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iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 18 No. 13 (2024) | OPEN ACCESS

https://doi.org/10.3991/ijim.v18i13.50249

PAPER

Design and Experimental Study of Interactive Experiences in Architectural Heritage Education Based on Mobile Augmented Reality Technology

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ABSTRACT

As globalization accelerates and technology advances, the education and transmission of architectural heritage face new challenges and opportunities. Mobile augmented reality (MAR) technology offers innovative means for presenting and educating about architectural heritage, enhancing user experiences and interactivity through the overlay of virtual information. This study explores the application of MAR in architectural heritage education, examining its potential to enhance educational outcomes, increase user engagement, and foster awareness of heritage conservation. While the technology has been widely explored in other educational fields, its application in architectural heritage remains insufficient, particularly in the design of collaborative tasks, assessment of user satisfaction, and implementation of incentive mechanisms. This paper encompasses three research components: a detailed description of collaborative tasks in architectural heritage education using MAR, the development of a satisfaction model to evaluate the effectiveness of these tasks, and the construction of an educational collaboration incentive mechanism. Through this study, the paper not only enriches the application of MAR in cultural heritage conservation but also provides theoretical and empirical support for future related studies.

KEYWORDS

mobile augmented reality (MAR) technology, architectural heritage, educational collaboration, user satisfaction, incentive mechanisms

1 INTRODUCTION

In today's era of rapid globalization and technological advancement, the preservation and inheritance of traditional architectural heritage face unprecedented challenges and opportunities. Architectural heritage not only carries rich historical and cultural values but is also an important resource for education and research [1–4]. With the development of mobile augmented reality (MAR) technology,

Zhong, J., Peng, Z. (2024). Design and Experimental Study of Interactive Experiences in Architectural Heritage Education Based on Mobile Augmented Reality Technology. *International Journal of Interactive Mobile Technologies (iJIM)*, 18(13), pp. 96–111. https://doi.org/10.3991/ijim.v18i13.50249

Article submitted 2024-03-25. Revision uploaded 2024-05-20. Final acceptance 2024-05-25.

this emerging technology provides new perspectives and methods for architectural heritage education, allowing the public to experience and learn about these valuable cultural heritages in entirely new interactive ways [5–7].

The significance of this study lies in exploring the potential applications of MAR technology in the field of architectural heritage education, particularly its role in enhancing learning motivation, improving educational experiences, and promoting heritage conservation awareness [8–10]. By introducing this technology, it cannot only make educational experiences more enjoyable and interactive but may also change the public's perception of architectural heritage, thereby enhancing public support and participation in cultural heritage conservation [11–14].

However, despite the application of MAR technology in the field of education, its use in architectural heritage education still has some obvious flaws and deficiencies [5, 6]. Most existing research focuses on technical implementation, with little consideration given to the depth and breadth of educational content, and how to effectively motivate user participation and increase satisfaction [8, 9, 11, 12]. In addition, current research lacks specific discussions on the design of collaborative tasks, which limits the potential of augmented reality technology in group educational interactions [13–15].

This study aims to fill these gaps through three main research contents: firstly, a detailed description of collaborative tasks in architectural heritage education based on MAR, exploring how technology can serve the deep transmission of educational content and learners' interactive participation; secondly, the development of a satisfaction evaluation model to quantify educational effectiveness and user engagement for architectural heritage education collaborative tasks; and lastly, designing an effective educational collaboration incentive mechanism aimed at increasing participants' enthusiasm and learning outcomes. These studies not only help optimize the methods of educating about architectural heritage but also provide an empirical foundation and theoretical support for the application of MAR technology.

2 DESCRIPTION OF COLLABORATIVE TASKS IN ARCHITECTURAL HERITAGE EDUCATION BASED ON MOBILE AUGMENTED REALITY

In architectural heritage education that utilizes MAR technology, the assignment of collaborative tasks is particularly crucial, as it directly impacts the quality and efficiency of the educational experience. Collaborative tasks in architectural heritage education have their own uniqueness in design and implementation. First, MAR provides users with an immersive interactive experience, making the tasks not just about the transmission of information but about deep cultural and historical education. Second, when implementing such tasks, it is not only necessary to consider the efficiency of information transmission but also the accuracy of educational content and the coherence of the interactive experience. In this scenario, the issue of task allocation for educational collaboration involves how to effectively organize and manage multiple task executors to ensure that each participant achieves satisfactory educational outcomes within the allotted time. This requires the task publisher not only to ensure the efficiency of task distribution but also to guarantee the quality of education and participation. Therefore, unlike the primary goal of mobile social network-based crowdsourcing, which is to minimize task completion time or cost, task allocation in architectural heritage education emphasizes the educational experience of participants and the quality of task completion.

Regarding specific task allocation strategies, it is first necessary to define the complexity of the task and the type of collaboration required. For example, some educational tasks may require participants to use augmented reality at a specific architectural site to explore historical information, which might involve multiple collaborators solving a puzzle about the building's history or completing a challenge. In such cases, the success of the task depends not only on its completion by individual users but also on the collective effort and interaction of a group of users. Therefore, the task allocation strategy should consider the geographical location of users, their historical knowledge background, and their familiarity with augmented reality technology. Next, for each task, a success rate threshold must be set, which is the minimum rate of successful completion of the task. This is similar to traditional crowdsourcing, but in architectural heritage education, this success rate is not just a technical standard for task completion but also a reflection of educational effectiveness. For example, a successful educational collaborative task not only requires the task to be correctly completed but also requires participants to learn knowledge through the task and experience the charm of the culture. Moreover, to ensure the efficiency and quality of educational tasks, task allocation should also consider the feedback and interaction of task executors. This requires the system to be able to monitor the task execution and participants' interactions in real-time, making timely adjustments to task allocation strategies or providing necessary assistance. For example, if a group of users encounters difficulties in completing a task, the system can provide additional information or hints immediately or dynamically adjust the tasks of other user groups to ensure the smooth progress of the overall educational activity. Figure 1 shows a schematic diagram of the architectural heritage education collaborative task allocation system. Figure 2 presents the framework of the architectural heritage education collaborative task allocation system.

