Online-Journals.org

iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 18 No. 12 (2024) | OPEN ACCESS

https://doi.org/10.3991/ijim.v18i12.49911

PAPER

Exploring Interactive Learning Environments Based on Augmented Reality Technology

Weifeng Deng[1], **Lin Wang**[1](✉), **Xue Deng**[2]

[1]Hainan Vocational University of Science and Technology, Haikou, China

[2]Hebei Vocational University of Technology and Engineering, Xingtai, China

wanglintaichi@163.com

ABSTRACT

With the rapid advancement of digital technology, the application of augmented reality (AR) in the field of education has emerged as a focal point of research aimed at enhancing learning efficiency and experience through innovative interactive learning environments. This study focuses on the application of AR technology in education. The goal is to address key technical issues present in existing AR interactive learning environments to promote their widespread adoption in educational settings. An analysis of the current application of AR technology in education is conducted, focusing on its potential to enhance learners' motivation and comprehension capabilities. However, a common shortfall in existing research methodologies has been identified, namely inadequate control over node consistency and deficient design of collaborative visualization components. These limitations restrict interaction and collaborative efficiency within AR learning environments. In response, a novel predictive algorithm for node consistency control is proposed, significantly enhancing real-time interaction and coherence among multiple learners through optimized information synchronization mechanisms. Furthermore, a set of collaborative visualization components is designed to be personalized according to learners' behavioral and cognitive characteristics, thereby supporting more effective team-based learning. The outcomes of this study not only provide new theoretical and technical support for the design and implementation of AR interactive learning environments but also offer a fresh perspective on the future direction of educational technology.

KEYWORDS

augmented reality (AR) technology, interactive learning environments, node consistency, collaborative visualization, educational technology

1 INTRODUCTION

With the rapid development of augmented reality (AR) technology, its application prospects in the field of education have increasingly attracted the attention of researchers and educational practitioners [1–4]. AR, overlaying virtual information onto the real world, offers new possibilities for creating engaging interactive

Deng, W., Wang, L., Deng, X. (2024). Exploring Interactive Learning Environments Based on Augmented Reality Technology. *International Journal of Interactive Mobile Technologies (iJIM)*, 18(12), pp. 15–29. https://doi.org/10.3991/ijim.v18i12.49911

Article submitted 2024-02-28. Revision uploaded 2024-04-17. Final acceptance 2024-04-30.

learning environments. Compared to traditional learning methods, interactive learning environments based on AR can offer more intuitive and immersive learning experiences. These experiences are conducive to enhancing learners' motivation and strengthening their understanding and memory of knowledge [5–7]. Therefore, the exploration of how to effectively construct and apply AR interactive learning environments has become an important research topic in the field of educational technology.

In educational practice, the introduction of AR technology is considered a revolutionary instructional tool. It not only changes traditional teaching methods but also provides new pathways for personalized and collaborative learning [8–10]. Studies have shown that AR technology can effectively enhance students' interest in learning and participation, while deepening their understanding of complex concepts [11–13]. Therefore, conducting thorough research on the design and implementation of AR interactive learning environments is of significant theoretical and practical importance for advancing innovative educational models.

However, existing studies on the construction of AR interactive learning environments often lack efficient mechanisms for controlling node consistency, which can lead to potential delays in information synchronization during multi-student interactions. This, in turn, affects the coherence and real-time nature of the learning experience [14–16]. Moreover, the design of current collaborative visualization components has not fully utilized the potential of AR technology to enhance collaborative learning. There is a lack of adaptivity in design to accommodate variations in students' behaviors and cognitive processes.

This study aims to optimize real-time interaction synchronization among multiple students by proposing a new predictive algorithm for node consistency control in AR interactive learning environments. This algorithm can predict and adjust node states to ensure timely updates and information sharing, thereby enhancing the interactivity and learning outcomes of the learning environment. Additionally, the thesis focuses on designing collaborative visualization components with strong adaptability. These components are personalized to cater to the performance and preferences of different learners, supporting more effective team-based learning. The discussion of these two research components not only addresses the deficiencies of existing research methodologies but also provides practical guidance for developing efficient and interactive AR learning environments. This holds significant academic value and offers broad application prospects.

2 PREDICTIVE ALGORITHM FOR NODE CONSISTENCY CONTROL

In AR interactive learning environments, maintaining node consistency is essential to facilitate collaborative interaction and shared experiences among students. Due to network latency and unstable communication, discrepancies in scene information and entity states among students may occur, thereby reducing the system's ability to provide real-time feedback and diminishing the students' sense of immersion. To address this issue, a predictive algorithm for node consistency control in AR interactive learning environments is proposed. This algorithm, specifically designed for AR learning contexts, considers the mobility and interactivity of students, as well as the unique requirements of educational content. It predicts and synchronizes the location, state, and actions of each student, optimizing the information transmission mechanism to ensure that all participants can share and collaborate instantaneously, regardless of changes in their geographical locations. Moreover, the algorithm pays special attention to the consistency requirements of entity information within educational environments. It ensures that all students receive uniform educational content and interactive experiences when engaging with shared virtual objects. The text provides a structural description of the interactive learning environment (as shown in Figure 1 below).

