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Application challenges of modern education technology in China's higher education teaching management: A fuzzy MARCOS method

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ABSTRACT

To systematically evaluate the barriers to the adoption of modern educational technology in the teaching management of higher education institutions in China, this study introduces an integrated evaluation framework based on MCDM to discuss existing problems. First, a comprehensive barrier evaluation indicator system is constructed by synthesizing existing studies on educational technology implementation and the practical objectives of teaching management in Chinese higher education. Second, a q-rung picture fuzzy set (q-RPFS) is employed to characterize experts' assessments, enabling a more flexible and accurate representation of uncertainty, hesitation, and conflicting judgments inherent in barrier evaluation. The weighted averaging (WA) operator is then applied to aggregate fuzzy evaluation information across indicators. Third, the Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS) method is adopted to rank the identified barriers by considering both ideal and anti-ideal solutions, thereby enhancing the robustness and discriminative power of the evaluation results. Finally, a case study involving representative higher education institutions in China is conducted to validate the feasibility and effectiveness of the proposed framework. This article considers different types of universities as alternatives, and digital competencies of teaching management staff has the greatest impact on them. The results demonstrate that the integrated approach provides a systematic and reliable tool for identifying and prioritizing key barriers to modern educational technology in higher education teaching management, offering valuable insights for policy formulation and managerial decision-making.

1. Introduction

The fundamental aim of modern educational programs is to maintain and enhance educational quality [1]. China's higher education system has entered a stage of universal access. According to statistics released by the Ministry of Education, the total number of higher education institutions nationwide reached 3,119 in 2024, with an overall student enrollment of approximately 48.46 million. The gross enrollment ratio has risen to 60.8%, reflecting a substantial expansion in student population and an increasing diversification of training models. In parallel with these changes,

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educational philosophies emphasizing a student-centered approach and outcome-based education (OBE) have become increasingly embedded in higher education practice. The traditional teaching management model that relies on manual and experiential methods is no longer able to meet the actual needs. This is mainly manifested in: irrational utilization of resources; inconsistency between courses and teaching strategies and the contemporary requirements and demands of educational participants [1].

The digital revolution has profoundly transformed industries across the board, making the ability to adapt to modern technologies increasingly critical for enhancing competitiveness [2]. Digital transformation and the adoption of new technologies have become increasingly essential priorities for organizations across diverse sectors and organizational structures [3]. In recent years, substantial and far-reaching technological advancements have exerted a profound influence on educational and academic practices, among which the recent incorporation of artificial intelligence stands out as a representative example [4]. Modern educational technologies, including big data analytics, artificial intelligence, and cloud computing, have reached an increasing level of maturity and are capable of addressing many of the limitations inherent in traditional educational models by providing robust technological support [5]. These technologies should not be viewed merely as instrumental tools; rather, they function as key enablers of systemic transformation in higher education. By enabling the comprehensive collection, organization, and analysis of data generated throughout the entire teaching and learning process, data-driven and visualization technologies make teaching management more transparent and actionable [6]. This, in turn, allows instructors to gain timely insights into students' learning conditions, identify emerging issues in the instructional process, and implement targeted and effective pedagogical interventions. The integration of modern educational technologies therefore necessitates a careful examination of how such technologies reshape the processes, structures, and operational models of teaching management in higher education.

Multi-criteria decision-making (MCDM) constitutes a methodological framework designed to support decision makers when faced with numerous competing alternatives [7]. However, conventional MCDM methods appear to give insufficient consideration to subjectivity when decision problems involve uncertainty [8]. Many real-world decision problems are characterized by imprecise information, subjective judgments, and linguistic assessments, which cannot be adequately captured by conventional deterministic MCDM methods[9]. This limitation is particularly evident in the context of modern educational technology adoption in higher education, where decision makers must evaluate multiple interrelated barriers based largely on expert judgment and qualitative assessments rather than precise quantitative data. Given that objectives and constraints are often expressed in terms of linguistic assessments and fuzzy variables, it becomes evident that the incorporation of fuzzy numbers into MCDM is necessary to address such problems in a more comprehensive manner [7]. Fuzzy theory–based models have gained prominence for their capacity to model complex real-world problems subject to uncertainty and imprecision[9]. Fuzzy set theory offers an effective means of addressing these limitations by allowing decision makers to represent uncertainty and vagueness in a mathematically tractable manner[10]. By integrating fuzzy sets into the MCDM framework, subjective evaluations expressed in linguistic terms can be systematically incorporated into the decision process, thereby enhancing the realism and robustness of the resulting analysis[11]. This integration is especially valuable for analyzing the multifaceted challenges associated with modern educational technology in teaching management, where institutional heterogeneity and contextual differences across higher education institutions further amplify uncertainty. This fusion has led to the development of fuzzy MCDM approaches, which have been widely applied to complex decision environments where ambiguity and human judgment play a central role [12].

