Evaluating Learning Effectiveness in Blended Electromagnetic Measurement Training Using a Hybrid EWM-AHP-DEMATEL Weighting Model

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ABSTRACT Blended practical training in engineering electromagnetic measurement is becoming increasingly prevalent in the context of digital transformation in education. However, due to the inherent complexity of this field, traditional evaluation methods are inadequate for effectively quantifying its technical challenges and accurately assessing student learning outcomes. To address this issue, this study proposes a blended practical training learning effectiveness evaluation method based on a combined EWM-AHP-DEMATEL weighting model. The method employs the Analytic Hierarchy Process (AHP) to determine subjective weights, the Decision Making Trial and Evaluation Laboratory (DEMATEL) technique to analyze inter-indicator correlations and dynamically adjust weights, and the Entropy Weight Method (EWM) to quantify objective weights from the information entropy of measured data, thereby establishing a comprehensive subjective-objective weighting framework. Empirical analysis of representative engineering electromagnetic measurement applications demonstrates that the proposed model effectively preserves expert experiential judgment while significantly reducing subjective bias through objective data-driven entropy analysis. This study provides a scientific diagnostic tool for optimizing blended instruction in electromagnetic measurement training and also offers valuable reference for cultivating high-quality applied talents in the field of electromagnetic non-destructive testing and sensing.

INDEX TERMS information entropy, fuzzy comprehensive evaluation, blended practical training, electromagnetic engineering education, antenna measurement

I. INTRODUCTION

ELECTROMAGNETIC measurement techniques are widely used in civil engineering. Typical methods—such as Ground Penetrating Radar (GPR) surveys, Transient Electromagnetic (TEM) exploration, electromagnetic wave positioning, and electromagnetic induction-based rebar detection—have become indispensable core technologies for non-destructive testing and safety assessment in engineering practice. These techniques can be collectively referred to as engineering electromagnetic measurement (EEM), which utilizes the interaction between electromagnetic waves and subsurface media or engineering structures to infer physical properties or internal defects by observing electromagnetic field responses. Blended practical training, through the systematic integration of online resources and offline practice, transcends the spatial and temporal constraints of traditional instruction and has demonstrated significant advantages across various engineering training contexts [1-3]. Its application is particularly critical in EEM education, where the curriculum encompasses diverse non-destructive testing and parameter measurement techniques—all requiring substantial hands-on training grounded in theoretical foundations. However, EEM practical training involves precision instrumentation, electromagnetic parameter configuration, and signal interpretation, with stringent requirements for operational standardization and measurement accuracy that are susceptible to environmental interference. These characteristics impose evaluation demands considerably more complex than those of general engineering training. Consequently, the scientific assessment of learning outcomes in blended EEM practical training has emerged as a pressing issue requiring immediate attention.

For decades, the evaluation of learning effectiveness in engineering practical training has relied predominantly on summative assessments—such as final examinations and operational performance tests—supplemented by qualitative observations from instructors. Such evaluation approaches exhibit two major limitations. First, they focus primarily on static snapshots of learning outcomes, neglecting the dynamic progression of skill acquisition and problem-solving capabilities. Second, the evaluation criteria are largely defined by instructors based on personal experience, rendering the results highly subjective and lacking objective data support, which compromises the stability and reproducibility of the assessments [4-5]. These limitations are particularly pronounced in EEM practical training, where the inherent technical complexity renders traditional evaluation approaches inadequate for accurate assessment; conventional frameworks also fail to integrate the multi-source heterogeneous data generated during the training process. In summary, traditional approaches have exposed systemic deficiencies when applied to the highly specialized and dynamically complex context of EEM practical training.

To overcome these limitations, recent studies have introduced non-precise mathematical theories—including fuzzy mathematics, neural networks, and grey system theory—into teaching evaluation to enhance objectivity [6-8]. Among these, the Fuzzy Comprehensive Evaluation Model (FCEM) has been widely adopted due to its advantage in handling fuzzy and uncertain information [9-10]. However, most studies still rely predominantly on subjective weighting methods such as AHP in the weight determination stage, without incorporating objective data for calibration. BP neural networks have also been employed to reduce subjectivity [11-12], yet their inherent "black box" nature compromises interpretability. Grey system theory has been applied to educational quality assessment [13-14], but its decision-making process remains largely subjective and lacks a robust objective foundation. Notably, none of these studies have specifically developed a systematic evaluation framework tailored to EEM practical training. The evaluation dimensions uniquely pertinent to EEM—precision instrumentation operation standards, electromagnetic parameter calibration, signal interpretation proficiency, and multi-stage causal propagation mechanisms—have received insufficient attention and effective quantification in the existing literature. The present study is motivated by this deficiency.