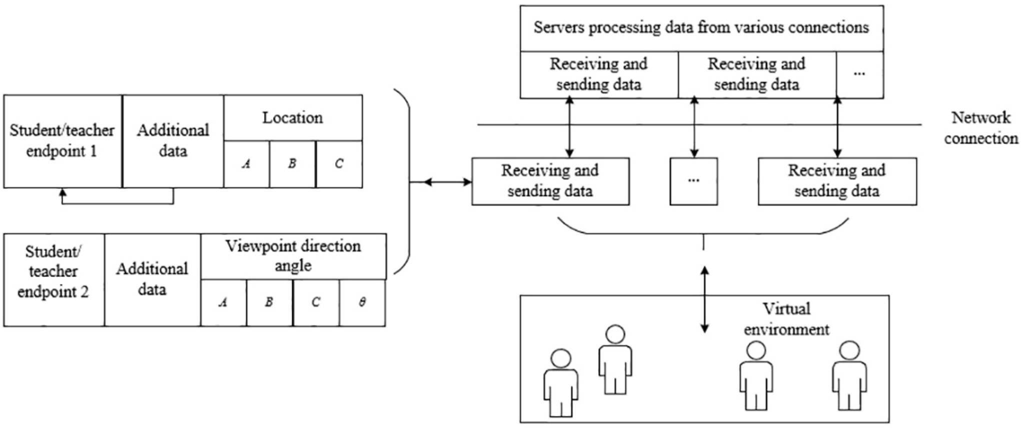

Fig. 1. Structural description of the interactive learning environment

In AR interactive learning environments, control strategies aimed at ensuring node consistency must take into account the dynamic interactions and real-time updates of learning content within the educational context. Such consistency control strategies are necessary to adjust to the increased frequency of student interactions and higher mobility demands. Within this environment, control over virtual characters and entities may need to be dynamically transferred based on the flow of educational interactions. For instance, while one node displays instructional content, other nodes should synchronously receive state updates. During student practical activities, control may be transferred among students, enabling them to interact and explore course content. Hence, the fundamental principles of the proposed consistency control strategy are to ensure real-time state synchronization and rational allocation of control, capable of dynamically adjusting according to the characteristics of educational scenarios.

The traditional nearest distance principle is described below. For two points in an O-dimensional space, the following equation provides the definition of distance between two O-dimensional vectors a and b:

$$f_R(a,b)=\sqrt{(a_1-b_1)^2+\ldots+(a_o-b_o)^2}=\sqrt{(a-b)^s(a-b)} \tag{1}$$

The Euclidean norm of point A can be obtained through the following equation:

$$f_R(a,0)=\|a\|_2=\sqrt{a_1^2+\ldots+a_o^2}=\sqrt{a^s a} \tag{2}$$

Then, the following equation represents the equality that must be satisfied by all points equidistant from the origin:

$$\|a\|_2=a_1^2+\ldots+a_o^2=z^2 \tag{3}$$

In AR interactive learning environments, it is essential to consider the interaction between physical entities and augmented content. Hence, the control region must be determined not only by spatial location but also by the dynamic characteristics of the entities, such as speed and direction. To achieve node consistency control in AR interactive learning environments, this paper adopts a control region setting based on the Mahalanobis distance concept. Utilizing Mahalanobis distance allows for consideration of the relative velocity and direction of movement between entities. This approach more accurately predicts the future position of entities and dynamic changes in control, thereby offering a consistent control mechanism for nodes within the learning environment. This mechanism can predict and adapt to actual interactions.

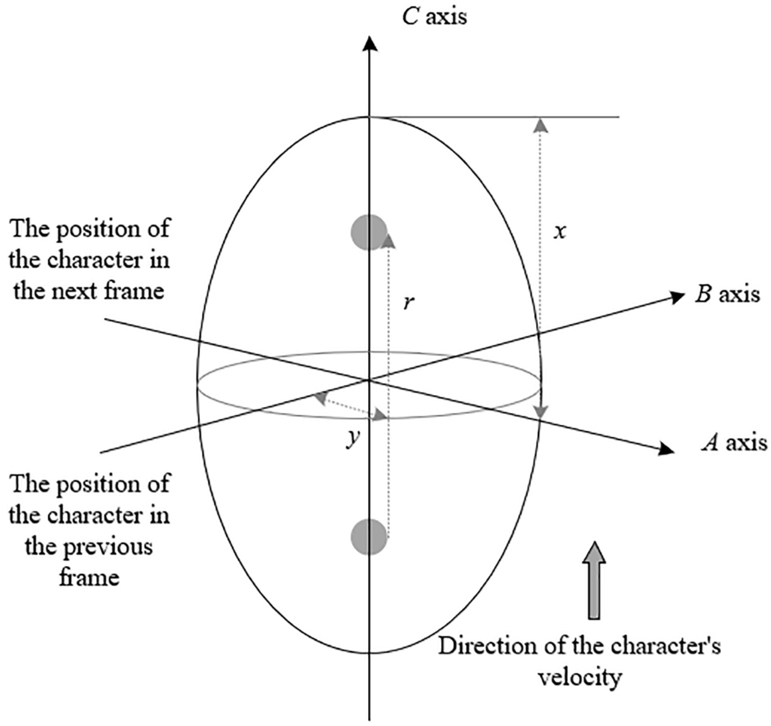

Fig. 2. Schematic diagram of node control regions in AR interactive learning environments

When formulating the predictive algorithm for node consistency control in AR interactive learning environments, the specific steps are as follows: First, motion trajectory data for nodes in physical space, including information on position, speed, and direction, is collected. Subsequently, based on this data, statistical methods are employed to calculate the covariance matrix of node movement, which reflects the degree of correlation between various dimensions of node motion. Based on this covariance matrix and the principles of Mahalanobis distance, the shape and size of each node's control region are determined. This region is represented as an ellipsoid region with the current velocity direction as its major axis, as illustrated in Figure 2. The center of this ellipsoidal region is predicted based on the current position and velocity, and its axes are adjusted according to the uncertainty of speed and potential changes in direction. During this process, specific requirements of the AR environment, such as the real-time nature of interactions, the scale of space, and students' behavior patterns, are also considered to ensure the applicability and accuracy of the algorithm.