This paper based on q-rung picture fuzzy set (q-RPFS) evaluates the barriers to modern education technology and these indicators systematically encompass technological, organizational, human, financial, institutional, and environmental challenges. The q-RPFS has become an effective method for managing fuzzy data in multi-criteria decision-making problems [13]. To tackle MCDM problems, some researchers have proposed different hybrid methods under the q-RPF framework. Li, Zhang, Wang, Shang and Bai [13] tackles the problem of greenhouse gas emission by introducing a novel MCDM framework that integrates different aggregation operators within complex q-rung picture fuzzy sets. Yang, Wang, Wang, Deveci and Delen [14] developed a decision-making framework using q-rung picture fuzzy sets to identify and analyze the driving factors of digital transformation implementation aimed at enhancing the financial resilience of small and medium-sized enterprises in the manufacturing sector, thereby addressing this gap. Under the uncertain environments, Aydoğan, Olgun, Smarandache, Ünver and Kumar [15] constructed a new approach based on q-RPFS and TODIM to apply to real-life construction project management problem. The introduction of q-RPFS enables us to effectively represent the uncertainty and fuzziness in decision-making scenarios, making them highly suitable for real-world applications where the input data is inherently uncertain[15]. These studies demonstrate that the introduction of q-RPFS enables a more accurate representation of uncertainty, hesitation, and subjective judgments in complex decision environments. Consequently, the q-RPFS-MARCOS framework provides a theoretically sound and practically suitable foundation for systematically analyzing barriers to modern educational technology adoption in higher education institutions.

Existing studies have not yet proposed a hybrid decision-making model integrating q-RPFS and the MARCOS method for examining modern education technology adoption. MARCOS, proposed by Stević, Pamučar, Puška and Chatterjee [16], represents a multi-criteria decision-making (MCDM) method that has been applied to portfolio selection problems. This method assesses alternatives by comparing their relative performance with both ideal and anti-ideal reference solutions, thereby providing a more refined evaluation of utility in this context [17]. The MARCOS method enhances the accuracy and comprehensiveness of objective ranking in decision-making environments, thereby making it a valuable tool for decision analysis across various domains[18].A wide range of established decision-making techniques, including DEMATEL, MABAC, AHP, TOPSIS, and VIKOR, have been widely applied to address uncertainty in various real-world decision contexts [19]. To improve the decision-making process of lifeboat selection for cargo ships, Aydin, Camliyurt, Gul, Sezer, Celik and Akyuz [20] have proposed an IT2F-MARCOS model for optimizing survival craft selection. Ecer, Tanrıverdi, Yaşar and Görçün [21] introduced a novel method combining LOPOW and MARCOS for airlines' sustainable aviation fuel supplier selection. To systematically compare the challenges associated with modern educational technology across different tiers of higher education institutions, this study employs the MARCOS method. By evaluating institutional alternatives with respect to both ideal and anti-ideal reference solutions, the MARCOS approach enables a nuanced assessment of relative barrier exposure under conditions of uncertainty[22]. When combined with fuzzy-based representations of expert judgment, this method provides a robust analytical foundation for prioritizing constraints and informing differentiated strategies for the effective integration of modern educational technology in teaching management.

