed through artificial intelligence [1], [3–4]. This article introduces a novel concept and algorithm designed to facilitate such technology by incorporating SBT into an intelligent gaming environment that can adjust the level of difficulty, thereby encouraging regular participation in training. Previous research has delved into adaptive gamification systems [5]; however, this article distinguishes between adaptive gamification, where the system adjusts to various scenarios, and personalised gamification, which allows the system to tailor its response more precisely to the specific situation and the traits of individual users.

Related work

Maintaining user engagement with educational tools presents a considerable challenge, especially after the initial allure and novelty have started to diminish over time [6–8]. It is critical to acknowledge the diversity within user demographics, as individuals from varied cultural and demographic backgrounds are known to exhibit distinct preferences [9], behaviours [10] and motivational drivers [11]. This diversity inherently leads to a wide array of responses and interactions when these individuals are placed under similar conditions or faced with similar educational content [12–13].

A pivotal element in keeping users motivated and engaged with educational content is the careful consideration of the perceived difficulty level of the tasks or challenges presented [14–15]. It is well established in educational psychology that primarily there are two forms of motivation that influence human behaviour and engagement: intrinsic and extrinsic motivation [6]. Intrinsic motivation is characterised by an individual's internal desire to partake in an activity purely because they find it inherently interesting or enjoyable. In contrast, extrinsic motivation is driven by external factors, such as the pursuit of rewards or the desire for acknowledgment and approval from others. For intrinsic motivation to be effectively fostered within an educational tool, it is crucial that the user perceives the content not only as challenging but also as something within their grasp to overcome [14]. When the content is perceived as overly simplistic, it can lead to a sense of boredom and disengagement. Conversely, if the content is deemed excessively difficult, it may result in feelings of frustration and discouragement, leading users to abandon the activity altogether. Leveraging the concept of Vygotsky's zone of proximal development [16], it is suggested that providing users with tasks that are challenging yet achievable with some guidance, promotes an optimal learning environment. Given the variance in skill levels among users within any given group, personalising the difficulty level of educational games or tools becomes a necessity to keep different users continuously engaged and motivated [17].

In contrast to human instructors, who can intuitively assess a learner's skill level, educational tools rely on computational models to evaluate and adapt to a user's skill level accurately. These models need to be fast, reliable and capable of adapting to various game scenarios or educational content types without hindering the user experience, which is achieved, for instance, by avoiding disruptive assessments such as skill-related questionnaires. The adaptation of teaching strategies to align with the individual user's skill level has been demonstrated to significantly enhance learning outcomes [18]. In the study conducted by the authors of [18], two distinct algorithms were utilised to model user skills: a straightforward additive model and a Bayesian network. While the additive model tends to be prone to local extremities, the Bayesian approach simplistically categorises skills into binary states: learned or not learned. In another noteworthy study by the authors of [19], an educational tool designed to teach word-reading skills employed a specially designed Bayesian Active Learning model. This model strategically selected words that were predicted to yield the most significant increment in knowledge acquisition, albeit without taking into account the learner's motivation levels.

In the broader context of computer-based learning, the development of intelligent tutoring systems (ITS) has made strides in delivering personalised educational experiences. These systems have proven to be effective tutors by offering individualised lessons tailored to the user's needs and skill levels [20]. ITS achieve this through sophisticated student modelling techniques that aim to capture and represent various user characteristics [21]. One method of assessing user skills within such systems is through the application of models from the item response theory (IRT). IRT comprises a set of statistical models that correlate a user's responses to specific items with latent traits or skills [22]. Typically, these models operate under the assumption that skill levels remain constant over time, an assumption that holds for skills that evolve very slowly or during short assessment periods. However, in educational settings where skills can develop rapidly, this static skill assumption may not be appropriate. More specialised models [23–24], such as Bayesian Knowledge Tracing [25], take into consideration the dynamic nature of learning, focusing on modelling the acquisition of skills over time, particularly for tasks that require a granular understanding, like solving intricate mathematical equations. Despite their potential, the practical implementation of these advanced models is often hindered by the extensive time and resources required for data collection and parameter tuning, and the necessity for domain-specific expertise, making them less flexible and more costly to deploy [26].