To address the above deficiencies, this study proposes a fuzzy comprehensive evaluation method for blended EEM practical training effectiveness based on a combined EWM-AHP-DEMATEL weighting model, based on three considerations. First, the evaluation indicators for EEM training encompass multiple dimensions—including precision instrumentation operation, data interpretation proficiency, and learning attitudes—involving both qualitative expert judgments and quantitative measured data, which a single weighting method cannot adequately integrate. Second, there exist significant causal interconnections among the various stages of the training process, which necessitate that the weighting calculation account for inter-indicator influences—a requirement that the conventional AHP, with its assumption of indicator independence, cannot fulfill. Third, the multi-source data generated during student training (online learning behaviors, operational performance scores, project completion rates, etc.) contain rich objective information, which can be quantified via information entropy to determine objective weights, thereby effectively counterbalancing subjective judgments. Accordingly, this study employs AHP to establish initial subjective weights, introduces DEMATEL to analyze causal inter-indicator relationships and dynamically adjust these weights, and adopts EWM to quantify objective weights—the three methods working in synergy to form a comprehensive weighting framework, which is then combined with the fuzzy comprehensive evaluation model for multi-level quantitative assessment of learning effectiveness. The contributions of this study are twofold: it applies the EWM-AHP-DEMATEL combined weighting model to teaching evaluation in EEM practical training, providing a systematic assessment tool for this field; and through empirical analysis, it validates the model's effectiveness in identifying instructional weaknesses, thereby offering a decision-making basis for optimizing blended instructional design and enhancing the quality of EEM talent cultivation.

II. METHODOLOGY

A. EWM-AHP-DEMATEL WEIGHTING MODEL

The core of employing the FCEM for learning effectiveness evaluation lies in the scientific determination of indicator weights. EEM practical training involves multi-dimensional evaluation indicators—spanning operational standardization, data interpretation proficiency, and team collaboration—characterized by both qualitative expert judgments and quantitative measured data, with significant causal interconnections among training stages. A single weighting method cannot adequately address such complexity. To this end, this study establishes a comprehensive weighting model integrating EWM, AHP, and DEMATEL: AHP determines subjective weights of hierarchical indicators; DEMATEL analyzes inter-indicator correlations and dynamically adjusts subjective weights; and EWM quantifies objective weights based on information entropy of measured data. The three methods work in synergy to form a comprehensive subjective-objective weighting framework. The EWM assignment model is as follows.

The weight of the j-th evaluation indicator for the i-th evaluation object is:

$$P_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{n} Y_{ij}} \tag{1}$$

Where, Y_{ij} is the value of the indicator after normalization.

Based on the indicator weights, the information entropy of the indicators can be calculated, and the expression of the information entropy is:

$$E_j = -\left[\ln(n)\right]^{-1} \times \sum_{i=1}^{n} \left[P_{ij} \times \ln(P_{ij})\right] \tag{2}$$

Where, n is the number of evaluation indicators. If $P_{ij} = 0$, $\lim_{P_{ij} \to 0} P_{ij} \times \ln(P_{ij}) = 0$.

The EWM weight of the j-th indicator is:

$$W_j' = \frac{1 - E_j}{\sum_{j=1}^{m}(1 - E_j)} \tag{3}$$

Where, m is the number of evaluation objects.

The EWM calculates weights solely based on the degree of variability in the indicator data, neglecting the incorporation of expert experience and subjective judgment. This oversight may result in a misalignment between the assigned weights and the actual problem at hand. Consequently, it is imperative to combine this method with subjective weight assignment to address complex issues effectively. To address the limitations of AHP (ignoring horizontal correlations) and DEMATEL (lacking hierarchical weighting), this study integrates both methods: initial weights are first obtained via AHP, then corrected using DEMATEL to account for inter-indicator correlations [15]. Thus, this study proposes a modified subjective weighting model based on the AHP-DEMATEL method to alleviate the limitations associated with the singular application of either method. The process for constructing the subjective weighting model is outlined as follows:

(1) The initial weight W is determined using the AHP method. The expression of the judgment matrix is presented as follows:

$$C = \begin{pmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{nn} \end{pmatrix} \tag{4}$$

Where: $C_{ij} = f(i, j)$, $f(x, y)$ represents the relative importance of indicator i over indicator j, $f(x, y) = 1/f(y, x)$.

From the judgment matrix C, the largest eigenroot $\lambda_{\max}$ is determined, and the eigenvector of the judgment matrix about the largest eigenroot $\lambda_{\max}$ is obtained.

$$\xi = \{x_1, x_2 \cdots x_n\} \tag{5}$$

After normalizing the feature vectors ξ, the AHP weights for each indicator can be obtained, namely:

$$W_{\mathrm{AHP}} = \{a_1, a_2 \cdots a_n\} \tag{6}$$

(2) Establish the AHP-DEMATEL model. The impact matrix A is as follows:

$$A = (a_{ij})_{n\times n} = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{pmatrix} \tag{7}$$

Where: n is the number of evaluation indicators, a_{ij} denotes the degree of influence of indicator i on indicator j. Experts rate the influence of indicator i on indicator j on a scale of 0 (no influence) to 3 (substantial influence).