The following is the calculation formula for the Mahalanobis distance of a multivariate vector $a = (a_1, a_2, a_3, \ldots, a_o)$ with a mean of $\omega = (\omega_1, \omega_2, \omega_3, \ldots, \omega_U)$ and a covariance matrix Σ:

$$F_l(a) = \sqrt{(a-\omega)^s \sum{}^{-1} (a-\omega)} \tag{4}$$

Further, based on the Mahalanobis distance, weights on components are set as follows:

$$i=\left(\frac{a_1}{T_1},\ldots,\frac{a_o}{T_o}\right)n=\left(\frac{b_1}{T_1},\ldots,\frac{b_o}{T_o}\right) \tag{5}$$

Let t_u be the standard deviation, and $F = diag(t_1^2,\ldots,t_0^2)$, the following equation defines the distance between a and b:

$$f(a,b) = f_R(i,n) = \sqrt{\left(\frac{a_1-b_1}{T_1}\right)^2+\cdots+\left(\frac{a_o-b_o}{T_o}\right)^2} = \sqrt{(a-b)^s F^{-1}(a-b)} \tag{6}$$

The modulus of a can be obtained through the following equations:

$$\|a\| = f(a,0) = f_R(i,0) = \|i\|_2 = \sqrt{\left(\frac{a_1}{T_1}\right)^2+\ldots+\left(\frac{a_o}{T_o}\right)^2} = \sqrt{a^s F^{-1} a} \tag{7}$$

$$\|a\| = \left(\frac{a_1}{T_1}\right)^2+\ldots+\left(\frac{a_o}{T_o}\right)^2 = z^2 \tag{8}$$

The direction of the character's velocity is chosen as the major axis direction for each node's control region. Assuming the current position at time $S = s_p$ is $X(s_p)$, the next position estimation can be represented as $X(s_1) = X(s_0) + n\ (s_1 - s_0)$. Assuming the change in distance for character X in each frame is represented by F, and the constant proportion coefficient *Scale* is represented by SC, the ellipse's major axis value can be calculated using the following equation:

$$x = F \times SC \tag{9}$$

The value of the ellipse's minor axis can be calculated through the following equation:

$$y = z = \sqrt{x^2 - \left(\frac{z}{2}\right)^2} \tag{10}$$

Through the methods described above, the algorithm can dynamically maintain a control region for each node that adapts to its behavior pattern. This enables the prediction and reduction of conflicts between nodes, thereby enhancing overall coordination and improving the student experience within the learning environment.

3 DESIGN OF COLLABORATIVE VISUALIZATION COMPONENTS

This study is dedicated to addressing the issue of static information presentation and limited learner interaction within traditional learning environments. By designing collaborative visualization components tailored for AR interactive learning environments, the presentation of data and concepts becomes more intuitive and dynamic, enhancing learners' spatial cognition and depth of understanding. Such a design takes into account the unique advantages of AR technology in information layering, natural interaction, and student collaboration, with the goal of enhancing learners' engagement and interaction efficiency. The limitation of traditional educational tools lies in their inability to provide a shared, interactive, three-dimensional information space. In contrast, AR technology can overcome this shortfall. Through the design of collaborative visualization components, not only can learner empathy and understanding be promoted, but new teaching methods are also provided for educators. This significantly enhances the educational experience and improves learning outcomes.

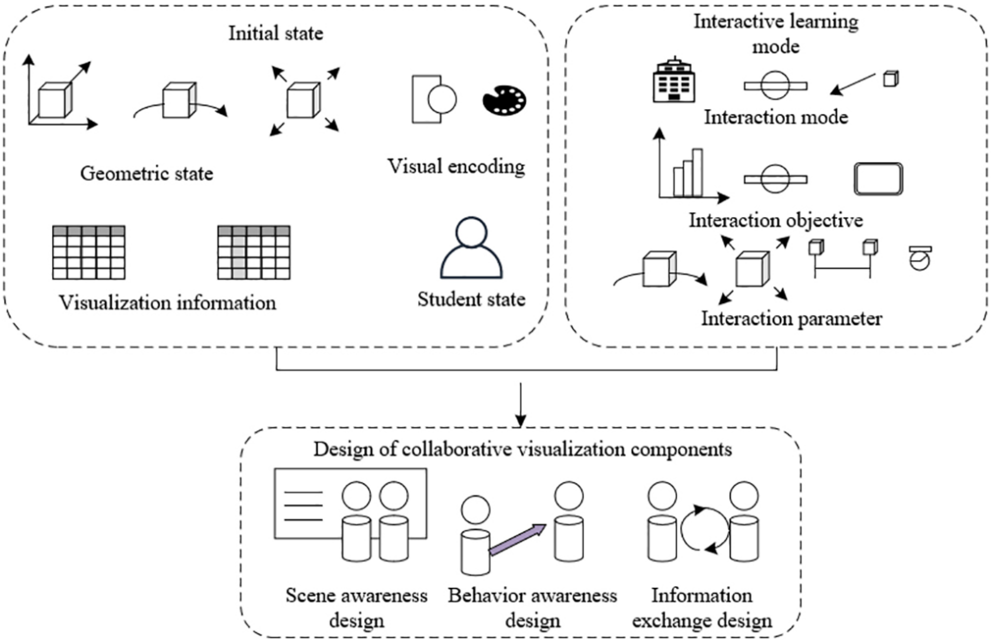

Fig. 3. Design space of collaborative visualization components in AR interactive learning environments

Figure 3 illustrates the design space for collaborative visualization components in interactive AR learning environments. In these environments, the design space for collaborative tasks can be constructed and understood in three dimensions to ensure the achievement of educational goals and optimize the student experience.

i) Scene awareness design: In educational applications, scene awareness design requires not only that participants share the same virtual learning environment but also that the teaching content is effectively presented and learning activities are organized. AR technology plays a key role here by seamlessly overlaying digital information onto the physical environment, integrating learners into the same educational scenario regardless of their physical location. Such a design ensures that all participants can not only view the same learning materials but also interact with virtual objects and collaborate with each other to complete learning tasks.

ii) Behavior awareness design: In interactive learning environments, the concept of behavior awareness focuses on capturing, analyzing, and responding to learners' behaviors. This includes recording learners' interaction trajectories, such as touching, pointing, and manipulating virtual objects, as well as collaborative interactions among learners. With this data, the system can reproduce and analyze the learning process, providing personalized feedback and coaching. Furthermore, behavioral awareness must also support learners in understanding their current learning state and interaction actions, thereby fostering more effective team collaboration. Figure 4 illustrates the implementation of teacher-student interactions in an interactive learning environment.