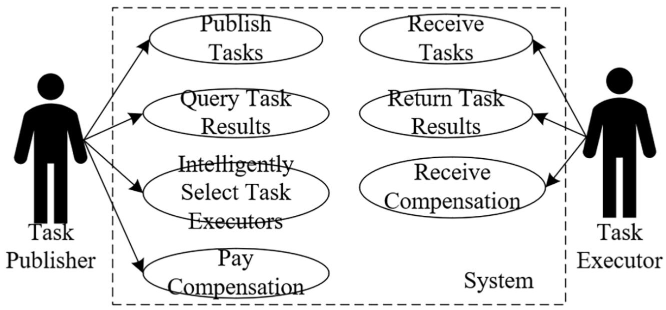

Fig. 1. Schematic diagram of the architectural heritage education collaborative task allocation system

We can envision a network comprising $v + 1$ users, represented by the mathematical set $I = \{i_0, i_1, i_2, i_3, ..., i_v\}$, where i_0 acts as the task publisher, responsible for designing and distributing educational tasks, while the set $\bar{I} = I - \{i_0\}$ contains the remaining v users as potential task executors. In this educational collaborative environment, the publication and execution of tasks depend not only on technological support but also on user interaction and collaboration. Each potential task executor possesses a user credibility value, represented by $\gamma = \{\gamma_1, \gamma_2, \gamma_3, ..., \gamma_v\}$, which reflects the probability of successfully completing tasks and returning valid results. This parameter is closely related to users' historical performance on tasks and is crucial for ensuring the reliability and effectiveness of task allocation. Additionally, considering the variability and interactivity of user locations in a mobile augmented reality environment, we introduce the user encounter index, represented by $\eta = \{\eta_1, \eta_2, \eta_3, ..., \eta_v\}$. This parameter maps the potential future encounters between the task publisher and potential task executors, where η_u represents the encounter probability between user i_0 and i_u, based on users' mobility patterns and location frequency. Unlike traditional mobile social network models, task allocation in architectural heritage education must also consider the transmission of educational content and the design of interactive experiences. Therefore, user credibility values and encounter indices must evaluate not only the efficiency of task completion but also the quality of educational content delivery and participants' educational experience. In practice, this means augmented reality applications must be able to adjust educational tasks in real-time to adapt to users' geographic locations, mobility trajectories, and interactive behaviors, thereby maximizing educational effectiveness and user engagement.

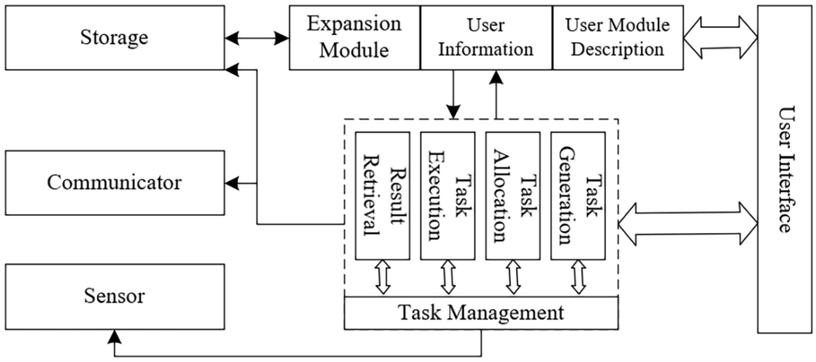

Fig. 2. Framework of the architectural heritage education collaborative task allocation system

In architectural heritage education based on MAR technology, task allocation strategies must consider not only the efficiency and reliability of task completion but also the depth of educational content and participants' educational experiences. When the task publisher i_0 encounters other potential task executors i_u, a predefined list of tasks is provided to i_u to select from, choosing tasks that are of interest and achievable. The tasks selected by i_u form an interested task list, which is sent back to i_0. Based on certain strategies and optimization goals, i_0 decides whether to assign one or some of the tasks to i_u for completion. Mathematically describing this process, we define the interested task list as the set $M = \{m_1, m_2, m_3, \ldots, m_l\}$, where each task mu has a defined minimum success rate threshold $\tau = \{\tau_1, \tau_2, \tau_3, \ldots, \tau_l\}$. These thresholds represent the lowest acceptable probability of each task being successfully completed, ensuring the quality and effectiveness of the educational activity. Each task also has a final validity time $S = \{s_1, s_2, s_3, \ldots, s_l\}$, corresponding to the deadline of each task, to ensure the timeliness and relevance of the educational content. Furthermore, considering the specificity and interactivity of educational tasks, task allocation is not only based on individual users' capabilities and interests but is also a team collaboration process. Thus, for each task m_u, we envision assigning it to a user group T_k, where members can collaborate with each other to complete the task, enhancing the quality of task completion and participants' interactive experience. The formation of each user group T_k is based on the members' potential for interaction, common interests, familiarity with augmented reality technology, and the availability of technical equipment.

