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PAPER

Revolutionizing Higher Education Teaching Evaluation with Interactive Mobile and Mixed Reality: A Methodological and Applied Analysis

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ABSTRACT

In higher education, it is imperative to maintain educational quality, which requires necessitates a thorough evaluation of teaching methods. The advent of mixed reality (MR) technology, combined with interactive mobile capabilities, introduces innovative possibilities for traditional educational assessment frameworks. This study is dedicated to investigating the application of MR and interactive mobile technologies in higher education teaching evaluations, with a focus on assessing their effectiveness and implementation outcomes. Research to date has explored MR's educational applications. However, the integration of interactive mobile technologies alongside MR in developing specific methodologies and evaluative tools for teaching evaluations has not been fully realized. This underutilizes the combined potential of these technologies. This paper is anchored in two principal research endeavors. Initially, it delves into the construction of a meta-model facilitated by MR-aided and interactive mobile-enhanced teacher-student interactions, utilizing a hierarchical remote interaction pyramid model. This process involves developing extensible associative functions, determining index weights, and establishing evaluation levels, which collectively enhance the evaluation's multidimensionality, interactivity, and scientific precision. Subsequently, the analytic hierarchy process (AHP) is employed to quantitatively assess the educational impact of MR and interactive mobile experiences on students. This approach provides support for customized and precise teaching evaluations. The findings reveal that integrating MR technology with interactive mobile capabilities significantly enhances the interactivity and systematic scientific approach of teaching evaluations. This fosters a more multidimensional and interactive framework for educational evaluation.

KEYWORDS

higher education, teaching evaluation, mixed reality (MR) technology, interactive mobile, meta-model, analytic hierarchy process (AHP)

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1 INTRODUCTION

In the realm of higher education, educational evaluation serves as a fundamental component of the quality assurance system, primarily tasked with supervising and encouraging the continuous advancement of educational and teaching methodologies [1–3]. The progression of educational technology, especially the emergence of mixed reality (MR) technology, has positioned it as a key driver of innovation within educational fields. The integration of MR technology, augmented with interactive mobile technologies, not only broadens the spectrum of teaching methodologies and content by combining virtual environments with real-life scenarios but also introduces innovative perspectives and tools for educational evaluation [4–6]. This amalgamation enhances the precision and interactivity of educational evaluations, marking a novel area of research within the educational technology landscape.

The integration of MR technology with interactive mobile technologies in higher education is widely acknowledged as crucial for improving the quality of teaching interaction and enhancing student learning experiences [7–9]. These technologies provide educators and learners with a collaborative virtual space, enabling teaching and learning environments that are more immersive and interactive, thereby facilitating a more engaging educational experience [10, 11]. Furthermore, the introduction of MR technology has led to transformative shifts in conventional educational evaluation methods, offering a more comprehensive capture of the various dimensions of teaching activities and resulting in more exhaustive and objective evaluation outcomes [12, 13].

Despite the promising applications of MR technology in conjunction with interactive mobile technologies in the educational sector, existing research identifies notable gaps in the methodologies and development of evaluation tools for educational assessment [14–16]. It has been observed that prevailing educational evaluation methods tend to oversimplify, inadequately capturing the complexities inherent in teaching activities. Moreover, the current design of evaluation tools has not fully exploited the potential of MR technology's interactive and immersive features, suggesting room for significant improvements in the precision and utility of the evaluation process and outcomes [17, 18].

This study is dedicated to investigating the utilization and influence of MR technology, augmented by interactive mobile technologies, in the realm of higher education teaching evaluations. The study initially focuses on creating a meta-model rooted in MR and mobile technology to facilitate teacher-student interactions. It utilizes a hierarchical remote interaction pyramid model to broaden the scope of educational evaluation. This approach aims to enhance the scientific validity and interactivity of teaching evaluations. Building upon this foundation, the study progresses to evaluate the educational and teaching impacts within MR-enhanced environments, employing the analytic hierarchy process (AHP) for a systematic and quantitative assessment of teaching activities. The outcomes of this investigation are expected to make a significant contribution to the enhancement of higher education evaluation theory and practice, equipping educators with sophisticated tools for evaluating teaching.

2 META-MODEL BASED ON MR TEACHER-STUDENT INTERACTION AND EXTENSIBLE EDUCATIONAL TEACHING EVALUATION

In the exploration of MR applications in education, a key scenario analyzed is remote laboratory learning, where teachers and students engage collaboratively in virtual laboratory operations across different physical locations using MR technology. The hierarchical remote interaction pyramid model serves as the basis for evaluating various aspects, including the immediacy of teacher guidance, the level of student participation, the quality of interactions, and the precision of operational tasks within virtual experiments. During a remote chemical experiment teaching session, students simulate experimental procedures in an MR environment. Meanwhile, teachers monitor the processes and outcomes remotely, offering real-time feedback. The evaluation conducted by this model is quantitative in nature, assessing both the efficiency and effectiveness of these interactive processes to ensure high-quality educational outcomes. This evaluation not only quantifies the efficacy of teaching methods and the extent of student engagement but also assesses the extent to which MR technology enhances the interactivity of educational experiences.