An alternative approach to skill assessment in educational tools is the utilisation of rating or ranking systems. These systems assign a numerical rating to represent the user's skill level, thus offering a holistic view of their capabilities. Such systems have been widely used in various contexts, including sports and competitive gaming, to match individuals or teams of comparable skill levels, leading to outcomes like wins, losses or draws [27]. They are also employed in educational settings to match users with tasks or items of appropriate difficulty levels [28]. Rating systems boast several significant advantages for use within educational tools. Firstly, they are relatively straightforward to implement and can be easily adapted to different types of applications without requiring extensive input from domain experts. Secondly, despite their simplicity, rating systems have been shown to achieve high levels of accuracy [28–29] effectively tailoring the difficulty level of tasks so that users can successfully complete approximately 70% of the challenges posed. This level of success rate is considered optimal for maintaining user engagement and motivation. Lastly, rating systems are not confined to any specific domain, making them versatile tools that can be applied across a wide range of skill-based educational content.

Contemporary rating systems, such as the Elo rating system [30], are based on the principle of paired comparison, similar to the Rasch model utilised in IRT [31]. In these systems, each user starts with an initial numerical rating that estimates their skill level. Similarly, each task or item is assigned a rating that reflects its difficulty level. The pairing of users with tasks is then facilitated by a selection algorithm that aims to minimise the discrepancy between the user's rating and the task's rating. Following the completion of a task, the ratings for both the user and the task are updated based on the outcome. When the difference between the user's rating and the task's rating is minimal, the likelihood of the user successfully completing the task approaches 50%. As the discrepancy widens, the system predicts a greater probability of success or failure, depending on whether the user's rating is higher or lower than the task's rating. The Elo system adjusts the ratings based on the outcome, rewarding users more significantly for overcoming challenging tasks and penalising them less for failing tasks that were deemed difficult. Conversely, for tasks that are easier relative to the user's skill level, the system applies a greater penalty for incorrect answers and a smaller reward for correct ones. The accuracy of these predictions and adjustments relies on the precision of the ratings, which are continually refined through each interaction, making the system increasingly reliable over time.

The Glicko rating system [29] builds upon the Elo system by incorporating an uncertainty factor represented by the rating deviation (RD), which is an estimate of the standard deviation of the rating. A high RD suggests a lack of recent user engagement with the system or limited gameplay, indicating that the rating may not be a reliable measure of the user's current skill level. Conversely, a low RD indicates consistent user engagement and a more dependable rating. The Glicko system adjusts ratings by taking into account the RD of both the user and the task, allowing for more significant rating changes when the RD is high. This feature enables the system to more rapidly approximate the user's true skill level, especially when the initial rating significantly deviates from the true rating. However, one inherent limitation of rating systems is their design goal of achieving a 50% success rate for users, which can lead to perceptions of the game being overly difficult.

Drawing from various studies [28], [32], it has been observed that users are optimally challenged and engaged when they successfully complete tasks around 70% of the time. Achieving this higher success rate requires a high degree of precision in the rating adjustment process. Rating systems can be calibrated to select tasks that increase the likelihood of user success, based on their current performance, thereby elevating the success rate from 50% to 70%. While rating systems perform optimally with a robust dataset for calibration, the practicality of gathering sufficient data to accurately estimate task difficulty remains a challenge.

Furthermore, it is essential to acknowledge situations where gamification strategies fail to make a positive impact on learning outcomes, or might even have adverse effects [33]. Such failures are often attributed to poor gamification design, such as the adoption of a one-size-fits-all approach that fails to accommodate the diverse needs and preferences of users [34–35]. Recent research efforts [36–37] have focused on incorporating user preferences and feedback into the design of educational content, employing machine learning algorithms to tailor the content based on this input. This approach represents a step towards creating a more personalised learning experience by considering individual user preferences during content creation. However, this data collection typically occurs before content generation, which suggests an opportunity for further enhancement. Allowing users to modify the content during their engagement could facilitate the automatic generation of a more varied and personalised experience, adapting in real time to user feedback and modifications.