Assuming the size of the user group collaborating to complete a task is represented by T_k, the historical task completion credibility of user i_u is represented by γ_u, and o_u represents the probability of task allocation to user i_u and their meeting with user i_0 before the task expires. The probability of user i_u alone successfully returning valid results is represented by θ_u, and $1 - \Pi_{iu \in Tk}(1 - \theta_u)$ represents the probability of successfully returning valid task results by group members before the task expires, with $(1 - \theta_u)$ representing the rate at which user i_u fails to return task results before expiration. The probability that none in the user group can return valid results is represented by $\Pi_{i_u \in T_k}(1 - \theta_u)$. The probability that at least one user in group T_k successfully returns valid task results before task m_k expires is represented by $1 - \Pi_{i_u \in T_k}(1 - \theta_u)$. The mathematical definition of the problem is as follows:

$$\begin{aligned}
&MINM \quad \left|T_k\right|; TH \\
&MAXM \quad 1-\prod\nolimits_{i_u \in T_k}(1-\theta_u) \\
&t.s. \quad 1-\prod\nolimits_{i_u \in T_k}(1-\theta_u) \geq \tau_k; \\
&\theta_u = \gamma_u \cdot o_u; \\
&T_k = \bar{I}
\end{aligned} \tag{1}$$

3 CALCULATION OF SATISFACTION VALUES FOR COLLABORATIVE TASKS IN ARCHITECTURAL HERITAGE EDUCATION BASED ON MOBILE AUGMENTED REALITY

In the allocation of collaborative tasks for architectural heritage education using MAR technology, the effect useful degree (EUD) is a key metric for assessing the actual usefulness of task outcomes to the task publisher. Figure 3 shows the process of task allocation in architectural heritage education collaboration. In this scenario, EUD not only measures whether the results returned by task executors are effective but also involves the probability of task executors encountering the task publisher again in the augmented reality environment. This probability of encounter directly affects the timeliness and accuracy with which task results can be conveyed to the task publisher. For example, in an educational activity, participants might need to explore specific architectural elements using augmented reality devices and answer related questions, where the quality of task completion depends on the accuracy of the information they gather and their chances of meeting the educator again to exchange feedback. Therefore, the calculation of EUD not only considers the quality of the content submitted by the task executors but also the feasibility of these interactions in physical space and time. This includes considering the design of user paths in augmented reality applications, the layout of information trigger points, and their synergy with user behavior patterns. The formula is defined as follows:

$$\theta = \gamma * o \tag{2}$$

From the above formula, EUD relates to two factors: first, the probability γ of generating effective results, i.e., the quality of the task results completed by the user; and second, the probability o that after the task is assigned to a user, the user successfully returns the task results, i.e., the physical probability that the user can meet the task publisher again and submit the results. However, the EUD value of a single user may not meet the minimum success rate threshold required by the educational task. In this case, we need to consider the joint effective result probability task union-useful degree (TUD) value when multiple users collaborate to complete a task. The TUD value considers the composite probability of a group of users assigned a task collaborating to complete it and successfully returning effective results. This involves the dynamics of collective collaboration, including user interactions, synergistic effects, and technological support. In architectural heritage education tasks using MAR, this type of collaboration is particularly important, as each participant may be interested in different parts of a building, and through the power of the group, they can more comprehensively explore and learn about various aspects of architectural heritage. For example, a task may require participants to explore multiple points around an ancient building and obtain different historical information through augmented reality technology. In this case, the TUD value of a user group will depend on the EUD values of each member within the group and the effectiveness of their collaboration.

In collaborative tasks for architectural heritage education based on MAR, understanding and predicting future encounters and the corresponding calculation of EUD values are crucial for ensuring the effective execution of educational tasks. This calculation process differs from traditional mobile social network-based crowd computing task allocation, primarily in terms of participant interaction methods and technological application. In an augmented reality environment, encounters between the task publisher and task executors are not just physical contacts but are more often facilitated through interactive features in augmented reality technology. This technology makes "encounters" between users more frequent and purposeful, enhancing the interactivity and immersion of education. The calculation of EUD values is particularly important here, as it not only reflects the probability of users completing specific educational tasks and returning valid results but also involves how augmented reality technology facilitates effective interaction among users. EUD values consist of two parts: one part is the effective task completion rate predicted based on past experiences and historical behavior, and the other part is the probability of users encountering and interacting through augmented reality technology. This probability of encounter depends not only on users' physical movement patterns but also significantly on how augmented reality application designs guide users to specific locations to perform specific tasks.

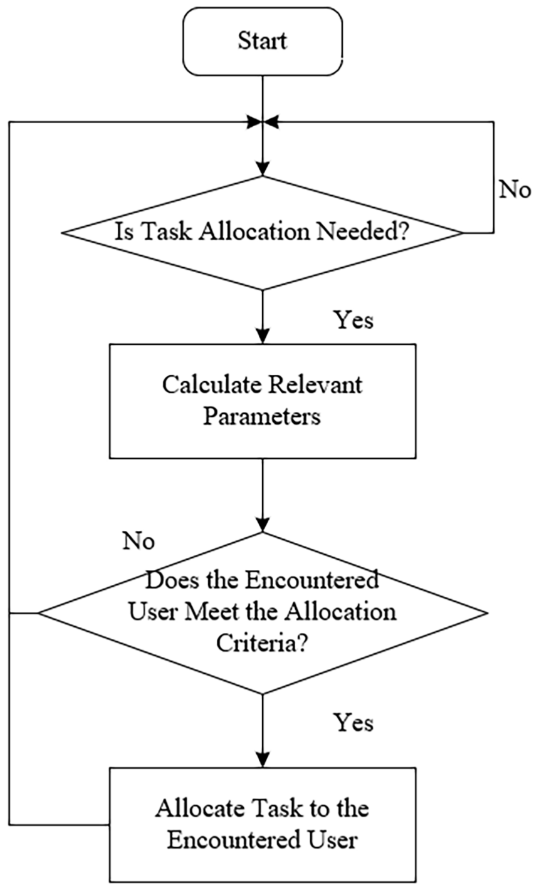

Fig. 3. Process of task allocation in architectural heritage education collaboration