2.1 Meta-model and extensible evaluation process

The development of an evaluation index system to assess the impact of MR teacher-student interactions adopts a hierarchical approach, encompassing a spectrum from tangible operational interactions to more abstract conceptual interactions. This approach ensures a comprehensive evaluation of the multidimensional interactive effects within MR environments. The construction of this index system is outlined as follows:

a) Operational interaction (a1):
Skill mastery (a11): The proficiency of students in performing practical skills in virtual environments, facilitated by MR technology, is assessed.
Operational accuracy (a12): Measurements are taken of the error rate and accuracy of student performance during virtual experiments or simulated operations.
Response time (a13): The duration required by students to transition from task reception to completion during interactions is computed.
System usage efficiency (a14): The fluency and efficiency with which students use the MR system for operational interactions are assessed.

b) Information interaction (a2):
Information acquisition (a21): The capacity and speed at which students acquire information from the MR environment are quantified.
Comprehension (a22): Evaluation is conducted on the depth of students' understanding of information presented within the MR environment.
Information application (a23): The assessment measures students' ability to utilize gathered information for specific tasks.

c) Affective interaction (a3):
Learning motivation (a31): The extent to which MR technology enhances students' motivation for learning is evaluated.
Immersion (a32): The level of student immersion and participation within the MR environment is assessed.
Emotional engagement (a33): Quantification is undertaken of the emotional investment of students in the learning process.

d) Conceptual interaction (a4):
Innovation ability (a41): The evaluation assesses students' capacity to comprehend, analyze, and creatively solve problems within the MR environment.
Conceptual understanding (a42): The extent to which students comprehend fundamental teaching concepts is measured.
Critical thinking (a43): The assessment evaluates students' ability to apply critical thinking in analyzing and solving problems.

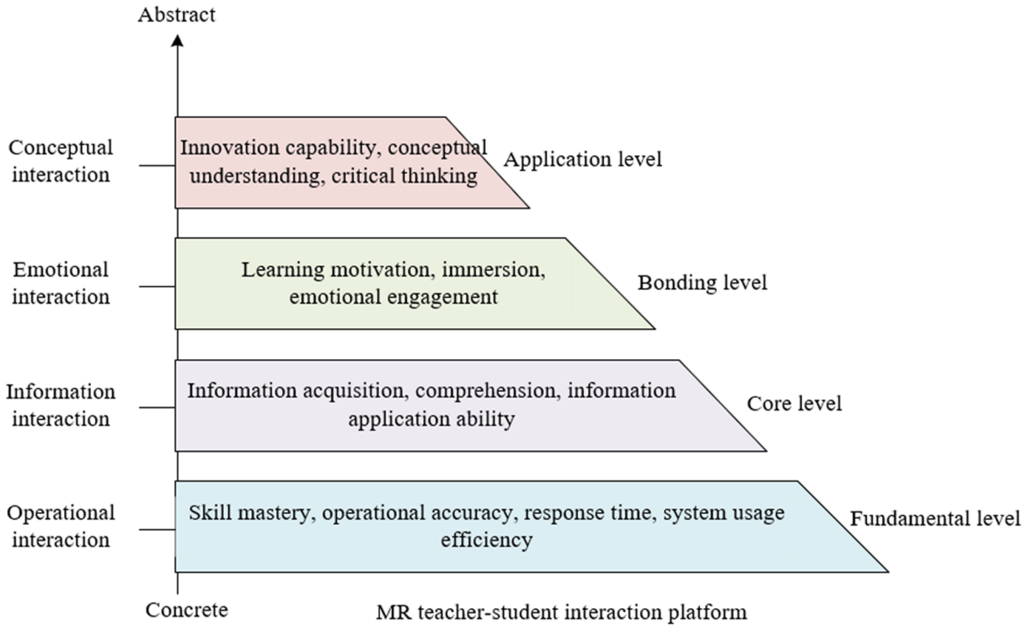

Fig. 1. MR teacher-student interaction effect evaluation model

In higher education, evaluating teacher-student interaction in MR faces the challenge of combining qualitative and quantitative measures while also dealing with the interplay and contradictions among these measures. Traditional methods often fall short of managing these complexities simultaneously. The implementation of the meta-model and extensible evaluation method, rooted in the theory of extensible sets, provides an effective solution to these challenges. This approach enables. the quantification of qualitative indices and the management of relationships, especially conflicts and contradictions, among evaluation indices. Consequently, it facilitates the depiction of complex teaching interaction effects within a holistic evaluation framework. The primary objective of adopting the meta-model based on MR teacher-student interaction is to enhance the adaptability and compatibility of the evaluation system, ensuring a comprehensive and precise assessment of MR technology application in higher education teaching contexts. Figure 1 depicts the evaluation model of the teacher-student interaction effect in mixed reality.