Algorithm for selecting the optimal level of difficulty adaptation

The proposed algorithm for personalising the level of perceived difficulty for a simulator user is based on dividing all evaluated scenario activities into blocks corresponding to particular actions (e.g. unscrewing a wheel, removing old brake pads) and using a large group of autonomous agents controlled via AI as a reference group trying to complete the same scenario as the user. This makes it possible to obtain a reference level of difficulty for each block of the scenario and to predict the user's future results by analogy with the group of agents to which his previous actions were most similar. This approach makes it possible to dynamically change the difficulty level of the user's next scenario block depending on the size of the effect [38] calculated between the user's predicted score and the reference distribution of the final scores of all agents. This approach allows the difficulty level of individual blocks to be optimally determined in response to the user's progress (see Fig. 1).

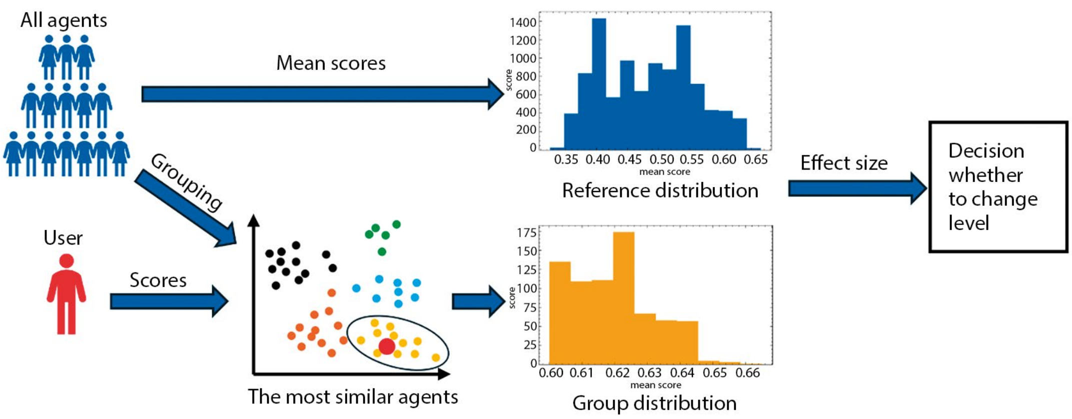

Figure 1. Visual representation of the steps of the proposed algorithm
Source: Own elaboration.

The detailed steps for implementing the algorithm are as follows:

Preparatory steps:

- Step 1. Designate a group of agents (using AI/first users). Each agent for each scenario block has a Score function value that determines the final score of the entire scenario (see Fig. 2).
- Step 2. Calculate the average value from the set of Score function values of all agents, and then prepare the distribution of these values (reference distribution) (see Fig. 3).

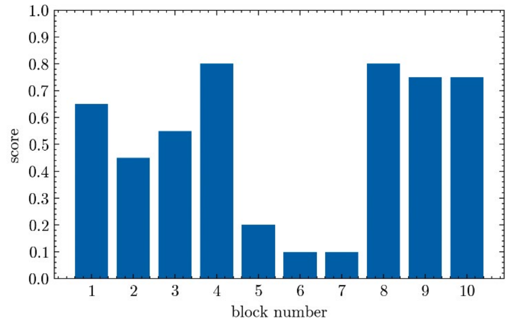

Figure 2. Example bar chart of single agent's Score function values for the entire scenario
Source: Own elaboration.

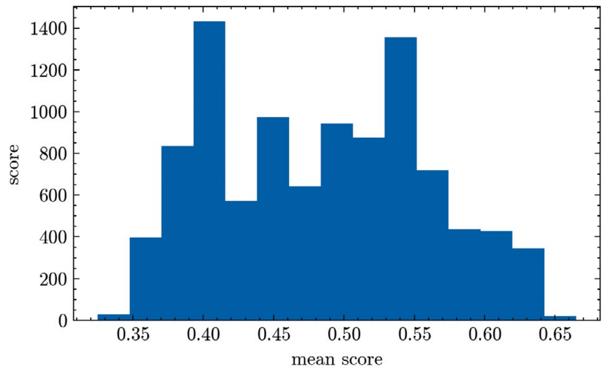

Figure 3. Example histogram showing the distribution of Score function values for all agents

Source: Own elaboration.