In summary, to systematically assess the barriers to the integration of modern educational technology in the teaching management of higher education institutions, this study develops a comprehensive decision-making framework that accounts for uncertainty and heterogeneity across different institutional tiers. The remainder of this paper is organized as follows. Section 2 presents the proposed model, including the construction of the barrier evaluation indicator system and the application of the q-rung picture fuzzy sets integrated MARCOS method. Section 3 provides a case study to demonstrate the applicability and effectiveness of the proposed framework. Finally, Section 4 concludes the paper and discusses the main findings.

2. Methodology

To systematically evaluate the challenges associated with the application of modern educational technology in higher education teaching management, this study proposes an integrated multi-criteria decision-making framework based on q-RPF sets and the MARCOS method. The proposed framework consists of three main stages: assessment information acquisition, evaluation process construction, and priority ranking generation. Expert linguistic assessments are first transformed into q-RPFNs to capture uncertainty and subjectivity. Subsequently, expert weights are determined using a score-function-based approach, and individual evaluations are aggregated into a group preference matrix through the q-RPF weighted averaging operator. Barrier weights are then derived using a distance-based computation mechanism. Finally, the MARCOS model is employed to prioritize alternatives by calculating utility degrees and the final utility function, resulting in a comprehensive ranking of both barriers and higher education institution alternatives. A flowchart illustrating this framework is presented in Fig.1.

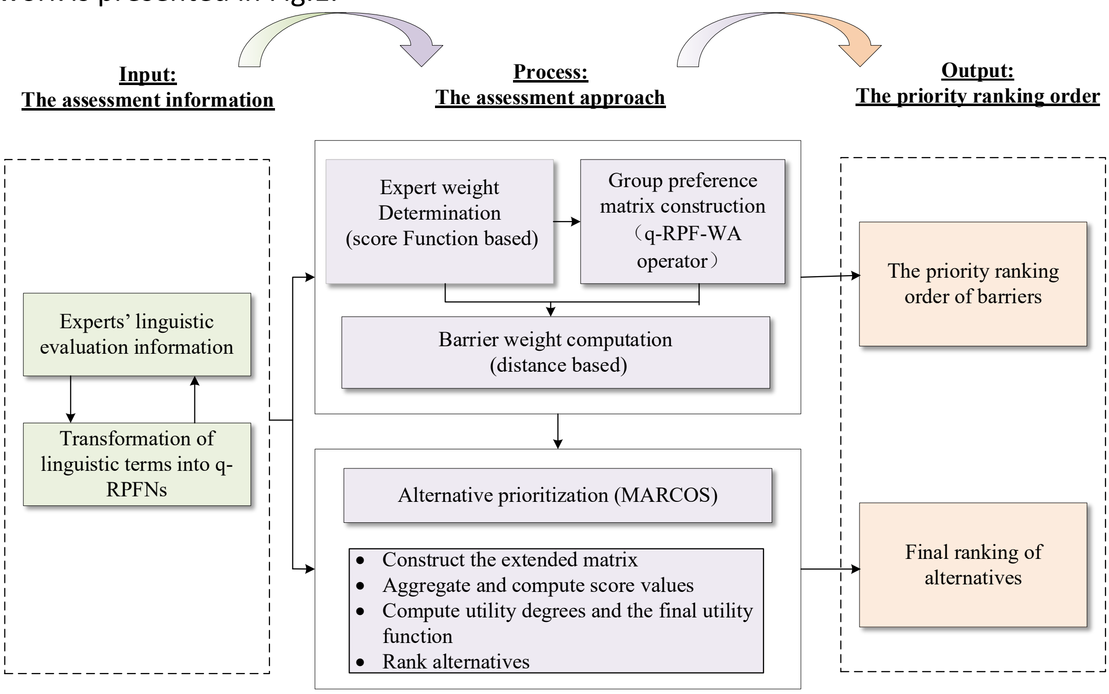

Fig. 1. The framework of the proposed methodology.