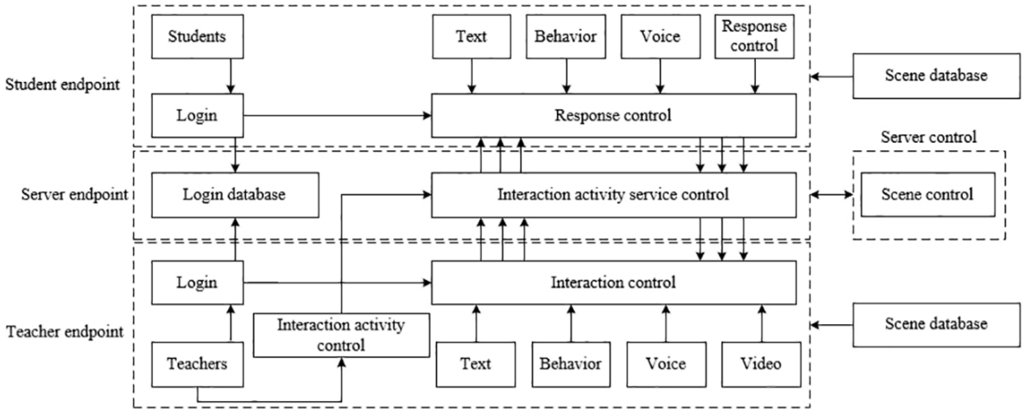

Fig. 4. Implementation of teacher-student interactions in an interactive learning environment

iii) Information exchange design: The dimension of information exchange design in AR interactive learning environments requires the support of direct communication and resource sharing among learners. This involves mechanisms that allow built-in and external communication tools, along with designing information exchange mechanisms that allow learners to easily share knowledge points, learning resources, and feedback. For example, learners may need to indicate or annotate shared virtual objects or exchange ideas and perspectives in real-time during learning activities. The design of information exchange must consider the specific requirements of the learning environment. This includes the need for particular methods of knowledge representation and data visualization tools to support the communication and understanding of complex concepts.

In AR interactive learning environments, the design steps for collaborative visualization components must consider the multidimensionality and interactivity of learning content, as illustrated in Figure 5. Within such environments, three-dimensional node-link diagrams are not only designed to present information intuitively but also to facilitate interaction and collaboration among learners. Utilizing AR technology, this paper outlines the steps to design a dynamic, interactive, three-dimensional social network graph. Learners can explore and analyze data while engaging in real-time communication and collaboration with peers.

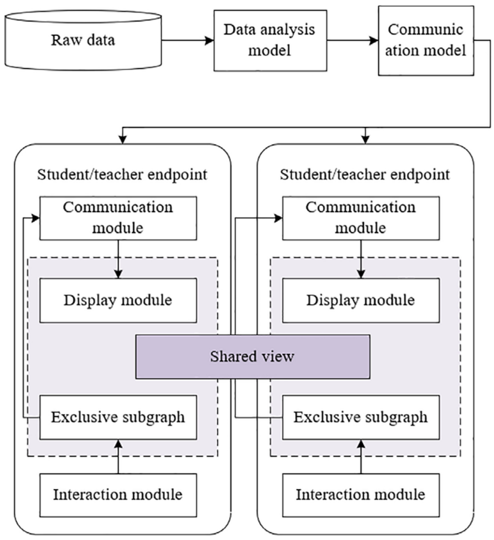

Fig. 5. Design steps for collaborative visualization components

Initially, the repulsion between simulated charges is calculated to push nodes apart, preventing overlap and enhancing readability. In AR environments, this can manifest as students using gestures or mobile devices to separate nodes that are too closely packed in three-dimensional space, thereby enhancing visual clarity and understanding. The Coulomb force, represented by *CF*, is calculated as:

$$CF = f^2 / j \tag{11}$$

The attraction between nodes based on link weight is computed, causing data points to draw closer due to their relevance. In AR applications, this step can be visualized through dynamic links, displaying the strength of connections between nodes. Students can explore the relationships between different nodes through interaction. Assuming the linear distance between nodes is represented by *f*, the spring constant by *j*, and the Hooke force by *HF*, the calculation is:

$$HF = -j^2 / f \tag{12}$$

Subsequently, the elasticity coefficient is determined. It affects the strength of attraction or repulsion between nodes, thereby adjusting the overall layout density of the graph. In AR environments, students can adjust this coefficient to explore network structures at different densities. Assuming the constant is represented by *z*, the range of node mobility by *AR*, and the number of nodes in the graph by *MU*(*VE*), the spring constant calculation formula is:

$$j = z\sqrt{AR / NU(VE)} \tag{13}$$

Further, the identification of sub-communities within the graph is facilitated by the Louvain algorithm, which helps learners understand the group structures within the network. In AR, this can be reinforced through color coding or other visual cues, enabling learners to intuitively perceive the distribution of communities. The modularity of the entire network is then calculated to assess the quality of community segmentation. In an AR environment, this metric can help learners understand the quality of clustering in the network and may enable feedback or fine-tuning of communities through interaction. The change in community modularity is represented by W. The number of links in the network is denoted by l, and any two nodes in the network by *n* and *q*, with the link weight between nodes *n* and *q* represented by X_{nq}, the degree of node *n* by z_n, and the community to which node *n* belongs by *Jn*. Whether nodes *n* and *q* are in the same community is denoted by (z_u, z_k). The expression for modularity *W* is given as:

$$W = \frac{1}{2l}\sum\nolimits_{u,k}\left[X_{uk} - \frac{j_u j_k}{2l}\right](z_u, z_k) \tag{14}$$