Steps for evaluating an exercise participant:

– Step 3. Update the value of the exercise participant's Score function upon completion of each block of the exercise scenario (see Fig. 4).

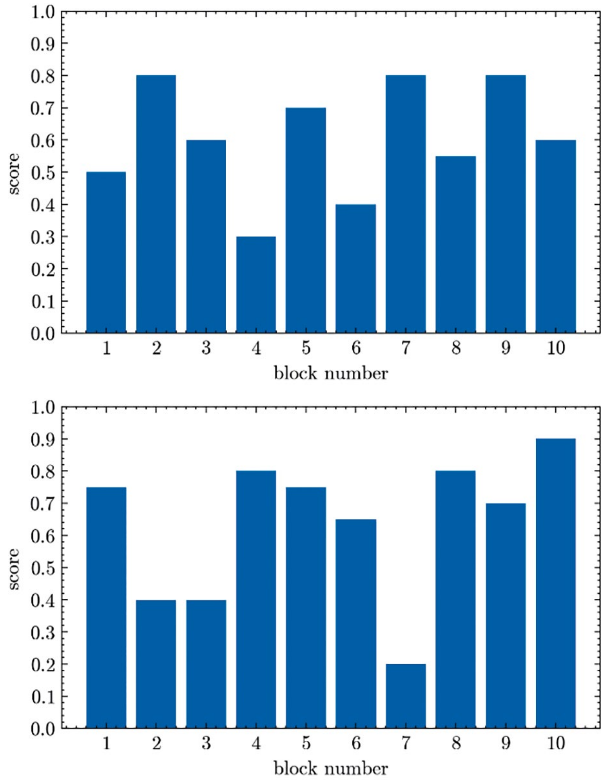

Figure 3. Example histogram showing the distribution of Score function values for all agents

Source: Own elaboration.

– Step 4. Group the values of the Score function in the result set containing the values of all agents and completed user exercises with the goal of ultimately finding results similar to the current journey through the scenario by the exercise participant under consideration. Implement the step by performing grouping using the k-means method with gap statistics, which automatically determines the number of target k groups for the k-means algorithm.

– Step 5. Calculate the centroids of the groups found in step 4 and use the Euclidean metric to find the group most similar to the current score of the exercise participant under consideration.

– Step 6. Calculate the mean value of the Score function for all values in the set of the group most similar to the current score of the exercise participant under consideration at that moment. Create a group distribution for this group (see Fig. 5).

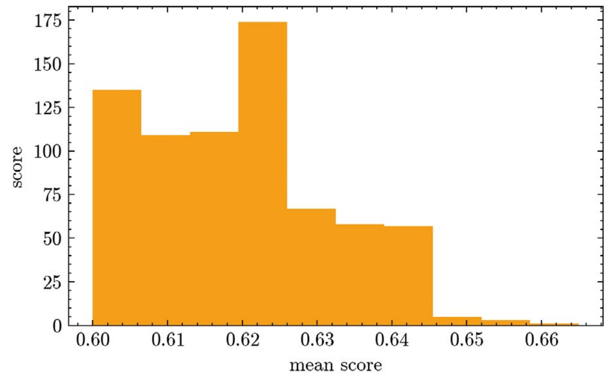

Figure 5. Example of the distribution of Score function values for the group of results most similar to the exercise participant currently under consideration

Source: Own elaboration.