2.1 Collect individual preference information

Step 1.1: Consider a barrier evaluation problem that consists of m alternatives, denoted by $\Theta=\{\Gamma_i \mid i=1,2,\cdots m\}$, and n barriers represented by $\Xi=\{\mathrm{H}_j \mid j=1,2,\cdots m\}$ .Assume that the expert panel is defined as $D=\{d_\tau \mid \tau=1,2,\cdots,t\}$, where the corresponding expert weight vector is $\mathrm{E}=\{\omega_\tau \mid \tau=1,2,\cdots,t\}$, satisfying atisfying $\omega_\tau\in[0,1]$ and $\sum_{\tau=1}^{t}\omega_\tau=1$. Meanwhile, let the attribute weight vector be expressed as $\mathrm{M}=\{w_j \mid j=1,2,\cdots,n\}$, where $w_j\in[0,1]$ and $\sum_{j=1}^{n}w_j=1$ .Based on the above assumptions, the decision matrix provided by the τ^{th} expert can be formulated as.

$$\mathrm{AX}_\tau=\left[ax_{ij}^{\tau}\right]_{m\times n}=\begin{bmatrix} ax_{11}^{\tau} & ax_{12}^{\tau} & \cdots & ax_{1n}^{\tau} \\ ax_{21}^{\tau} & ax_{22}^{\tau} & \cdots & ax_{2n}^{\tau} \\ \vdots & \vdots & \ddots & \vdots \\ ax_{m1}^{\tau} & ax_{m2}^{\tau} & \cdots & ax_{mn}^{\tau} \end{bmatrix} \tag{1}$$

where ax_{ij}^{τ} represents a q-RPFN, defined as $ax_{ij}^{\tau}=\left\langle \phi_{ax_{ij}^{\tau}},\varphi_{ax_{ij}^{\tau}},\gamma_{ax_{ij}^{\tau}}\right\rangle$, which is assigned by the τ^{th} expert according to the linguistic evaluation scale described in Ref.[23].

2.2 Generate the group preference matrix

Step 2.1: Calculate the score function. The value of score function is calculated as follows:

$$K(ax_{ij}^{\tau})=\frac{(\phi_{ax_{ij}^{\tau}}^{q}+1-\gamma_{ax_{ij}^{\tau}}^{q})}{2} \tag{2}$$

Step 2.2: Compute the summation form of the score function. The value of the product of the score functions is obtained through consecutive addition calculation, which is expressed as follows:

$$\Phi_\tau=\sum_{i=1}^{n}\sum_{j=1}^{m}K(ax_{ij}^{\tau}) \tag{3}$$

Step 2.3: Obtain the weight of expert. Based on the continuous addition of the scoring function, the expert weights are calculated as follows:

$$\omega_\tau=\frac{\Phi_\tau}{\sum_{\tau=1}^{t}\Phi_\tau} \tag{4}$$

Step 2.4: Construct group preference matrix. To obtain the group decision-making matrix, we employ the q-RPF-WA operator to combine individual decision matrices by taking into account the experts' weight. The calculation formula is as follows:

$$AX_{ij}=\left(\sqrt[q]{1-\prod_{\tau=1}^{t}\left[1-\left(\phi_{ax_{ij}^{\tau}}\right)^{q}\right]^{\omega_\tau}},\prod_{\tau=1}^{t}\left(\varphi_{ax_{ij}^{\tau}}\right)^{\omega_\tau},\prod_{\tau=1}^{t}\left(\gamma_{ax_{ij}^{\tau}}\right)^{\omega_\tau}\right) \tag{5}$$

2.3 Obtain the weight of barriers

Step 3.1: Obtain the average preference matrix. Initially, assuming uniform barrier weights, the comprehensive preference matrix is derived by the following formula.

$$\overline{AX_i} = \left(\sqrt[q]{1 - \prod_{j=1}^{m} \left[1 - \left(\phi_{AX_{ij}} \right)^q \right]^{\frac{1}{m}}}, \prod_{j=1}^{m} \left(\varphi_{AX_{ij}} \right)^{\frac{1}{m}}, \prod_{j=1}^{m} \left(\gamma_{AX_{ij}} \right)^{\frac{1}{m}} \right) \tag{6}$$