If we consider the community as a whole, where the sum of link weights within a community is represented by Σ_{uv} and the sum of link weights between communities is represented by $\Sigma_{TO}s$, the modularity expression shown above can be simplified to:

$$W = \sum\nolimits_z\left[\frac{\sum_{uv}}{2l} - \left(\frac{\sum_{TO}}{2l}\right)^2\right] \tag{15}$$

The change in modularity is evaluated to explore the dynamic characteristics of the network structure over time or under different conditions. In an interactive

AR learning environment, students can observe this by using a time slider or other interactive tools to visualize the evolution of the network structure. The change in modularity can be characterized by the following equation:

$$Q=\left[\frac{\sum_{uv}+j_{uv}}{2l}-\left(\frac{\sum_{TO}+j_{uv}}{2l}\right)^{2}\right]-\left[\frac{\sum_{uv}}{2l}-\left(\frac{\sum_{TO}}{2l}\right)^{2}-\left(\frac{j_{u}}{2l}\right)^{2}\right] \tag{16}$$

Finally, by calculating the betweenness centrality (BC) of nodes, key nodes within the network are identified as bridges connecting multiple communities. In AR applications, this can be achieved by enhancing the visual prominence of significant nodes, such as increasing node size or brightness, to make them more noticeable during interaction. Furthermore, the importance of nodes is quantified using BC. The number of shortest paths passing through node u is represented by v_{ts}^{u}, and the number of shortest paths between nodes t and s represented by h_{ts}. The number of shortest paths involving node u is calculated by the following formula:

$$Y_{u}=\frac{1}{(B-1)(B-2)/2}\sum_{t\neq u\neq s}\frac{b_{ts}^{u}}{h_{ts}} \tag{17}$$

In the design of collaborative visualization components within AR interactive learning environments, a mechanism for creating sub-views allows students to construct a detailed focus area by selecting specific nodes on the main view. This sub-view is spatially independent from the main view, and its content remains unaffected by subsequent changes to the main view, maintaining the specificity and stability of the information. Only links whose terminal nodes are both included in the selected range are displayed in this sub-view, simplifying the view and avoiding the interference of irrelevant information. This feature is particularly important in AR interactive learning environments as it enables learners to immerse themselves in a distraction-free, highly focused learning environment. Through real-time and three-dimensional information interaction, learners deepen their understanding of data relationships and concepts. Furthermore, this approach supports multi-student collaboration, enabling learners to explore and discuss information within the sub-view together, thereby enhancing the learning experience and effectiveness.

Additionally, the functionality of auxiliary views is crucial. They include bar charts and path diagrams, which offer data visualization support from various perspectives. Bar charts serve as an intuitive way to display node attribute information and are used to summarize information about other nodes adjacent to a specific node. In AR environments, however, they are typically hidden due to screen space limitations and displayed in the top-right corner of the personal computer (PC) interface, allowing students to access detailed node attribute information. Path diagrams are generated based on students entering specific node numbers, mapping the reachability information between nodes. If a path exists between two nodes, it is visually displayed between the markers of the two nodes, with other nodes on the path also arranged in sequence along this line. During this process, the actual spatial coordinates of nodes are abstracted, displaying only the positional relationships relevant to the path. This simplifies the visual presentation and prevents distributions caused by excessive spatial location information. The design of auxiliary views in AR interactive learning environments not only enhances the understandability and interactivity of data but also promotes collaboration and communication among learners through immersive visual presentation. Compared to traditional

AR application environments, this approach emphasizes providing personalized and context-relevant information display methods that cater to the requirements of learning scenarios.

4 EXPERIMENTAL RESULTS AND ANALYSIS

A comparative experiment was designed from two perspectives: in the first-person view, the webcam was fixed on a tripod behind and to the left of the participant; in the third-person view, the webcam was affixed to the front of a helmet worn by the participant. The results depicted in Figure 6 indicate that high scores of consistency prediction accuracy were achieved across seven different learning segments in both the first-person and third-person views. Specifically, the first-person view scored above 4 points in learning segments 1, 3, 4, and 7, demonstrating higher predictive consistency. In contrast, the third-person view reached or exceeded 3 points in all learning segments, showing stable predictive capability despite slightly lower scores in learning segments 2 and 5. This suggests that regardless of the learner's perspective, the algorithm proposed in this study effectively predicts and adjusts node states to maintain real-time information updates and sharing. The analysis concludes that the AR interactive learning environment's node consistency control prediction algorithm proposed in this study is significantly effective. Particularly in the first-person view, the algorithm exhibited superior predictive accuracy. This could be attributed to the more direct interaction experience offered by this perspective. Here, the demand for information updates and synchronization is more urgent, and the algorithm effectively meets this demand. Even in the third-person view, the algorithm still demonstrated good performance, proving its ability to work consistently across different perspectives and learning environments. This effectively enhances interactivity and improves learning outcomes in the educational setting.