– Step 7. Compare the group distribution with the reference distribution using a measure called effect size, specifically Hedge's g, a measure of effect for differentially distributed groups with different standard deviations [38–39]:

$$g=\frac{\overline{x}_1-\overline{x}_2}{s_{pooled}},\ s_{pooled}=\sqrt{\frac{(n_1-1)*s_1^{\,2}+(n_2-1)*s_2^{\,2}}{n_1+n_2-2}}.$$

– Step 8. Interpret the result. If the value of the result is considered the so-called large positive effect, then change the level of difficulty to more difficult. If the value of the result is considered to be a so-called large negative effect, then change the level of difficulty to an easier one. Typically, values greater than or equal to 1.3 are taken as the absolute value of g for large effect.

A pivotal step within the proposed algorithm involves the comparison of the exercise participant's score distribution with a reference distribution established based on AI-controlled agents. To facilitate this comparison, the algorithm adopts Hedge's g as a measure of effect size, enabling the identification of significant deviations and supporting dynamic adjustments to difficulty levels. While this method proves effective in addressing large-scale differences, it does not inherently evaluate the likelihood that the observed data align with the assumed distributions. An alternative approach might involve the explicit calculation of distributional consistency through statistical means. Methods such as the Kolmogorov–Smirnov test or Bayesian inference techniques could offer a more rigorous assessment of the fit between observed data and the reference distributions. Although such methods provide a robust framework for validation, they are computationally demanding, which might render them impractical for real-time applications. The selection of Hedge's g reflects a deliberate emphasis on computational efficiency and operational simplicity. Designed for scenarios where rapid adjustments are critical, Hedge's g is particularly well suited for comparing distributions with differing standard deviations. Its clear thresholds for identifying substantial positive or negative effects streamline decision-making within dynamic VR training environments, where responsiveness to user performance is paramount. However, it is important to acknowledge that this approach may omit finer aspects of statistical alignment, which could lead to subtle inconsistencies in the adaptation process. Future refinements to the algorithm could incorporate methods capable of directly estimating distributional consistency. For instance, likelihood-based metrics or advanced machine learning models could augment the existing framework, yielding a more nuanced understanding of the relationship between observed performance and the reference standards. Such enhancements would not only elevate the precision of the algorithm but also broaden its applicability across a range of training scenarios, ultimately contributing to the robustness of personalised VR learning environments.

The proposed algorithm leverages artificial intelligence-controlled agents as a reference group to evaluate the difficulty levels of scenario blocks. To ensure the agents' performance aligns with human behaviours, a structured training process was implemented using the proximal policy optimization (PPO) reinforcement learning algorithm, known for its stability in dynamic environments. The training process began with the collection of initial datasets derived from human participants completing similar scenarios during earlier experiments. These datasets included detailed behavioural metrics such as task completion times, error rates and decision-making pathways, serving as a foundation for training the agents. The reward functions for the agents were designed to emulate desirable human performance metrics specific to each simulator. In the public speaking simulator, rewards were assigned for maintaining consistent eye contact, minimising filler words and adhering to optimal speech pacing. In the hydrogen electrolysis simulator, rewards prioritised achieving correct process parameters, minimising material waste and maintaining safety standards. Similarly, in the mechanical technician simulator, agents were rewarded for accurately diagnosing issues, selecting appropriate tools and following precise repair procedures. Agents were trained on over 10,000 iterations per scenario block, with the complexity of the simulated environments increasing progressively. Initial training iterations focused on simple task environments to allow agents to grasp foundational behaviours, while later iterations introduced variability, such as random errors or unexpected conditions, to simulate real-world challenges. After completing training, the agents' performance was validated against expert human users through key metrics, including success rates, task completion times and decision-making accuracy. Statistical analyses, including paired t-tests and effect size calculations, revealed that the agents achieved approximately 92% alignment with human performance across all simulators. However, discrepancies were observed in context-dependent decisions, such as managing audience questions in the public speaking simulator or diagnosing rare mechanical faults. Despite the promising alignment, these results indicate that further improvements are necessary to enhance the agents' ability to replicate nuanced human decision-making processes. Future enhancements could involve incorporating advanced neural architectures, such as transformer-based models, to improve context sensitivity. Additionally, the integration of human-in-the-loop training methods, where experts provide real-time feedback during the agents' training process, could refine their behaviour. Domain-specific refinements, including embedding expert knowledge into simulator scenarios, may further enhance the agents' reliability. Overall, the training process underscores the importance of robust data collection, carefully designed reward systems and iterative refinement. While the current approach demonstrates that AI agents can provide a statistically consistent baseline for scenario difficulty evaluation, future work should explore longitudinal studies comparing agent-guided adaptations with human-only baselines to deepen understanding of their effectiveness in high-stakes training environments.