Step 3.2: Calculate the total similarity. The total similarity between the j^{th} barriers and average matrix is obtained as follows:

$$S_j = \sum_{i=1}^{n} S\left(AX_{ij}, \overline{AX_i} \right) \tag{7}$$

where the function $S\left(AX_{ij}, \overline{AX_i} \right)$ is defined as.

$$\begin{aligned} S\left(AX_{ij}, \overline{AX_i} \right) &= 1 - D\left(AX_{ij}, \overline{AX_i} \right) \\ &= 1 - \left(\frac{1}{2} \left(\left(\phi_{AX_{ij}}^q - \phi_{\overline{AX_i}}^q \right)^2 + \left(\varphi_{AX_{ij}}^q - \varphi_{\overline{AX_i}}^q \right)^2 + \left(\gamma_{AX_{ij}}^q - \gamma_{\overline{AX_i}}^q \right)^2 \right) \right)^{1/2} \end{aligned} \tag{8}$$

Step 3.3: Compute the weight of experts. The weight w_j is calculated as follows:

$$w_j = \frac{S_j}{\sum_{j=1}^{m} S_j} \tag{9}$$

2.4 The q-RPF-MARCOS'H approach for alternative prioritization

Step 4.1: Construct the extended group preference matrix.

$$G\left(AI \right) = \begin{cases} \max AX_{ij}, j \in B \\ \min AX_{ij}, j \in NB \end{cases} \tag{10}$$

$$G\left(AAI \right) = \begin{cases} \min AX_{ij}, j \in B \\ \max AX_{ij}, j \in NB \end{cases} \tag{11}$$

Then, we add the positive ideal points and negative ideal points to the original perceptual utility matrix, thereby establishing an extended perceptual utility matrix.

$$\dot{A}X = \left(\dot{A}X_{ij} \right)_{(m+2)\times n} = \begin{pmatrix} AX_{i1}^{AAI} & AX_{i2}^{AAI} & \cdots & AX_{in}^{AAI} \\ AX_{11} & AX_{12} & \cdots & AX_{1n} \\ AX_{21} & AX_{22} & \cdots & AX_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ AX_{m1} & AX_{m2} & \cdots & AX_{mn} \\ AX_{i1}^{AI} & AX_{i2}^{AI} & \cdots & AX_{in}^{AI} \end{pmatrix} \tag{12}$$

Step 4.2: Aggregate the preference matrix. The q-RPF-WA operator is employed to compute the aggregated matrix, as shown below:

$$\dot{A}X_i = \left(\sqrt[q]{1 - \prod_{j=1}^{m} \left[1 - \left(\phi_{\dot{A}X_{ij}} \right)^q \right]^{w_j}}, \prod_{j=1}^{m} \left(\varphi_{\dot{A}X_{ij}} \right)^{w_j}, \prod_{j=1}^{m} \left(\gamma_{\dot{A}X_{ij}} \right)^{w_j} \right) \tag{13}$$

Step 4.3: Determine the score functions. The score values of the aggregated matrix are then calculated to measure the relative closeness of each alternative to the reference solutions. Accordingly, the negative and positive score functions are computed as follows:

$$f^-(AX_i) = \frac{K\left(\dot{A}X_i\right)}{K\left(\dot{A}X_{AI}\right)} \tag{14}$$

$$f^+(AX_i) = \frac{K\left(\dot{A}X_i\right)}{K\left(\dot{A}X_{AAI}\right)} \tag{15}$$

Step 4.4: Obtain the utility function. The utility functions for each anti-ideal and ideal alternative are computed by Eqs. (16) and (17).

$$UF^-(AX_i) = \frac{f^+(AX_i)}{f^-(AX_i) + f^+(AX_i)} \tag{16}$$

$$UF^+(AX_i) = \frac{f^-(AX_i)}{f^-(AX_i) + f^+(AX_i)} \tag{17}$$

Step 4.5: Gain the final utility function $F(AX_i)$ of the alternatives. The value of $F(AX_i)$ is calculated by employing Eq. (18).

$$F(AX_i) = \frac{f^-(AX_i) + f^+(AX_i)}{1 + \frac{1 - UF^+(AX_i)}{UF^+(AX_i)} + \frac{1 - UF^-(AX_i)}{UF^-(AX_i)}} \tag{18}$$

3. Case study

This section presents a case study that evaluates the application challenges of modern educational technology in teaching management across different types of Chinese higher education institutions.