In this scenario, we assume that task publisher i_0 encounters user i_u at a certain point in time and may assign task m_k to that user. Task m_k has a definite final validity time s_k, which is usually much longer than the expected completion time of the task, to give users enough time to complete the task in the augmented reality environment. This setting is based on recognizing that in augmented reality applications, users' movement and interaction patterns are more complex and may involve multiple points of participation and interaction, thus requiring a longer time window to ensure task completion. Additionally, predicting the probability of future encounters is particularly important in architectural heritage education, as these encounters depend not only on users' physical movement but also on the design of augmented reality applications, such as the attractiveness of specific exhibits or the setup of interaction points. This model of encounters can follow an exponential distribution, as although participant visits might be random, each visit point could become an opportunity for future encounters. Assuming the final validity deadline of task m_k is represented by s_k, the current time by i_0, and η as the encounter index parameter between i_0 and i_u, o_u as the probability of i_0 encountering i_u again in the future, then i_u is given by the following formula:

$$o_u = \int_0^{s_k - s_0} \eta_u \cdot r^{-\eta_u} fs = 1 - r^{-\eta_u \cdot (s_k - s_0)} \tag{3}$$

Assuming the updated user history credibility value after i_u encounters i_0 is represented by γ_u, and if task m_k is assigned to user i_u, the EUD value when user i_u completes the task alone is represented by θ_u, based on the above formula, the calculated EUD value is:

$$\theta_u = \gamma_u * o_u = \gamma_u * (1 - r^{-\eta_u \cdot (s_k - s_0)}) \tag{4}$$

4 INCENTIVE MECHANISMS FOR ARCHITECTURAL HERITAGE EDUCATION BASED ON MOBILE AUGMENTED REALITY

In architectural heritage education based on MAR technology, the design of incentive mechanisms takes into account how two different payment methods affect users' task completion. If the task publisher pays in advance at the time of task allocation, this prepaid method can significantly enhance user engagement and the quality of task completion. In the context of architectural heritage education, this means that participants might be more actively using augmented reality devices to explore relevant content, knowing that their efforts are already rewarded regardless of the outcome. This payment method is particularly suitable for well-designed augmented reality applications that can attract deep user involvement. On the other hand, a post-payment method, which pays rewards after task completion, although possibly less motivating, provides a cost-control strategy for task publishers, especially when the enthusiasm and quality of user task completion are difficult to guarantee. In augmented reality applications, this means that rewards are given only when users genuinely complete tasks according to educational goals and provide valuable feedback.

The design of incentive mechanisms in architectural heritage education using MAR technology also needs to understand and apply user credibility and the probability of encounters. In this setting, the task allocation system adopts an incentive scheme based on user credibility, which considers not only users' historical task completion rates but is closely linked to their behavioral performance in the augmented reality environment. Credibility is divided into the recent average minimum credibility $\varepsilon 0$ and average maximum credibility ε, reflecting the reliability and quality of task completion by users in different situations. Additionally, the incentive mechanism relies on the probability of encounters, a particular focus of augmented reality technology, as users must meet the task publisher at specific locations and times to receive and submit tasks. To optimize costs and efficiency, the system calculates the overall cost based on the average probability of encounters and credibility of user group members, which helps determine the optimal payment strategy under specific incentive mechanisms. If full payment *c* is made at the first encounter between users and the task publisher, this usually inspires greater user participation and enthusiasm for completing tasks. However, this upfront payment model requires the system to accurately assess user credibility and encounter probability to avoid overpayment and resource waste. The payment proportion coefficient is shown in the following formula:

$$a = \frac{z'}{z} \tag{5}$$

Assuming the average probability of encounters between users and the task publisher is o, and the task group consists of j members, the total actual compensation paid can be calculated through the following formula:

$$Z(j,o,a) = jaz + jo(z - az) \tag{6}$$

This paper adopts the following two payment schemes:

1. A strategy of prepaying the full amount at the first encounter between the user and the task publisher. This method can greatly enhance the user's initial participation and enthusiasm for completing the task. In an augmented reality environment, this means that users receive clear incentives at the beginning of their experience, which can increase their motivation to immerse themselves in the task and learning, especially when exploring specific architectural heritage and cultural content.
2. In contrast, a post-payment strategy pays compensation only after the task is completed and verified. While this method can reduce economic losses from unfinished tasks, it may not sufficiently stimulate initial user engagement. In applications of architectural heritage education, this could lead to uneven user experiences, especially if the task completion and verification process is complex or lengthy.