2.2 Calculating the extensible association function for the matter-element to be evaluated

Figure 2 illustrates the correlation mechanism within teacher-student interactions in MR. Utilizing the theory of extensible sets, the association function emerges as a crucial mathematical tool that quantifies the degree of resemblance or proximity between a matter-element under evaluation and predefined evaluation levels. In MR teaching evaluations, this function is adeptly crafted to measure the congruence between various instructional interaction indices, encompassing aspects such as learning outcomes, student engagement, skill proficiency, and the set standards. The resulting degree of association, an output of the association function, represents the extent to which a matter element aligns with the designated evaluation levels. In practical applications of this evaluation methodology, the degree of association is perceived as an indicator of belongingness. This metric is instrumental in determining the placement of specific instructional interactions across a range of quality levels, thereby assigning a score of belongingness to each level. For example, if a specific teacher-student interaction in the MR setting shows an association degree close to 1 on the immersion index, it indicates the interaction's outstanding performance in promoting immersive experiences.

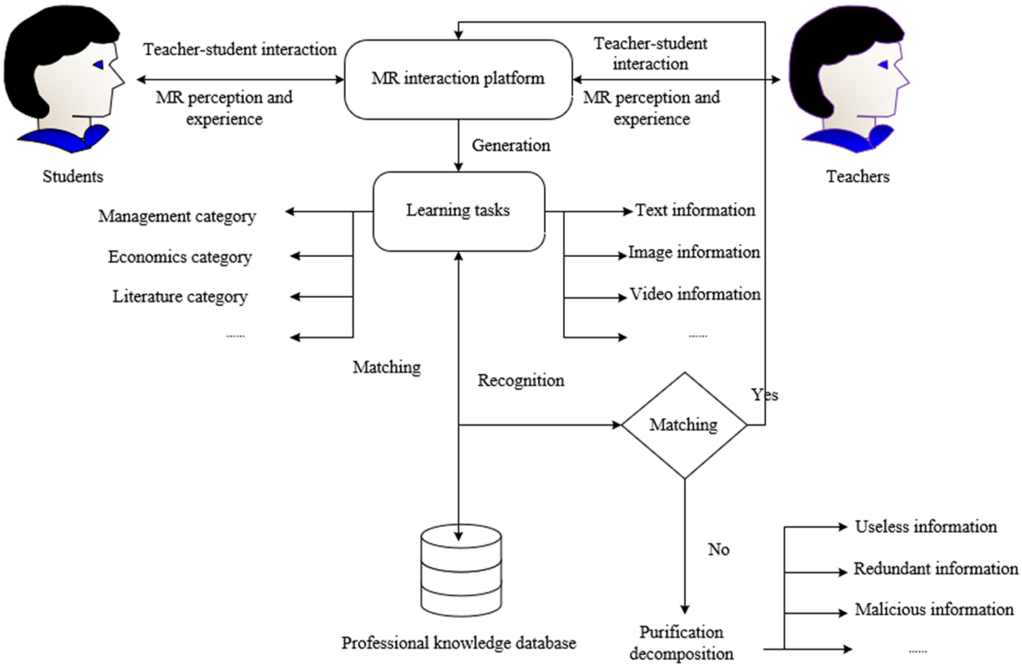

Fig. 2. MR teacher-student interaction correlation mechanism

The formulation of the association function within the framework of extensible sets is designed to provide a scientific and systematic approach for assessing and quantifying the complexities of educational interaction effects. Particularly in the context of MR technology's integration into higher education teaching, the implementation of association functions facilitates detailed analyses and comparisons of diverse teaching interaction outcomes. This process plays a critical role in identifying both strengths and areas for improvement, thereby informing teachers and technology developers in their efforts to refine teaching methodologies and applications of technology.

In this analytical model, the proximity of the u-th index value associated with MR teacher-student interaction effects to the classical and section domains is articulated by $f(n_u, n_{ru})$ and $f(n_u, n_{ju})$, respectively. The equations provided below elucidate the degree of distance between the matter-element and both the classical and quantum domains.

$$f(n_u, n_{ru}) = \left| n_u - \frac{o_{ru} + w_{ru}}{2} \right| - \frac{o_{ru} + w_{ru}}{2} \tag{1}$$

$$f(n_u, n_{ju}) = \left\| n_u - \frac{o_{ju} + w_{ju}}{2} \right\| - \frac{o_{ju} + w_{ju}}{2} \tag{2}$$

Furthermore, the proximity of the u-th measurement index related to MR teacher-student interaction effects to the k-th level of evaluation is represented by $|n_{ru}|=|w_{ru}-o_{ru}|, Q_k(n_u)$. This representation forms the basis of the association function, as indicated in the following expression:

$$Q_k(n_u)=\begin{cases}\dfrac{-f(n_u,n_{ru})}{|n_{ru}|} n_u \in n_{ru}\\ \dfrac{f(n_u,n_{ru})}{f(n_u,n_{ju})-f(n_u,n_{ru})} n_u \notin n_{ru}\end{cases} \tag{3}$$