3.1 Description of alternatives

This study considers three representative types of higher education institutions in China as evaluation alternatives, reflecting differences in institutional missions, governance structures, and management capacities [24].

①Higher vocational colleges (Γ_1)

Higher vocational colleges mainly provide post-secondary vocational education with an emphasis on practice-oriented training. These institutions aim to cultivate technically skilled personnel by integrating general cultural foundations with specialized theoretical knowledge, applied technologies, and occupational competencies, building upon students' secondary education background.

②Local general higher education institutions (Γ_2)

Local general higher education institutions are typically administered by provincial-level or equivalent local authorities, including those under autonomous regions and municipalities. Financial support for these institutions is largely derived from local government budgets. Their primary mission is to support regional development by educating applied and professional talents and responding to local economic and social needs.

③Local key higher education institutions (Γ_3)

Local key higher education institutions are established to enhance institutional quality and foster the development of high-level and distinctive universities at the regional level. These institutions focus on strengthening prioritized disciplines and faculty teams, improving the effectiveness of talent development and scientific research, and expanding their role in supporting both regional and national economic and social advancement.

3.2 Definition of the evaluation criteria

The evaluation criteria in this study are defined as key barriers affecting the application of modern educational technology in higher education teaching management. Based on a synthesis of relevant literature and practical considerations, eight criteria are identified to reflect technological, organizational, human, financial, institutional, and environmental challenges. These criteria collectively capture the multidimensional nature of obstacles encountered during the adoption and implementation process and serve as the basis for subsequent multi-criteria decision analysis. The definition of the barriers is displayed in Table 1.

Table 1. Definition of the barriers

Symbol	Barriers	Definition
H_1	Limitations of technological infrastructure and system integration	Fragmentation of digital platforms, limited system interoperability, and the presence of data silos that constrain the effective application of educational technologies in teaching management
H_2	Data governance and standardization	Inconsistent data definitions, lack of unified standards, and inadequate data governance mechanisms affecting data sharing and utilization
H_3	Digital competencies of teaching management staff	Insufficient digital literacy and limited data analysis capabilities among administrative and management personnel
H_4	Organizational structure and management processes	Difficulties in cross-departmental coordination and resistance to process reengineering during technology-enabled management transformation
H_5	Financial investment and operational sustainability	High initial implementation costs and long-term operation and maintenance pressures related to modern educational technologies
H_6	Security, privacy, and regulatory compliance	Risks associated with data security, personal information protection, and compliance with relevant laws and regulations
H_7	Organizational culture and technology acceptance	Resistance to organizational change and low willingness among stakeholders to adopt and use educational technologies
H_8	Policy and institutional support mechanisms	Lagging institutional policies and insufficient incentive mechanisms supporting the application of modern educational technologies

3.3 Implementation of the proposed model

Step 1.1: First, the linguistic estimation matrix is provided by three experts. Then, the individual preference matrix based on q-RPF is created by applying the transformation rule.

Step 2.1-2.3: Compute the weight of each expert. First, we calculate the score value $S(x_{ij}^{\tau}) = S_{ij}^{\tau}$ by using Eq. (2) with $q = 3$ [25], which is displayed in Table 2. Then, we can obtain the weight of experts through Eq. (3) and (4). The weight of expert is $\omega_{\tau} = \{0.3516, 0.3231, 0.3253\}$.