The analysis of the two schemes is as follows:

Assuming the user's recent average minimum credibility is γ_0, and the average maximum credibility is γ_1, with the payment ratio as a, the following formula gives the calculation for the user's actual credibility at the time of receiving the task:

$$\gamma = \gamma_0 + a * (\gamma_1 - \gamma_0) \tag{7}$$

The formula for calculating the average *EUD* value of the user is:

$$\theta = \gamma \cdot o = (\gamma_0 + a(\gamma_1 - \gamma_0))o \tag{8}$$

Assuming the minimum threshold for the task to successfully return valid results is represented by τ, and the average *EUD* value of the user group is represented by θ, then the inequalities are as follows:

$$1 - (1 - \theta)^j \geq \tau \tag{9}$$

$$j \geq \log(1 - \tau)/\log(1 - \theta) \tag{10}$$

The value of j is given by log(1 − τ)/log(1 − θ), where τ is a fixed value, hence we can assume X's value as LOG(1 − τ), and thus further calculate j based on the following formula:

$$j = X/\log(1-\gamma_0 o - a(\gamma_1 - \gamma_0)o) \tag{11}$$

For the first payment scheme, the total actual compensation paid can be calculated through the following formula:

$$Z(j, o, 1) = jz = Xz/\log(1-\gamma_1 o) \tag{12}$$

Similarly, for the second payment method, the total actual compensation paid is:

$$Z(j, o', 0) = jzo' = Xzo'/\log(1-\gamma_0 o') \tag{13}$$

$$Z(j,o,1) - Z(j,o',1) = Xz/\log(1-\gamma_1 o) - Xzo'/\log(1-\gamma_0 o') \tag{14}$$

Since γ_1, γ_0, o, and o' are all values less than 1, when $o < \gamma_1$, $o' < \gamma_0$, the impact of the encounter probability will be greater than the impact of credibility:

$$1-\gamma_1 o \approx 1-\gamma_0 o' \tag{15}$$

$$\log\left(1-\gamma_1 o\right) \approx \log\left(1-\gamma_o o'\right) \tag{16}$$

From the above analysis, it is clear that the value of $Z(j, o, 1)$ is greater than the value of $Z(j, o, 0)$.

When the average probability of encounters among the user group is relatively high, with $\gamma_1 o > \gamma_0 o'$, then there are:

$$\frac{1-\gamma_0 o'}{(1-\gamma_1 o)^{o'}} \geq \frac{1-\gamma_0 o'}{1-\gamma_1 o} \geq 1 \tag{17}$$

$$\because X < 0$$
$$\therefore Xz * \log\frac{1-\gamma_0 o}{(1-\gamma_1 o)^{o}} \leq 0 \tag{18}$$

$$\because \log(1-\gamma_0 o) \leq 0, \log(1-\gamma_1 o) \leq 0 \tag{19}$$

$$\therefore \frac{Xz * \log\dfrac{1-\gamma_0 o'}{(1-\gamma_1)o'}}{\log(1-\gamma_0 o') * \log(1-\gamma_1 o)} \leq 0 \tag{20}$$

$$\therefore Z(j, o, 1) - Z(j, o, 0) \leq 0 \tag{21}$$

It can be concluded that when the value of o is much lower than γ_0, Scheme 2 is better; when the value of o is close to or exceeds γ_0, Scheme 1 is better.

5 EXPERIMENTAL RESULTS AND ANALYSIS

According to the data provided in Figure 4, it can be observed that under different task deadlines, three different task allocation methods (based on EUD, based on encounters, and the method proposed in this paper) show varying performances in terms of average number of users in groups and TUD values. From the perspective of the average number of users in groups, as the task deadlines extend, the average number of users required by the methods based on EUD and encounters gradually decreases, possibly because a longer deadline allows the task publisher to select from a larger pool of users, thus optimizing the allocation strategy. In contrast, the proposed method maintains a consistently lower average number of users across all time periods (from 1.8 to 1.2), indicating significant improvements in user utilization efficiency. From the standpoint of TUD values, the proposed method consistently shows higher TUD values (from 0.951 to 0.961) compared to the method based on EUD (0.939 to 0.949) and the method based on encounters (0.942 to 0.95), suggesting that the proposed method performs better in ensuring the effectiveness of task outcomes. The increase in TUD values reflects high satisfaction and success rates of task results, implying that the method not only improves user utilization efficiency but also ensures the quality and satisfaction of task allocation.