2.3 Determining index weights

The process of weighting the evaluation index system for teacher-student interaction effects in MR employs the extensible weight method. This approach requires a thorough analysis of educational goals and expected outcomes to identify the key indicators within the evaluation system. The extensible weight method then proceeds to analyze the interconnectedness and mutual influence between each index and educational effectiveness, dynamically assigning weights to each index. This approach acknowledges the relative significance of the indices and their distinct contributions in different teaching contexts and learning environments. It emphasizes the interdependence of indices rather than viewing them as isolated units. This approach minimizes subjective judgment biases through mathematical modeling, leading to more accurate and objective evaluations. The weight assigned to the u-th sub-index under the r-th category of interaction effects, denoted as d_{ru}, and the count of primary and corresponding secondary indices, represented by r (r = 1, 2, …, v) and u (u = 1, m, 2, …, l), are factored into the following equation for secondary index calculation:

$$d_{ru}=\frac{e_{ru}}{\sum_{u=1}^{l} e_{ru}}\left(\sum_{u=1}^{l} d_{ru}=1\right) \tag{4}$$

The determination of primary index weights is articulated through the following formula:

$$d_r=\frac{e_r}{\sum_{r=1}^{v} e_r}\left(\sum_{r=1}^{v} d_r=1, e_r=\sum_{u=1}^{l} e_{ru}\right) \tag{5}$$

Additionally, the computation of index weight coefficients using the extensible weight method is captured in the following expression:

$$e_{ru}(n_u,n_{ru})=\begin{cases}\dfrac{2(n_u-o_{ru})}{w_{ru}-o_{ru}} n_u \le \dfrac{o_{ru}+w_{ru}}{2}\\ \dfrac{2(w_{ru}-n_u)}{w_{ru}-o_{ru}} n_u \ge \dfrac{o_{ru}+w_{ru}}{2}\end{cases} \tag{6}$$

In instances where n_u is included within n_{ru}, a condition arises where $e'_{ru}(n_u,n_{ru})$ equals the maximum value within the set of $e'_{ru}(n_u,n_{ru})$. This scenario leads to the following formula, which delineates the value of e_{ru}:

$$e_{ru} = \begin{cases} k_{MAX} * (1 + e'_{ru}(n_u, n_{ruMAX}))e'_{ru}(n_u, n_{ruMAX}) \geq -0.5 \\ k_{MAX} * 0.5 \quad e'_{ru}(n_u, n_{ruMAX}) \leq -0.5 \end{cases} \tag{7}$$

2.4 Evaluation level determination

In the methodology for evaluating the effects of teacher-student interaction in MR, the process of determining evaluation levels begins with identifying the primary indices that impact these effects. Standards for evaluating levels are established for each primary index. By using the association function, the alignment between the actual performance of each primary index and different established evaluation level standards is quantified. This process typically involves a comparative analysis of the actual performance against the established evaluation standards. Suppose l denotes the total number of secondary indices associated with a specific primary index. In this context, the following equation is used to calculate the degree of association of the evaluation matter element E with the evaluation level k:

$$Q_k(E_r) = \sum_{u=1}^{l} d_{ru} Q_k(n_{ru}) \tag{8}$$

Subsequently, the association degrees of primary indices, ascertained in the preceding step, are consolidated. This integration aims to assess the overall degree of association of the matter element being evaluated with each level of evaluation. This step involves allocating weights based on the significance of different primary indices, followed by applying these weights to adjust the summation or mean value of the association degrees. Assuming the total number of primary indices for the evaluation matter element is v, the association degree of the matter element E in relation to the evaluation level k is articulated through the following formula:

$$Q_k(E) = \sum_{r=1}^{v} d_r Q_k(E_r) \tag{9}$$

The evaluation process involves a comparative assessment of the association degrees for each element with respect to various evaluation levels. Following the principle of maximum association degree recognition, the evaluation level for an element is determined by the level that corresponds to the highest association degree. This principle facilitates the identification of the evaluation level for each matter-element under scrutiny, as represented by the following expression:

$$Q_{k'}(E) = MAXQ_k(E) \tag{10}$$

Upon determining the evaluation level to which a matter-element is assigned, an aggregate or mean calculation of all feature quantity values within that level is conducted. This computation yields a representative feature quantity value for that specific level, as expressed in the following formula:

$$k^* = \frac{\sum_{k=1}^{v} k \cdot \overline{Q_K}}{\sum_{k=1}^{v} \overline{Q_K}} \left(\overline{Q_K} = \frac{q_k(E) - MINq_k(E)}{MAXq_k(E) - MINq_k(E)} \right) \tag{11}$$