Method test results

The proposed algorithm was tested on the scenarios of the available three proprietary VR simulators. The first step of the research was to convert the activity in the simulator scenario evaluations into blocks. To facilitate comparison of the algorithm's performance, it was assumed for each case that the scenarios should be divided into 10 blocks. The first simulator provided training in public speaking. Its scenario, after being divided into 10 consecutive blocks, looked as follows:

– Analysis of the target group and establishment of training objectives.
– Preparation of the training program, including speaking and presentation techniques.
– Gathering teaching and support materials.
– Setting up the training room in a way that supports interaction.
– Starting the training with ice-breaker exercises and presenting the agenda.
– Conducting the theoretical part on the structure and construction of speeches.
– Implementing practical exercises on speaking and self-presentation.
– Recording participants' speeches and analysing them.
– Discussing individual feedback and ways to overcome stage fright.
– Summarising the training and establishing a plan for further development of participant skills.

The second simulator provided training in hydrogen electrolysis. Its scenario, when divided into 10 consecutive blocks, was as follows:

- Selecting a suitable electrolyser and preparing the workstation.
- Preparing an electrolyte solution, such as water with the addition of electrolyte.
- Connecting the electrolyser to a power source (DC voltage).
- Dipping the electrodes into the electrolyte solution.
- Starting the electrolysis process by turning on the current.
- Observing the release of gases at the electrodes (hydrogen at the cathode, oxygen at the anode).
- Monitoring process parameters, such as current and solution temperature.
- Collecting the separated hydrogen in a suitable container.
- Terminating the electrolysis by turning off the current.
- Analysing the efficiency of the process and the quality of the hydrogen produced.

The third simulator allowed training in the operations of a mechanical technician. Its scenario, when divided into 10 consecutive blocks, was as follows:

- Analysing the technical documentation of the machine or equipment.
- Preparing the tools and materials needed to perform the task.
- Performing visual inspection and diagnosis of the condition of the equipment.
- Disassembling damaged or worn parts.
- Cleaning and preparing the area for new components.
- Installing new or reconditioned parts.
- Adjusting and calibrating installed components.
- Carrying out trial runs and operation tests.
- Making any corrections and adjustments.
- Preparing a report on the work performed and commissioning the device.

For each simulator, the reference number of AI agents who tried to achieve the best possible result on a given scenario was taken as 10,000. Then, 30 people were asked to test each simulator with the implemented dynamic mechanism, OLA, for changing the difficulty level of a particular block. Each of the above blocks had three variants: easy, medium and difficult. The default starting variant for each tester was the medium level. The number of difficulty level switches and the final score that the tester obtained were studied.

This section shows the results obtained when testing on Scenario 1, Scenario 2 and Scenario 3 (see Table 1).

Table 1. Results obtained for Scenarios 1, 2 and 3

User no.	Number of difficulty level switches – Scenario 1	Final result – Scenario 1	Number of difficulty level switches – Scenario 2	Final result – Scenario 2	Number of difficulty level switches – Scenario 3	Final result – Scenario 3
1	0	65	0	64	1	60
2	0	68	1	98	1	55
3	1	71	1	64	1	85
4	0	60	1	88	0	69
5	1	80	1	77	0	72
6	1	75	0	55	1	91
7	1	77	1	95	1	52
8	1	83	1	90	1	78
9	1	90	1	92	1	78
10	1	95	2	80	0	57
11	1	88	1	92	1	73
12	1	56	1	55	1	55
13	2	67	2	69	1	96
14	2	71	1	94	1	87
15	2	73	2	63	1	94
16	2	76	2	61	2	68
17	1	80	1	84	1	98
18	1	82	1	88	0	66
19	1	83	1	93	1	80
20	2	70	1	95	1	97
21	2	77	2	56	1	91