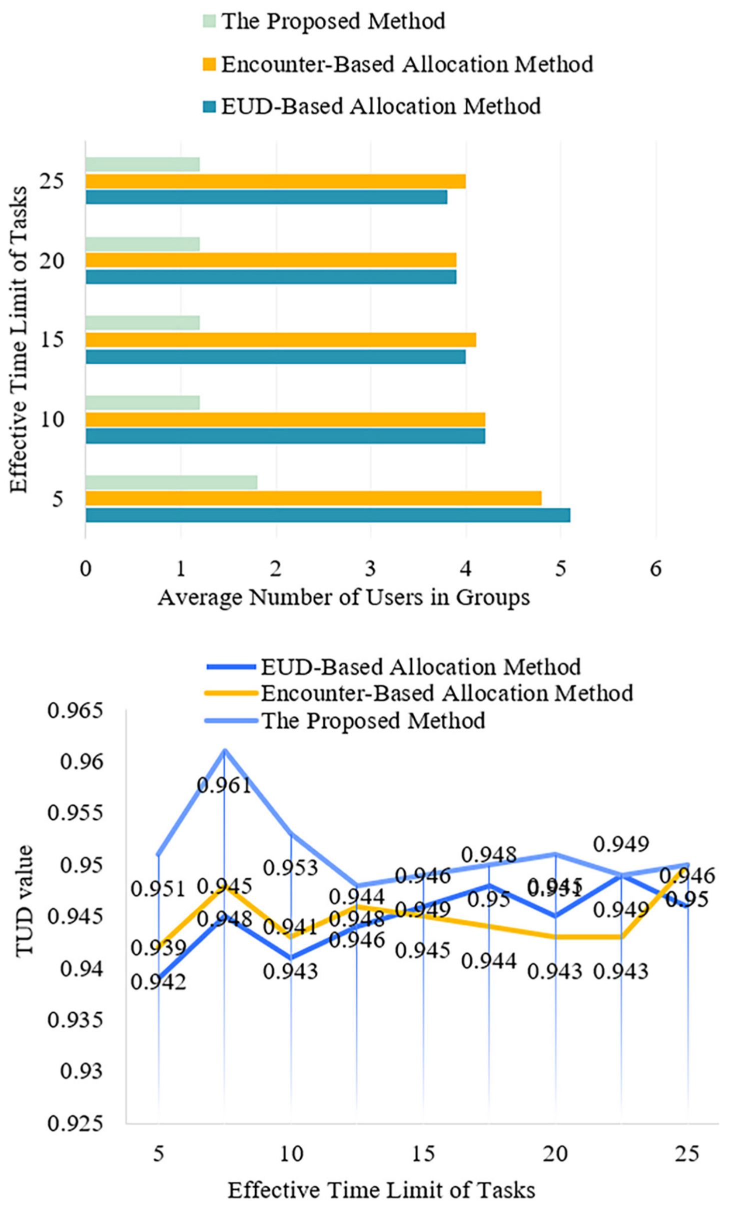

Fig. 4. Average number of users and TUD values for different task deadlines

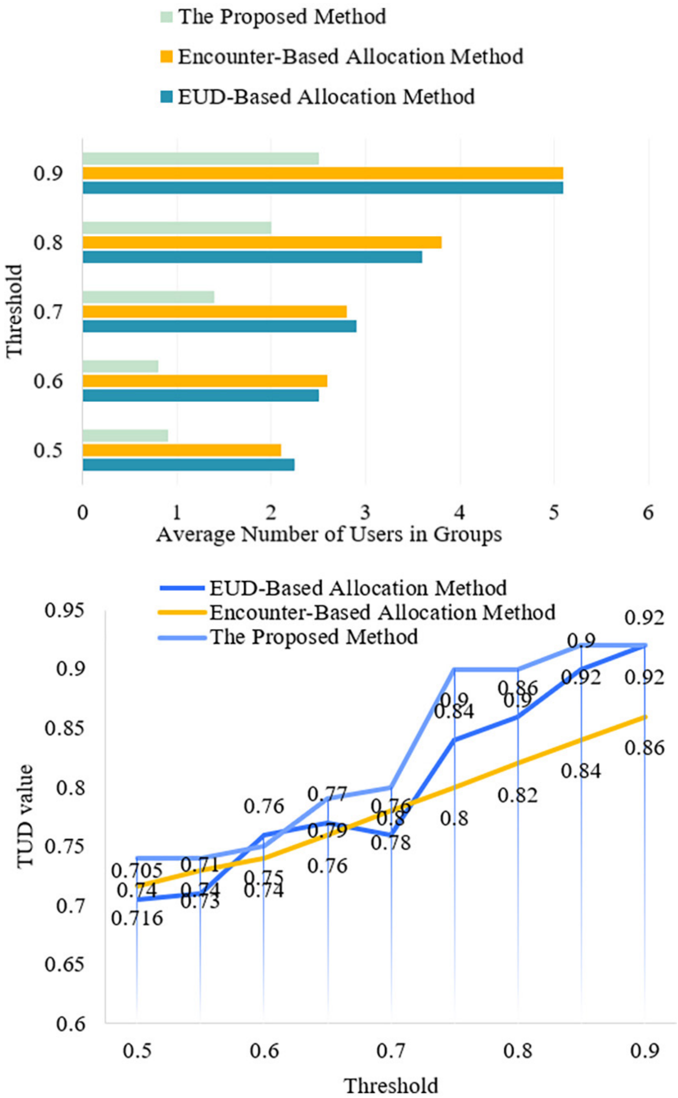

Fig. 5. Average number of users and TUD values under different thresholds

According to the data provided in Figure 5, it can be observed that under different thresholds for successfully returning valid task results, the three different task allocation methods—based on EUD, based on encounters, and the proposed method—show varied performances in terms of average number of users in groups and TUD values. For the average number of users in groups, as the success thresholds increase, the average number of users required by the methods based on EUD and encounters gradually increases, indicating that a higher threshold requires more users to meet more stringent task completion standards. The proposed method shows a lower demand for users across all threshold settings, particularly under low threshold conditions (0.5–0.7), significantly below the other two methods, indicating that the proposed method is more efficient in user resource allocation. In terms of TUD values, the proposed method demonstrates stable and high task result satisfaction across all threshold conditions, particularly under high threshold conditions (0.8–0.9), where TUD values reach 0.92. Compared to other methods under the same thresholds, the method not only maintains higher satisfaction but also uses user resources more economically. This indicates that the method not only effectively enhances task result satisfaction but also optimizes resource allocation, reducing unnecessary user involvement.