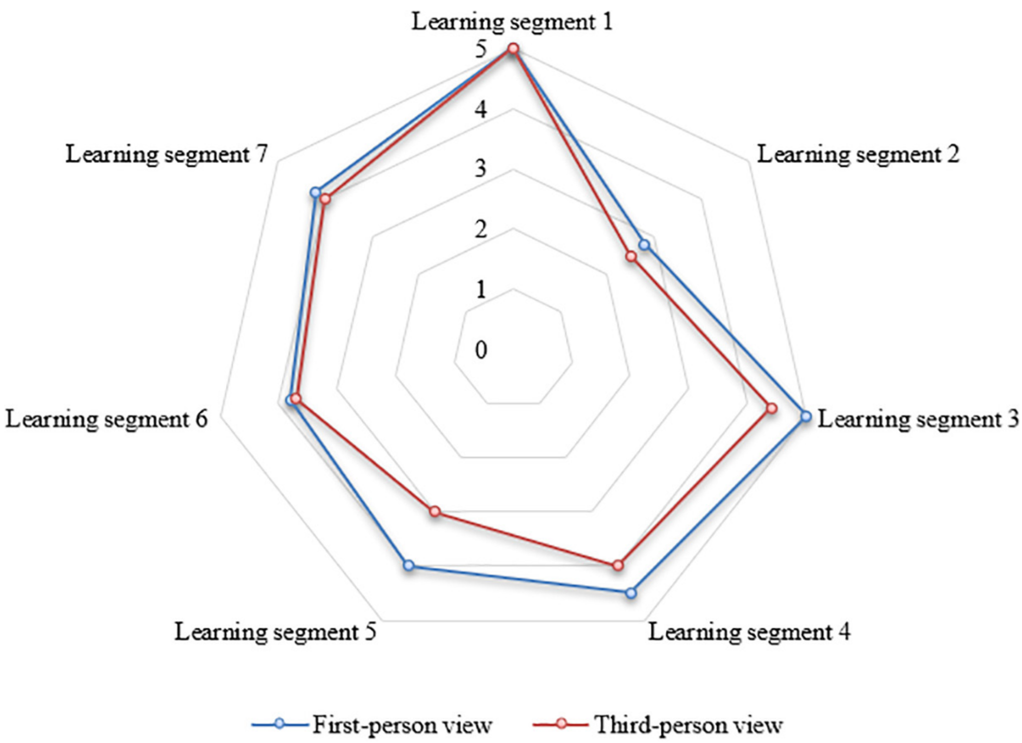

Fig. 6. Consistency prediction accuracy scores across different learning segments

Based on the data in Table 1, the average completion time (*M*) for the learning segments is 15.12 minutes in the first-person view and 13.21 minutes in the third-person view, indicating a shorter completion time in the third-person view. However, the t-test result for completion time ($t = -0.69$, $df = 12$, $p = 0.52$) indicates that, from a statistical standpoint, the difference in completion time between the two perspectives is not significant ($p > 0.05$), suggesting that the algorithm does not lead to a significant difference in time efficiency across different perspectives. Regarding consistency prediction accuracy, the average accuracy in the first-person view is 72.15%, while the average accuracy for task completion time is 55.69%. Although the first-person view has a higher accuracy rate, the t-test result ($t = 1.51$, $df = 13$, $p = 0.16$) shows that this difference is not statistically significant ($p > 0.05$). This might imply the influence of other factors on consistency and prediction accuracy. Although the differences in completion time and consistency prediction accuracy are not statistically significant, from a practical application perspective, the higher consistency prediction accuracy in the first-person view may suggest that learners can make more accurate predictions, potentially enhancing their engagement in learning tasks. Furthermore, even though the data do not show a significant difference in completion time, the shorter completion time in the third-person view might indicate that the third-person perspective could assist learners in completing learning tasks more quickly in specific scenarios. Overall, even in the absence of statistical significance, the AR interactive learning environment's node consistency control prediction algorithm proposed in this study still demonstrates potential practical value, especially in enhancing consistency prediction accuracy. This improvement may contribute to enhancing the user experience and learning outcomes.

Table 1. Analysis of learning segment completion time and consistency prediction accuracy

Variable	M	SD	t	df	p
Completion time			–0.69	12	0.52
First-person view	15.12	3.69			
Third-person view	13.21	5.78			
Consistency prediction accuracy			1.51	13	0.16
Task completion time	55.69%	21.36			
First-person view	72.15%	15.69			

The experimental results shown in Figure 7 indicate that in the aspects of 3D positioning, operation adjustment, guidance efficiency, and collaboration efficiency, scores for the third-person view generally exceeded those of the first-person view, with scores of 4.6 and 4.75 compared to 4.1 and 4, respectively. This suggests that participants experienced better spatial positioning, operational adjustment, guidance efficiency, and more effective team collaboration when using the third-person view. However, in terms of overall completion, both perspectives scored 3.4, indicating no significant difference in completing the entire learning task between the first-person and third-person views. This suggests that while 3D spatial perception and interactive operations were enhanced in the third-person view, this did not directly result in an increased completion rate of learning tasks.

The analysis concludes that despite the lack of a significant difference in overall completion between the two perspectives, the higher scores in 3D positioning, operation adjustment, guidance efficiency, and collaboration efficiency for the third-person view underscore the effectiveness of the design of collaborative visualization components in the AR interactive learning environment proposed in the study. Efficient spatial perception and interactive operations are crucial for the learning experience in AR environments. Personalized collaborative visualization components significantly enhance these experiences for users.