User no.	Number of difficulty level switches – Scenario 1	Final result – Scenario 1	Number of difficulty level switches – Scenario 2	Final result – Scenario 2	Number of difficulty level switches – Scenario 3	Final result – Scenario 3
22	2	66	2	50	2	57
23	1	90	2	55	0	73
24	2	56	1	96	1	78
25	1	88	2	66	0	69
26	2	55	1	73	1	80
27	0	70	0	70	1	86
28	1	73	0	61	0	60
29	1	80	0	75	0	70
30	1	82	1	84	1	99

Source: Own elaboration.

In order to analyse the number of necessary scenario changes, an analysis was made of the average performance of the algorithm during the analysed scenarios (see Table 2).

Table 2. Summary of the average number of difficulty level switches and the average final scores of test participants per scenario

Scenario No.	Average number of difficulty level switches	Average final score
Scenario 1	1.16	74.9%
Scenario 2	1.10	76.1%
Scenario 3	0.80	75.8%

Source: Own elaboration.

The average final score of approximately 75% is close to the considered preferred value of 70%, which means that the scenario was neither too easy nor too difficult for the testers, regardless of their starting level of competence in the scenario. The average number of difficulty level switches of individual blocks above 1 means that the dynamic adaptation of the perceived difficulty level influenced the final result. We interpret the results as very promising and requiring further research into how to dynamically determine the number of scenario blocks and whether the difficulty levels should have discrete or more continuous values.

Conclusions

The OLA (Optimising Level Adaptation) algorithm represents a significant advancement in the realm of scenario simulations for professional training within VR environments. This algorithm, through its dynamic adjustment of difficulty levels, addresses a critical aspect of personalised learning and training – maintaining optimal engagement and challenge levels for users. The study's findings, derived from testing the OLA algorithm across three distinct VR simulators, offer several key insights and implications for the future of professional training and educational technologies.

Firstly, the algorithm's ability to adapt the difficulty of scenarios in real time, based on the user's performance, underscores the importance of personalised learning environments. Traditional one-size-fits-all approaches often fail to meet the diverse needs of learners, leading to either under-challenging or overwhelming. OLA's dynamic adjustment mechanism ensures that each user is continuously engaged at an optimal level of difficulty, thus enhancing learning effectiveness and user satisfaction. The test results across different scenarios – public speaking, hydrogen electrolysis and mechanical technician operations – highlight the algorithm's versatility and effectiveness. With an average final score of approximately 75% across all scenarios, the OLA algorithm successfully maintained a balance between challenge and achievability. This balance is crucial for promoting user engagement and motivation, in line with educational theories such as Vygotsky's zone of proximal development. The average number of difficulty level switches observed during the tests indicates that the algorithm actively responds to user performance, making necessary adjustments to maintain the ideal difficulty level. This dynamic adaptation not only supports personalised learning but also reflects a significant improvement over static educational content, which cannot adjust to individual user needs. Moreover, the OLA algorithm's foundation in comparing user performance with that of a reference group of AI-controlled agents introduces a novel approach to difficulty adjustment. This method allows for a more objective and data-driven determination of difficulty levels, potentially offering a more standardised and fair training environment across different users. The promising results of this study suggest several avenues for future research and development. Exploring the dynamic determination of the number of scenario blocks and the granularity of difficulty levels could further enhance the algorithm's effectiveness. Additionally, integrating more nuanced user feedback and preferences into the algorithm's adjustments could create even more personalised and engaging learning experiences.

In conclusion, the OLA algorithm represents a step forward in the integration of intelligent adaptive systems into educational technologies, particularly in high-stakes professional training environments. Its ability to tailor learning experiences to individual user needs not only enhances learning outcomes but also opens up new possibilities for the application of VR and AI in education and training. Further research and development in this area have the potential to revolutionise how professionals are trained, making learning more effective, engaging and tailored to individual needs.

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