3 EVALUATION OF EDUCATIONAL AND TEACHING EFFECTS OF STUDENTS BASED ON MR EXPERIENCES

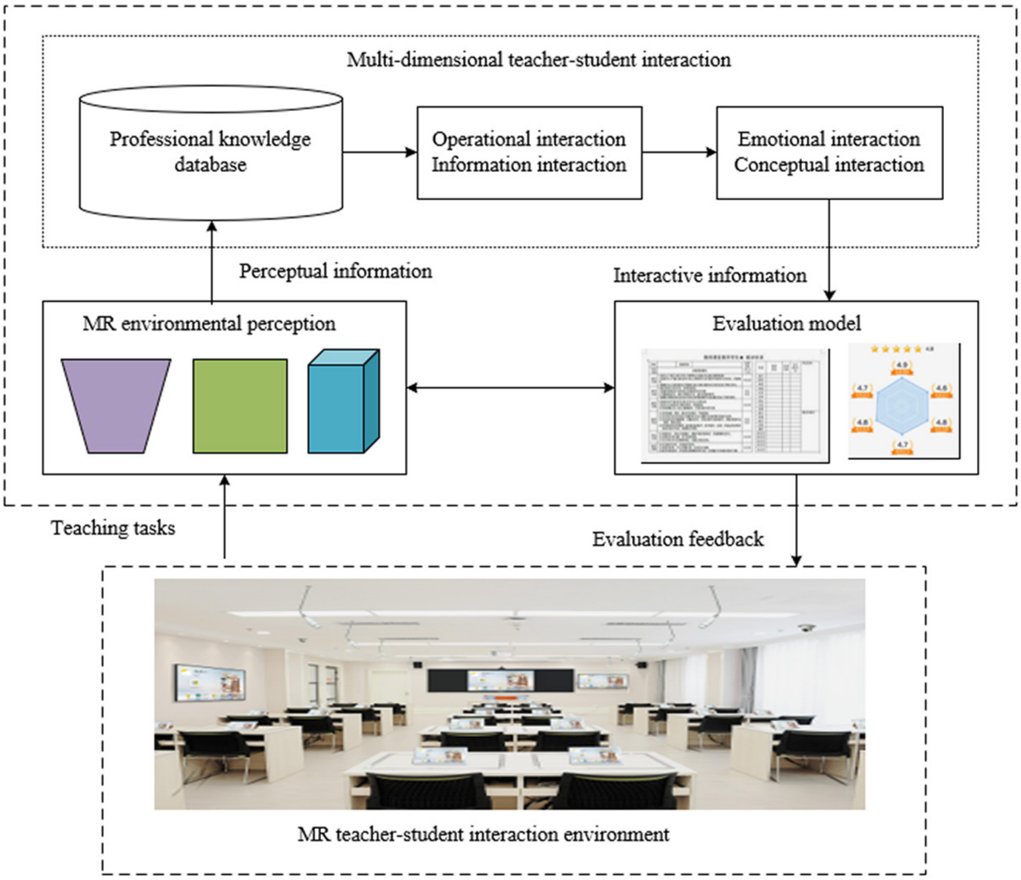

Fig. 3. Evaluation system structure for educational and teaching effects on students in MR environments

In constructing the evaluation index system for the educational and teaching effects of students' experiences with MR technology, it is imperative to consider the distinct features of MR technology and its application objectives in higher education (see Figure 3). This index system aims to encapsulate various aspects: students' learning experiences, knowledge acquisition, skill development, and emotional and cognitive changes within the MR environment.

a) Learning experience
Immersion: The assessment focuses on the degree of students' immersion in the MR environment.
Interactivity: The evaluation focuses on students' ability to engage with the virtual environment or educational content.
User interface friendliness: The usability and intuitiveness of the MR system interface are evaluated.

b) Knowledge acquisition
Theoretical knowledge understanding: The assessment evaluates students' level of comprehension and mastery of theoretical knowledge.
Practical skill application: The evaluation assesses students; ability to apply theoretical knowledge in practical scenarios.

c) Skill development
Operational skills: The assessment of students' proficiency in performing specific tasks within the MR environment is conducted.
Problem-solving skills: The ability of students to solve problems in virtual environments is assessed.
Innovation and creativity: The assessment evaluates students' capacity to engage in innovative thinking and creative tasks utilizing MR technology.

d) Emotional and cognitive changes
Learning motivation: The level of students' enthusiasm for participating in MR-based learning activities is evaluated.
Cognitive load: The cognitive load perceived by students during the learning process is measured.
Satisfaction: The overall satisfaction of students with MR teaching methodologies is assessed.

e) Teaching interaction
Teacher-student interaction: The level of support and guidance provided by teachers in the MR environment is assessed.
Student interaction: The extent of collaboration and communication among students within the MR setting is evaluated.