Table 2. The score function of individual preference matrix

	Expert 1			Expert 2			Expert 3		
	Γ_1	Γ_2	Γ_3	Γ_1	Γ_2	Γ_3	Γ_1	Γ_2	Γ_3
H_1	0.6912	0.4219	0.2281	0.7993	0.5918	0.4083	0.7993	0.5918	0.4083
H_2	0.4219	0.3171	0.6912	0.5918	0.5000	0.6895	0.5918	0.5000	0.6895
H_3	0.6912	0.4219	0.2281	0.6895	0.5918	0.4083	0.6895	0.6895	0.4083
H_4	0.4219	0.4219	0.5457	0.5918	0.5918	0.6895	0.6895	0.5918	0.6895
H_5	0.8611	0.5457	0.4219	0.9270	0.6895	0.5000	0.9270	0.6895	0.5918
H_6	0.2281	0.3171	0.5457	0.5000	0.6895	0.6895	0.5000	0.5000	0.6895
H_7	0.5457	0.4219	0.2281	0.6895	0.5918	0.4083	0.6895	0.6895	0.4083
H_8	0.4219	0.5457	0.2281	0.5918	0.6895	0.5000	0.5918	0.5918	0.5000

Step 2.4: Based on the weight of experts, the group preference matrix is calculated by Eq. (5), and the results are given in Table 3.

Table 3. The group preference matrix

	Γ_1			Γ_2			Γ_3		
	ϕ	φ	γ	ϕ	φ	γ	ϕ	φ	γ
H_1	0.8500	0.2000	0.2500	0.6500	0.4000	0.4500	0.4500	0.4000	0.6500
H_2	0.6500	0.4000	0.4500	0.5500	0.5000	0.5500	0.7929	0.2601	0.3109
H_3	0.7929	0.2601	0.3109	0.6884	0.3643	0.4147	0.4500	0.4000	0.6500
H_4	0.6884	0.3643	0.4147	0.6500	0.4000	0.4500	0.7500	0.3000	0.3500
H_5	0.9500	0.1000	0.1500	0.7500	0.3000	0.3500	0.6226	0.4299	0.4801
H_6	0.5201	0.4623	0.5833	0.6377	0.4239	0.4753	0.7500	0.3000	0.3500
H_7	0.7500	0.3000	0.3500	0.6884	0.3643	0.4147	0.4500	0.4000	0.6500
H_8	0.6500	0.4000	0.4500	0.7228	0.3294	0.3798	0.5201	0.4623	0.5833

Step 3.1-3.4: Calculate the weight of barriers. The total similarity and weight of barriers is computed by Eqs. (6)-(9), which are displayed in Table 4.

Table 4. The total similarity and weight of barriers

	H_1	H_2	H_3	H_4	H_5	H_6	H_7	H_8
S_j	2.7117	2.5429	2.8016	2.7386	2.6184	2.5648	2.7683	2.6740
w_j	0.1266	0.1187	0.1308	0.1278	0.1222	0.1197	0.1292	0.1248

Step 4.1-4.5: Ranking the alternatives. First, the utility degree and utility function for each anti-ideal and ideal financial solutions is computed through Eqs. (14)-(17), as provided in Table 10. Finally, the utility function of the four financial solutions is obtained through Eq. (18), as given in Table 5.

Table 5. The final ranking of alternatives

	$f^-(AX_i)$	$f^+(AX_i)$	$UF^-(AX_i)$	$UF^+(AX_i)$	$F(AX_i)$	Ranking order
Γ_1	1.2713	0.8715	0.4067	0.5933	0.6815	2
Γ_2	1.0928	0.9779	0.4723	0.5277	0.6874	1
Γ_3	1.0837	0.9396	0.4644	0.5356	0.6699	3

As shown in Table 5, the comprehensive evaluation results indicate clear differences among the three alternatives in terms of the severity of barriers to the application of modern educational technology in higher education teaching management. Among the alternatives, Local general higher education institutions (Γ_2) achieves the highest overall assessment value (0.6874) ranking first, which suggests that this type of institution faces relatively more pronounced overall barriers under the considered criteria. Higher vocational colleges (Γ_1) ranks second with an overall value of 0.6815, reflecting substantial challenges, particularly in resource-related and capacity-related dimensions. In contrast, Local key higher education institutions (Γ_3) obtains the lowest comprehensive value, indicating comparatively lower overall barrier levels among the three alternatives.

The ranking results demonstrate that although local key higher education institutions generally possess stronger technological foundations, their barriers remain non-negligible due to organizational complexity and governance requirements. Meanwhile, local general higher education institutions exhibit the highest composite challenge level, highlighting the cumulative effects of moderate infrastructure, governance, and resource constraints. Overall, the findings confirm the effectiveness of the proposed evaluation framework in distinguishing the relative challenge levels across different institutional types.