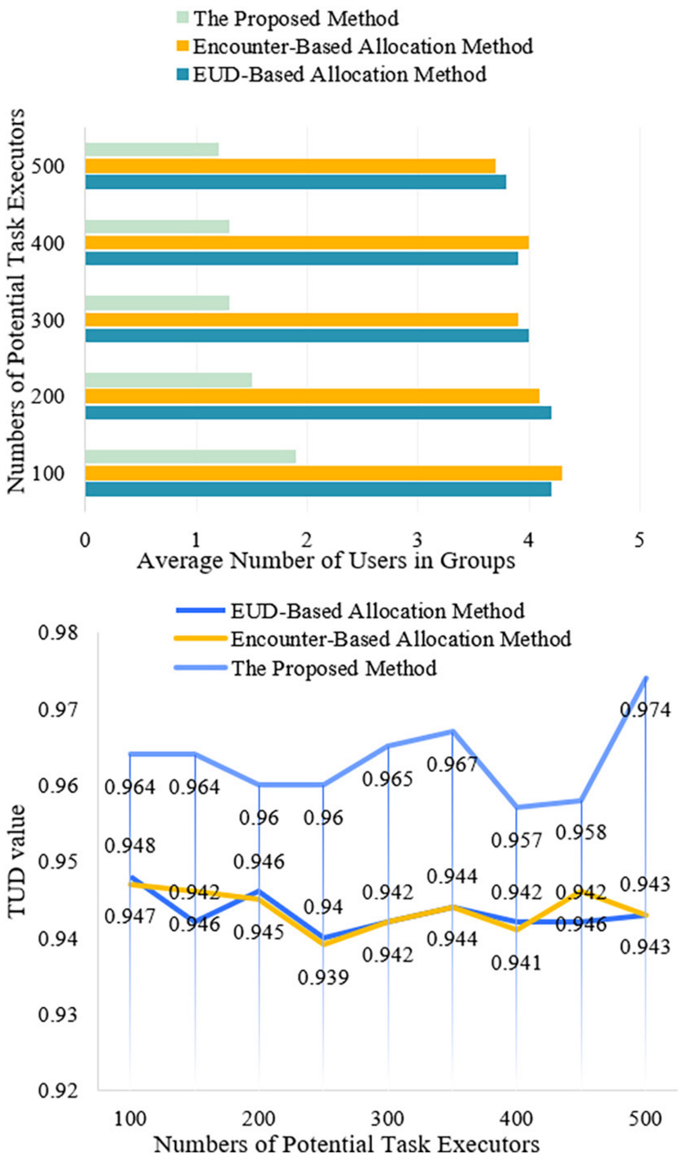

Fig. 6. Average number of users and TUD values under different numbers of potential task executors

Analysis of the data in Figure 6 shows that as the number of potential task executors increases, the average number of users in groups for the three task allocation methods shows corresponding trends. For the methods based on EUD and encounters, the average number of users in groups slightly decreases with an increase in potential executors, suggesting that with more potential executors participating, the task publisher has more options and can more precisely select suitable task executors, thereby reducing the average number of users. Particularly with the proposed method, this effect is especially pronounced, with the average number of users decreasing from 1.9 when there are 100 potential executors to 1.2 when there are 500, showing a clear advantage of the proposed method in enhancing user selection efficiency. From the perspective of TUD values, the proposed method maintains higher TUD values than the other two methods across all levels of potential task executors, reaching the highest at 0.974 with 500 potential executors. This reflects the significant effect of the method On enhancing task satisfaction. In contrast, although the TUD values of the methods based on EUD and encounters are stable, they are lower than those of the proposed method, indicating that while these methods can adapt to a larger pool of executors, there is still room for improvement in the satisfaction of task outcomes.

From the data provided in Figure 7, it is evident that under varying task quantities, the three different task allocation methods exhibit distinct characteristics. In terms of average group size, the methods based on EUD and encounters show relatively higher and less variable numbers of users, ranging from 3.5 to 4.1. This indicates that these methods require a larger number of users to meet the demands of the tasks. However, the proposed method shows a significantly lower average number of users, especially as the number of tasks increases. The number of users required not only remains low but even shows a downward trend (from 1.5 to 0.8), indicating that the proposed method is highly efficient in user utilization. It can maintain or even reduce the required user resources while increasing task quantity, significantly improving task allocation efficiency. From the perspective of TUD values, the proposed method also demonstrates superior performance across all task quantity levels. Despite an increase in task quantity from 200 to 1000, the TUD values consistently remain above 0.942, peaking at 0.974 when the task quantity is 800, showcasing its stability and advantage in ensuring task result quality. In contrast, although the methods based on EUD and encounters also exhibit high TUD values, they fluctuate more and are occasionally lower than the method proposed in this paper.