In employing the AHP for evaluating educational and teaching effects within MR experiences, a structured procedure is adopted, detailed in the following steps:

Step 1: The initial phase involves establishing the criteria layer of the evaluation system, incorporating various indices such as immersion, interactivity, and knowledge acquisition. For each index within this criterion layer, a judgment matrix is constructed. This process involves educational experts or evaluators who conduct pairwise comparisons of the indices' importance, rating their relative significance on a scale of 1 to 9. Each numerical value in the judgment matrix is subject to the following condition:

$$x_{uk} > 0, x_{uk} = \frac{1}{xku}, x_{uu} = 1 \tag{12}$$

Step 2: The elements within each row of the judgment matrix, denoted by X, are multiplied together. The product of each row is represented by L_u, and the calculation is conducted as follows:

$$L_u = \Pi_{k=1}^{v} x_{uk}, u = 1,2,3,\ldots,v \tag{13}$$

The judgment matrix's order, denoted by v, is used to calculate the v-th root of each row's product, in which yields an unnormalized weight vector $[Q_1\ Q_2\ \ldots\ Q_v]^T$. This vector is subsequently normalized by dividing it by the sum of all its elements. The weights of the indices, represented by Q_u, are ascertained, leading to the derivation of the final weight vector.

$$Q_u = \frac{\mu_u}{\sum_{u=1}^{v} \mu_u} \tag{14}$$

Step 3: This step of the AHP involves calculating the maximum eigenvalue, η_{MAX}, of the judgment matrix X, which represents the ideal state value of a consistent matrix. The expression for this calculation is structured as follows:

$$\eta_{MAX} = \sum_{u=1}^{v} \frac{(X \cdot Q)_u}{vQ_u} \tag{15}$$

Where,

$$X \cdot Q = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1v} \\ x_{21} & x_{22} & \cdots & x_{2v} \\ \vdots & \vdots & \cdots & \vdots \\ x_{v1} & x_{v2} & \cdots & x_{vv} \end{bmatrix} \cdot \begin{bmatrix} Q_1 \\ Q_2 \\ \vdots \\ Q_v \end{bmatrix} \tag{16}$$

$$(X \cdot Q)_u = x_{u1}Q_1 + x_{u2}Q_2 + \ldots + x_{uv}Q_v \tag{17}$$

Step 4: This step in the methodology involves the consistency index, denoted as Z_1, using the following formula:

$$Z_1 = \eta_{MAX} - v/(v-1) \tag{18}$$

Subsequently, for matrices of similar order, reference is made to the average random consistency index, denoted as E_1. The consistency ratio, denoted as Z_E, is then calculated using the formula:

$$Z_E = (Z_1 / E_1) \tag{19}$$

A judgment matrix is considered to have achieved satisfactory consistency if Z_E is equal to or less than 0.1. Should Z_E exceed this threshold, an adjustment of the judgment matrix is necessary.

4 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1 in the study presents the degrees of association between primary indices of MR teacher-student interaction effects and four evaluation levels: poor, fair, good, and excellent. It is discerned that for index a1, the third level Q3 (good) exhibits the highest positive association degrees (0.387 and 0.458) in two instances, suggesting a tendency towards a positive evaluation of MR teacher-student interaction effects in these aspects. Conversely, the second level Q2 (fair) reveals higher positive association degrees (0.278 and 0.135) in two other instances, indicating that the interaction effects are assessed as "fair" for these indices. The levels Q1 (poor) and Q4 (excellent) consistently demonstrate negative association degrees across all instances, suggesting a weaker correlation of these primary indices with the poor and excellent levels. The representative feature quantity values corresponding to different levels denote distinct measurement or evaluation standards. This implies that actual levels of association exert a moderating effect on anticipated evaluation levels. Overall, these findings suggest that at the primary index level, teacher-student interaction effects in MR predominantly show positive associations with "good" and "fair" levels.

Table 1. Primary indices of MR interactions and evaluation levels

Primary Indices	Q1(Wi)	Q2(Wi)	Q3(Wi)	Q4(Wi)	K′	K*
a1	–0.534	–0.331	0.387	–0.245	3	3.12
a1	–0.245	0.278	–0.187	–0.458	2	2.14
a1	–0.289	0.135	–0.065	–0.421	2	2.25
a1	–0.478	–0.213	0.458	–0.256	3	2.89

Table 2. MR interaction effects and evaluation levels

Primary Index	Q1(W)	Q2(W)	Q3(W)	Q4(W)	K′	K*
A	−0.378	0.002	0.079	−0.356	3	2.49

In Table 2, the association degrees of MR teacher-student interaction effects with various evaluation levels are illustrated for primary index A. The data reveal that the highest positive association degree is observed at the Q3 (good) evaluation level (0.079). Although this value is relatively small, it suggests some degree of positive correlation between MR teacher-student interaction effects and the good evaluation level. The association degree for Q2 (fair) is approximately zero (0.002), indicating a neutral correlation between MR teacher-student interaction effects and the fair evaluation level, or a minimal impact of this index at this level. Negative association degrees are noted for Q1 (poor) and Q4 (excellent) levels, indicating weaker positive correlations with these evaluation levels. The last two columns of the table, which represent the feature quantity values for different levels, reflect the adjusted evaluation levels based on association degrees. This suggests that while the anticipated evaluation level was 3 (good), the actual association degree data slightly lowers the evaluation level, approaching a midpoint between fair and good. In summary, the evaluation method proposed in this paper demonstrates its potential effectiveness, especially in revealing a nuanced understanding of teacher-student interaction effects in MR environments. It suggests an evaluation range between fair and good. This type of evaluation can help educators identify strengths and areas for improvement in the application of MR technology, guiding future pedagogical practices and technological enhancements. However, the observed negative association degrees require further examination to ensure the accuracy and reliability of the evaluation system.