3.4 management implication

Based on the empirical findings of this study and the proposed multi-criteria evaluation framework, several managerial implications are derived to address the challenges of applying modern educational technology in higher education teaching management in Chin

(1) The findings indicate that challenges in applying modern educational technology to teaching management are not solely determined by technological conditions, but are closely related to organizational processes, human capabilities, financial sustainability, and institutional support mechanisms. Higher education administrators should therefore move beyond technology-centered approaches and adopt barrier-oriented management strategies that systematically address the most restrictive factors affecting teaching management digitalization.

(2) The comparative results show that different types of higher education institutions in China face distinct combinations and intensities of application barriers. Local general higher education institutions, in particular, experience the highest overall challenge level, suggesting the need for targeted policy support and managerial interventions. Education authorities and institutional leaders should formulate differentiated governance and support mechanisms that align with institutional missions and management capacities in order to effectively reduce teaching management barriers.

(3) The proposed q-RPF-MARCOS framework provides a structured and uncertainty-aware approach for evaluating the complex challenges associated with modern educational technology adoption in teaching management. By integrating expert judgment with multi-dimensional barrier assessment, this framework can serve as a practical decision-support tool for higher education managers to diagnose existing problems, prioritize improvement actions, and monitor the effectiveness of digital management initiatives over time.

4. Conclusions

This study develops an integrated q-RPF-MARCOS decision-making framework to systematically evaluate the challenges associated with the application of modern educational technology in higher education teaching management in China. By incorporating q-rung picture fuzzy sets, expert-weight aggregation, and a utility-based ranking mechanism, the proposed approach effectively addresses uncertainty, subjectivity, and heterogeneity in expert judgments. The framework enables a comprehensive assessment of application barriers while providing a robust and transparent basis for comparative analysis across different types of higher education institutions.

The barrier weight analysis indicates that data governance and standardization, organizational and management processes, and digital competencies of teaching management staff constitute the most influential obstacles to the effective application of modern educational technology. These results suggest that institutional challenges are not merely technological in nature but are deeply rooted in governance mechanisms, human capacity constraints, and systemic coordination issues. The prominence of these barriers highlights the need to move beyond infrastructure-oriented solutions and focus on institutional transformation and management capability enhancement. The case study results further reveal significant differences in the overall challenge levels faced by different types of higher education institutions. Local general higher education institutions exhibit the highest composite barrier level, reflecting the cumulative impact of moderate technological foundations, limited governance capacity, and resource constraints. Higher vocational colleges also face substantial challenges, particularly in terms of financial sustainability and staff digital competencies. In contrast, local key higher education institutions demonstrate comparatively lower overall barrier levels, although challenges related to organizational complexity, data governance, and compliance remain non-negligible. These findings underscore the heterogeneity of teaching management contexts and the necessity of differentiated digital governance strategies.

Overall, this study contributes a methodologically robust and application-oriented evaluation framework for diagnosing the challenges of modern educational technology adoption in higher education teaching management. By integrating uncertainty modeling with multi-criteria analysis, it offers both theoretical advancement and practical guidance for higher education administrators and policymakers. The proposed framework can support evidence-based decision-making, facilitate targeted barrier mitigation strategies, and promote more effective and sustainable digital transformation in higher education teaching management systems.

Author Contributions

Conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, supervision, project administration, and funding acquisition: Huawei Wang.
The author has read and agreed to the published version of the manuscript.

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Data Availability Statement

In this section, please provide details regarding where data supporting reported results can be found, including links to publicly archived datasets analyzed or generated during the study. You might choose to exclude this statement if the study did not report any data.

Conflicts of Interest

Declare conflicts of interest or state "The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper." Authors must identify and declare any personal circumstances or interest that may be perceived as inappropriately influencing the representation or interpretation of reported research results. Any role of the funders in the design of the study; in the collection, analyses or interpretation of data; in the writing of the manuscript, or in the decision to publish the results must be declared in this section. If there is no role, please state "The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results".

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