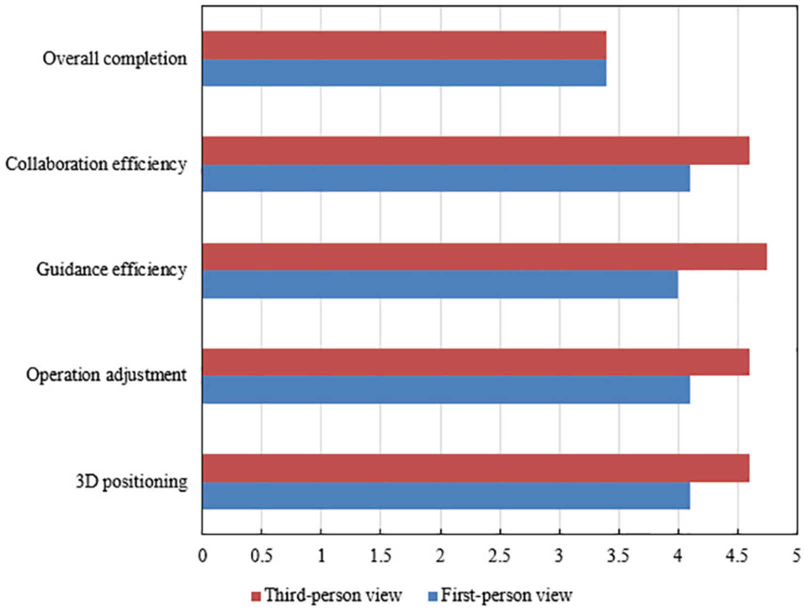

Fig. 7. Participants' evaluation results for the completion status of collaborative visualization component design

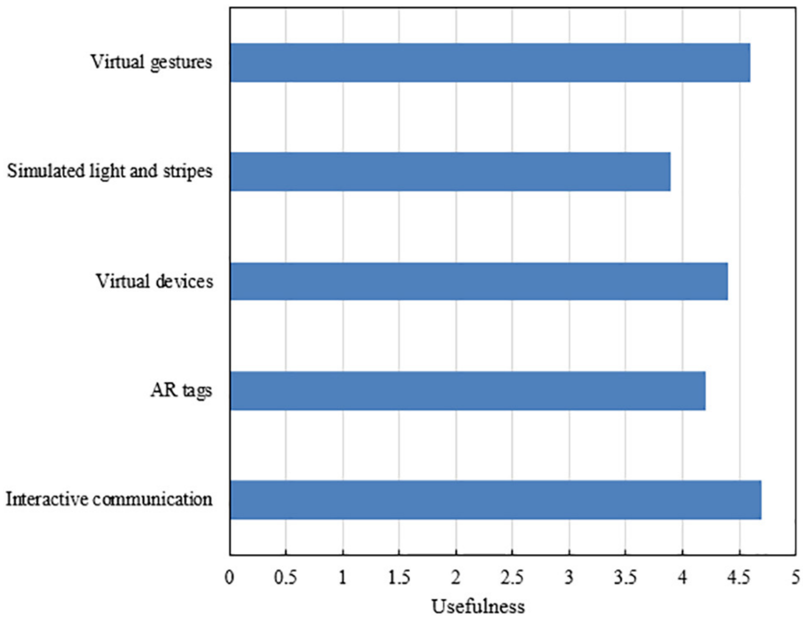

Fig. 8. Participants' evaluation results on the usefulness of auxiliary view elements in the collaborative visualization system

The experimental results presented in Figure 8 show that participants assessed the usefulness of various visual auxiliary elements within the AR interactive learning environment. The element of interactive communication received the highest rating (4.7), indicating that participants consider effective interactive communication within an AR environment to be crucial for the learning experience. The element of virtual gestures also received a high rating of 4.6, demonstrating that users find interacting with virtual content through gestures to be intuitive and useful. AR tags (4.2) and virtual devices (4.4) also achieved high scores, indicating that these supplementary visual elements are considered beneficial in an AR learning environment. The element of simulated light and stripes received a slightly lower score of 3.9. Although it is still above 4, it was considered less useful compared to other elements.

These results further emphasize the effectiveness of the collaborative visualization component design strategy proposed in the paper. High-scoring items underscore the significance of adaptive and personalized design elements such as interactive communication and virtual gestures in an AR learning environment. These elements enhance team collaboration efficiency by boosting engagement and intuitiveness. Even the relatively lower-scoring simulated light and stripes are considered useful, although they may require further optimization to match the effectiveness of other elements.

5 CONCLUSION

This study proposes an innovative algorithm for predicting node consistency control in an AR interactive learning environment. The algorithm aims to optimize the synchronicity of multi-user interactions and enhance the fluidity of real-time interactions. By predicting and adjusting node states, the algorithm ensures timely updates and the sharing of information, thereby enhancing the learning interaction experience and educational outcomes. Moreover, the study focuses on developing adaptive collaborative visualization components that can be dynamically adjusted based on learners' individual performance and preferences. This approach aims to foster more efficient, collaborative team learning.

Experimental results have demonstrated that the consistency prediction algorithm proposed in this study achieved high accuracy scores across different learning segments, indicating its effectiveness in predicting node states and thus enhancing interaction synchronicity. The analysis of learning segment completion time and consistency prediction accuracy further confirmed the algorithm's efficacy. Participants also gave positive feedback on the design of collaborative visualization components and the utility of system auxiliary view elements, highlighting the significance of adaptive and personalized components in enhancing collaborative learning outcomes. Aggregation reports and stress test results of the AR server revealed efficient and stable performance of the backend server, providing robust support for the collaborative visualization components.

Overall, the node consistency control prediction algorithm and the design of adaptive collaborative visualization components proposed in this paper have significantly improved the AR learning environment. These enhancements are particularly notable for boosting the synchronicity of multi-user real-time interactions and the efficiency of team collaborative learning. These advancements hold significant research value for the development of high-quality educational technology solutions. However, limitations of the study may include the applicability of the algorithm across various devices and network conditions, and the effectiveness of personalized components may vary among different types of learners. Future research directions could involve further optimizing the algorithm to accommodate a broader range of application scenarios, expanding the design of personalized components to meet more diverse learning needs, and validating the universality and stability of the research findings across a larger user group.

6 ACKNOWLEDGMENT

This paper was supported by the 2022 key research project of school-level education and teaching reform (HKJGZD2022-07); the Hainan Provincial University Scientific Research Support Project (Hnkyzc2022-19); and the 2021 School-level Curriculum Reform Research Project of Hainan Vocational University of Science and Technology (EKKG2021-09).