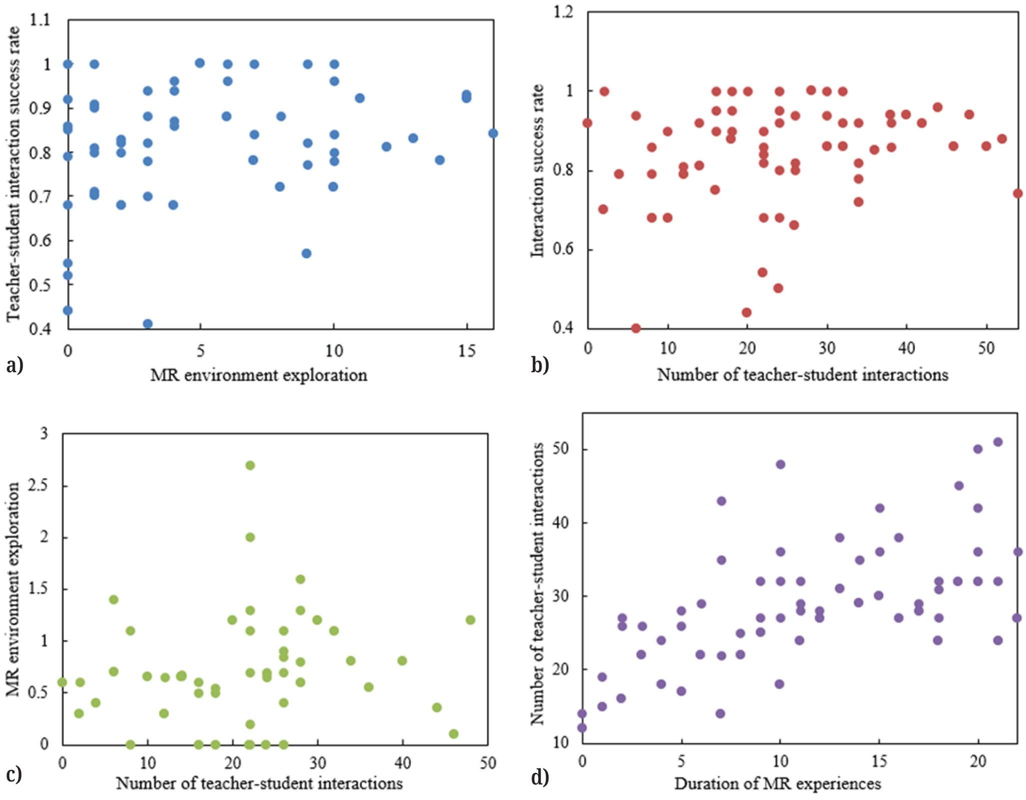

Fig. 4. *(Continued)*

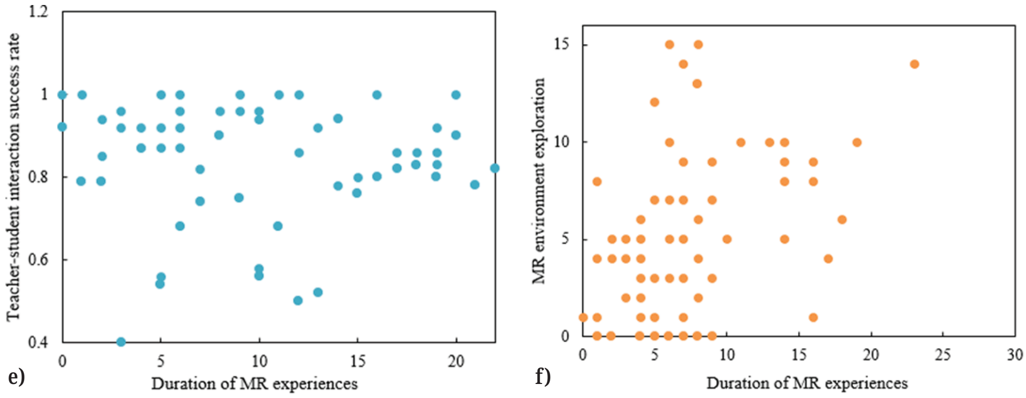

Fig. 4. Correlation analysis results of teacher-student interaction behaviors based on MR experiences