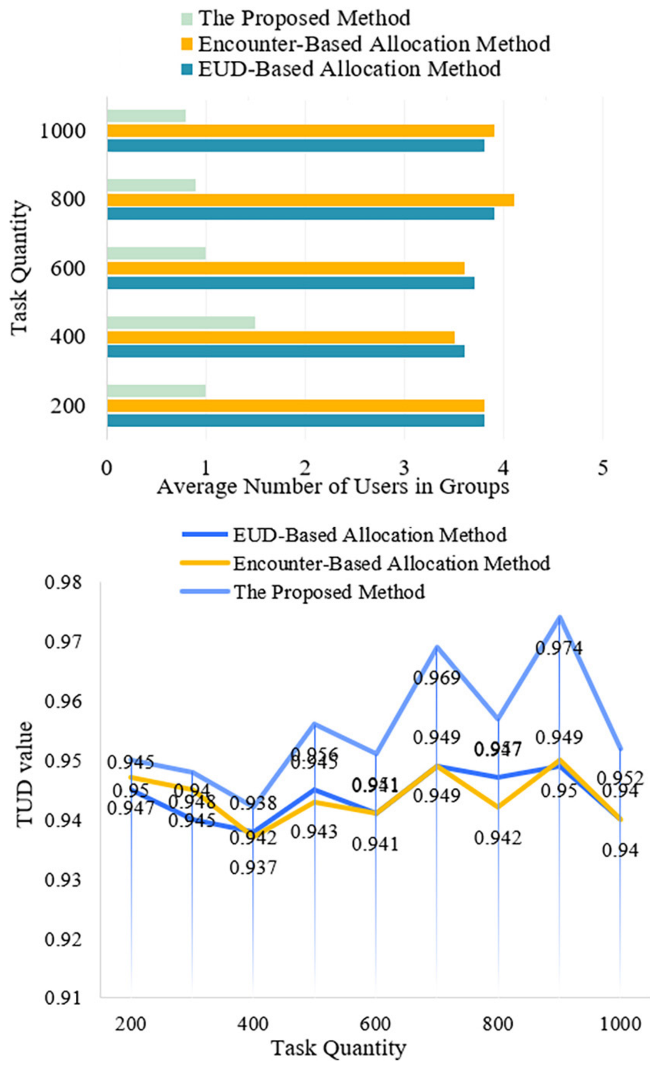

Fig. 7. Average number of users and TUD values under different task quantities

The data from Figure 8 show that different effective time limits and task thresholds significantly impact the total costs for Schemes 1 and 2. In terms of effective time limits, the total costs for Scheme 1 significantly decrease as time increases, dropping from 405 to 80. This indicates that Scheme 1 can more effectively reduce costs over extended periods. In contrast, scheme 2 starts with higher costs in the initial phase (280) and then tends to stabilize (around 170) as the task duration extends, showing that Scheme 2's cost control is relatively stable and less affected by extended time. In the analysis of task thresholds, the costs for Schemes 1 and 2 show different trends as the task thresholds increase. Scheme 1 has lower costs at lower thresholds (68), but sees costs sharply increase to 135 as the threshold increases to 0.9, indicating that the costs of Scheme 1 rapidly rise under higher quality demands. Scheme 2 starts with higher costs at lower thresholds (75) and gradually increases to 220 as the threshold rises, exhibiting a steady but continuous growth in costs. This shows that although Scheme 2's costs increase with higher threshold demands, the overall control remains balanced.

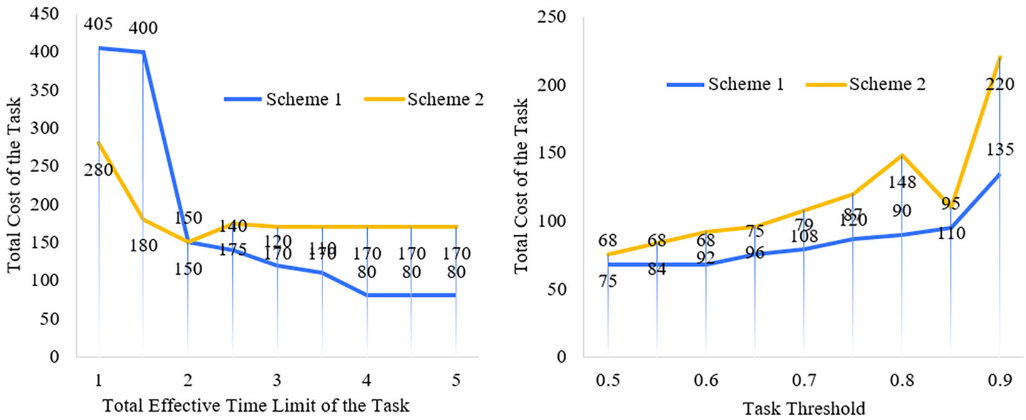

Fig. 8. Total costs under different effective time limits and task thresholds

6 CONCLUSION

This study, through a comprehensive analysis of data across multiple dimensions, systematically presents the various metrics and performances of collaborative tasks in architectural heritage education based on MAR. The research primarily includes the effects of factors such as effective time limits of tasks, task thresholds, the number of potential task executors, and the quantity of tasks allocated on the efficiency and effectiveness of task distribution.

Firstly, the analysis of total costs under different task effective time limits and task thresholds found that tasks with longer time limits help reduce total costs, while costs increase under high threshold conditions, indicating the importance of time management and quality control in resource allocation. Secondly, by analyzing the impact of different thresholds, potential executor numbers, and task quantities on the average number of users in groups and TUD values, the paper reveals optimization pathways for user resource allocation, task satisfaction, and educational outcomes. In particular, the method presented in this paper excels in reducing the required number of users and improving task satisfaction (TUD values), confirming its efficiency and practicality in real-world applications.

These experimental results emphasize the research value of collaborative tasks in architectural heritage education based on mobile augmented reality technology, not only because it enhances the economy and efficiency of task execution but also because it enriches the quality and engagement of educational experiences through precise user and task management. However, the study also has limitations, such as potential biases in experimental condition controls, sample size, and diversity, which might affect the universality and applicability of the results.

7 ACKNOWLEDGEMENTS

The study was supported by the Quality Engineering Project "Special topics 4 of Architectural Design" in Anhui Province (Grant No.: 2023szsfkc0293); the Key projects of humanities and social sciences in University of Anhui Province (Grant No.: SK2020A0464); the Key Research Projects of Social Science Innovation and Development in Anhui province (Grant No.: 2023CX104).

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