7 REFERENCES

[1] C. Boel, T. Rotsaert, M. Valcke, Y. Rosseel, A. Vanhulsel, and T. Schellens, "Are students ready to be immersed? Acceptance of mobile immersive virtual reality by secondary education students," in *International Conference on Immersive Learning*, 2023, pp. 84–95. https://doi.org/10.1007/978-3-031-47328-9_6

[2] F. M. Zain, S. N. Sailin, M. Kasim, A. M. A. Karim, and N. N. Zameri, "Developing an Augmented Reality Immersive Learning Design (AILeaD) framework: A fuzzy delphi approach," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 16, no. 11, pp. 65–90, 2022. https://doi.org/10.3991/ijim.v16i11.30063

[3] H. Herwin, L. D. Prasojo, B. Saptono, and S. C. Dahalan, "Analyzing the impact of augmented reality on student motivation: A time series study in elementary education," *Ingénierie des Systèmes d'Information,* vol. 28, no. 5, pp. 1197–1203, 2023. https://doi.org/10.18280/isi.280507

[4] J. Ma, Y. Wang, S. Joshi, H. Wang, C. Young, A. Pervez, Y. Qu, and S. Washburn, "Using immersive virtual reality technology to enhance nursing education: A comparative pilot study to understand efficacy and effectiveness," *Applied Ergonomics,* vol. 115, p. 104159, 2024. https://doi.org/10.1016/j.apergo.2023.104159

[5] U. Cahyana, J. R. Luhukay, I. Lestari, I. Irwanto, and J. S. Suroso, "Improving students' literacy and numeracy using mobile game-based learning with augmented reality in chemistry and biology," *International Journal of Interactive Mobile Technologies (iJIM),* vol. 17, no. 16, pp. 4–15, 2023. https://doi.org/10.3991/ijim.v17i16.42377

[6] Rukayah, J. Daryanto, I. R. W. Atmojo, R. Ardiansyah, D. Y. Saputri, and M. Salimi, "Augmented reality media development in STEAM learning in elementary schools," *Ingénierie des Systèmes d'Information,* vol. 27, no. 3, pp. 463–471, 2022. https://doi.org/10.18280/isi.270313

[7] L. Zhang and D. A. Bowman, "Exploring effect of level of storytelling richness on science learning in interactive and immersive virtual reality," in *Proceedings of the 2022 ACM International Conference on Interactive Media Experiences,* 2022, pp. 19–32. https://doi.org/10.1145/3505284.3529960

[8] Septinaningrum, K. A. Hakam, W. Setiawan, and M. Agustin, "Developing of augmented reality media containing Grebeg Pancasila for character learning in elementary school," *Ingénierie des Systèmes d'Information,* vol. 27, no. 2, pp. 243–253, 2022. https://doi.org/10.18280/isi.270208

[9] A. Marougkas, C. Troussas, A. Krouska, and C. Sgouropoulou, "How personalized and effective is immersive virtual reality in education? A systematic literature review for the last decade," *Multimedia Tools and Applications,* vol. 83, no. 6, pp. 18185–18233, 2024. https://doi.org/10.1007/s11042-023-15986-7

[10] M. Peng, "Evaluation and analysis of the implementation effects in practical-course blended learning based on virtual reality technology," *International Journal of Emerging Technologies in Learning,* vol. 18, no. 15, pp. 94–108, 2023. https://doi.org/10.3991/ijet.v18i15.42379

[11] Y. Lin, Y. Lan, and S. Wang, "A novel method for improving the perceptual learning effect in virtual reality interaction," *Multimedia Tools and Applications,* vol. 81, no. 15, pp. 21385–21416, 2022. https://doi.org/10.1007/s11042-022-12542-7

[12] I. Miguel-Alonso, D. Checa, H. Guillen-Sanz, and A. Bustillo, "Evaluation of the novelty effect in immersive virtual reality learning experiences," *Virtual Reality,* vol. 28, no. 1, p. 27, 2024. https://doi.org/10.1007/s10055-023-00926-5

[13] H. Wang, M. He, C. Zeng, L. Qian, J. Wang, and W. Pan, "Analysis of learning behavior in immersive virtual reality," *Journal of Intelligent and Fuzzy Systems*, vol. 45, no. 4, pp. 5927–5938, 2023. https://doi.org/10.3233/JIFS-231383

[14] M. C. Moruzzi, S. Santhosh, M. Corsi, S. Bagassi, and F. De Crescenzio, "Design and implementation of eye tracking application for generation of augmented reality content on spatial see through display of Remote and Virtual Control Tower (RVT)," *International Journal on Interactive Design and Manufacturing (IJIDeM),* vol. 17, no. 4, pp. 1859–1867, 2023. https://doi.org/10.1007/s12008-023-01288-7

[15] Y. Liu and J. Li, "Measures for the integration of digital media art and film and animation creation based on virtual reality technology," *Applied Mathematics and Nonlinear Sciences,* vol. 9, no. 1, pp. 1–19, 2023. https://doi.org/10.2478/amns.2023.2.01565

[16] L. Raya, J. J. Ruiz, M. Fabian, A. Ron, J. Garcia, and C. Verdú, "Development of a virtual reality tool for the treatment of pediatric patients in the ICU," *IEEE Computer Graphics and Applications,* vol. 43, no. 2, pp. 69–77, 2023. https://doi.org/10.1109/MCG.2023.3239676

8 AUTHORS

Weifeng Deng, Hainan Vocational University of Science and Technology, Haikou 571126, China.

Lin Wang, Hainan Vocational University of Science and Technology, Haikou 571126, China (E-mail: wanglintaichi@163.com).

Xue Deng, Hebei Vocational University of Technology and Engineering, Xingtai 054000, China.