The correlation analysis experiment, focusing on teacher-student interaction behaviors within MR settings, yields insightful results as depicted in Figure 4. This analysis is essential for comprehending the dynamics of interactions in educational settings enhanced by MR technology. The analysis shows that there is no significant correlation between the extent of exploration within the MR environment and both the frequency and success rate of teacher-student interactions. Equally, the success rate of these interactions does not show a significant correlation with either their frequency or the duration of MR experiences. However, the duration of MR experience shows a significant positive correlation with both the frequency of interactions and the extent of exploration within the MR environment. These findings offer a nuanced understanding of the interrelationships among various aspects of teacher-student interactions in MR contexts. In light of these results, it is pivotal to revisit the primary research objectives of this study, which focus on assessing the utilization and impact of MR technology in the realm of higher education teaching evaluation.

Firstly, it has been established that there is no significant correlation between exploratory behaviors within the MR environment and both the frequency and effectiveness of teacher-student interactions. This finding suggests that students' engagement with MR technology, characterized by exploratory behaviors, does not necessarily results in an increase or enhancement of instructional interactions. Therefore, students' initial intrigue or interest in MR technology does not automatically translate into effective learning behaviors. Secondly, the analysis reveals that the success rate of teacher-student interactions is not significantly correlated with the frequency of these interactions, suggesting that the effectiveness of such interactions is not dependent on their frequency. Frequent interactions, therefore, do not inherently ensure high-quality interactions. Effective teacher-student interactions are based more on the depth and quality of the interaction rather than its frequency. Similarly, the lack of a significant correlation between the success rate of teacher-student interactions and the duration of MR experiences indicates that the quality of instructional interactions depends more on the design and execution quality of these interactions than on the duration of engagement. Lastly, a significant positive correlation is observed between the duration of MR experiences and both the number of teacher-student interactions and the extent of environmental exploration. This indicates that longer durations of MR experience are associated with an increased frequency of interactions and a greater inclination towards in-depth exploration. This highlights the importance of providing students with enough time to adjust to and explore the MR environment in order to promote effective interactions.

In summary, these results emphasize the importance of educational and teaching activities based on MR prioritizing interaction quality over quantity. Providing students with ample time to immerse themselves in and explore MR technology is crucial. The proposed evaluation methodology in this paper effectively highlights the nuanced yet vital dynamics in the application of MR in educational settings. It emphasizes the significance of interaction quality and sufficient exploration time in enhancing teaching and learning experiences.

The analysis of variance (ANOVA) test results critically evaluate teacher-student interaction behaviors within MR experiences. ANOVA, a statistical method, is used to determine if the differences in mean values among three or more groups are statistically significant. Specifically, it determines whether the differences between groups exceed the random variances within each group. The application of ANOVA in this context is crucial for examining the interplay between various aspects of teacher-student interactions (such as frequency, success rate, environmental exploration, and duration of experience) and their subsequent impact on educational and teaching effectiveness. It is observed that the frequency of teacher-student interactions varies significantly among different groups (F-score: 21.45; significance level: $p < 0.001$). This indicates a significant difference in interaction frequencies across various teaching scenarios. Equally notable is the success rate of these interactions, showing a significant difference among groups (F-score: 13.28; significance level: $p < 0.001$), highlighting the variability in interaction effectiveness. Furthermore, exploratory behaviors within the MR environment reveal significant group variances (F-score: 63.59; significance level: $p < 0.001$), indicating different levels of engagement in exploratory activities. The duration of the MR experience, with the highest F-score of 84.59 at a significance level of $p < 0.001$, indicates significant differences in the time spent within the MR environment across various educational settings.

5 CONCLUSION

This investigation focuses on evaluating the use and impact of MR technology in assessing teaching within higher education. The primary objective has been to enhance the scientific accuracy and interactivity of teaching evaluations by using quantitative evaluation methods and to validate the effectiveness of MR technology in educational settings. The study began with the development of a meta-model based on MR-facilitated teacher-student interactions and utilized the AHP to create a comprehensive evaluation index system. This system spanned an array of dimensions, encompassing operational, informational, emotional, and conceptual interactions. Utilizing this index system, a correlation analysis was undertaken to examine the associations between various secondary indices and distinct evaluation levels, ranging from poor to excellent. The findings highlighted positive correlations between specific indices and higher evaluation levels, suggesting their beneficial impact on the assessment of teacher-student interaction effects. A sensitivity analysis was subsequently conducted to evaluate the responsiveness of various dimensional evaluation indices to variations. This analysis emphasized the crucial importance of certain aspects in enhancing teaching effectiveness. Moreover, the study implemented an ANOVA to ascertain the statistical significance of the correlation between primary indices of teacher-student interaction behaviors and educational outcomes. The outcomes indicated that the frequency of teacher-student interactions, their success rate, the level of exploration within the MR environment, and the duration of the MR experience each have a significant impact on the effectiveness of teaching.

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