Using the normalization formula to derive the criteria matrix X:

$$X = \frac{A}{\max\limits_{1\le i\le n} \sum_{j=1}^{n} a_{ij}} \tag{8}$$

The integrated impact matrix is:

$$T = (I - X)^{-1}X \tag{9}$$

Where, I is the unit matrix.

Influence degree D_i is the value of the combined influence measure of each row of the matrix on other indicators, which is expressed as:

$$D_i = \sum_{j=1}^{n} t_{ij} \tag{10}$$

Influenced degree R_i is a measure of how much the indicators in each column of the matrix are influenced by the other indicators, and is expressed as follows:

$$R_i = \sum_{i=1}^{n} t_{ij} \tag{11}$$

The cause degree N_i is the interaction between the indicators. The expression for N_i is as below:

$$N_i = D_i - R_i \tag{12}$$

The centrality degree M_i reflects the importance of the indicator, and its expression is as follows:

$$M_i = D_i + R_i \tag{13}$$

(3) Calculate the AHP-DEMATEL weight, and the formula is as below:

$$W_i^* = \frac{M_i \times W_{\mathrm{AHP}}^i}{\sum_{j=1}^{n} M_i \times W_{\mathrm{AHP}}^i} \tag{14}$$

Where: W_i^* is the AHP-DEMATEL weight of the i-th indicator, and W_{AHP}^i is the AHP weight of the i-th indicator.

Combining the EWM weight and the AHP-DEMATEL weights, composite weight can be obtained using a linear weighted combination method.

$$W_i = \alpha W_i^* + (1 - \alpha)W_i' \tag{15}$$

Where: W_i is the composite weight; W_i^* is the AHP-DEMATEL weight; α is the subjective weight coefficient, which can be determined by the expert consultation method; W_i' is the EWM weight.

B. MULTI-LEVEL FUZZY EVALUATION MODEL

In EEM practical training evaluation, qualitative indicators such as operational standardization and data interpretation proficiency are difficult to quantify directly, while the hierarchical relationships among indicators remain inherently fuzzy. The Fuzzy Comprehensive Evaluation Model (FCEM), through membership functions, converts qualitative indicators into quantifiable values, effectively addressing both the fuzziness and hierarchical complexity inherent in teaching evaluation. Building upon the comprehensive weighting framework established above, this study constructs a hybrid multi-level FCEM, with its detailed formulation presented as follows.

(1) Determine the factor set and factor subset according to the indicator evaluation system:

$$U = (U_1 \quad U_2 \quad \cdots \quad U_s) \tag{16}$$

Where, s is the number of factor subsets, i.e., the number of primary indicators.

The factor subset can be expressed as:

$$U_k = (U_{k1} \quad U_{k2} \quad \cdots \quad U_{km}) \tag{17}$$

Where, m is the number of secondary indicators for the k th primary indicator.

(2) Primary evaluation of factor subset

Based on the importance of each indicator in the factor subset, the weights of the indicators are determined by the comprehensive assignment model:

$$A_k = (a_{k1} \quad a_{k2} \quad \cdots \quad a_{km}) \tag{18}$$

Where A_k is the vector of weights for the secondary indicator in the subset of k-th factors and satisfies $\sum_{j=1}^{m} a_{kj} = 1$.

Based on the rating scale of each factor in the indicator system, the one-factor evaluation matrix for the k-th factor subset is obtained as follows:

$$R_k = \begin{pmatrix} r_{k11} & r_{k12} & \cdots & r_{k1n} \\ r_{k21} & r_{k22} & \cdots & r_{k2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{km1} & r_{km2} & \cdots & r_{kmn} \end{pmatrix} \tag{19}$$

Where, n is the number of rating scales.

The primary evaluation results can be calculated by the weighting matrix:

$$B_k = A_k \times R_k = (b_{k1} \quad b_{k2} \quad \cdots \quad b_{kn}) \tag{20}$$

Where, b_{ki} is the membership value of the secondary indicator.

(3) Comprehensive Evaluation

First, the factor subsets are regarded as s single factors. Then, based on the weights of these subsets, the weight vector A of the evaluation results is determined as follows:

$$A = (a_1 \quad a_2 \quad \cdots \quad a_s) \tag{21}$$

Where, A_i is the weights of the i-th level evaluation indexes and satisfies $\sum_{k=1}^{s} a_k = 1$.

The total evaluation matrix is formed based on the results of the primary evaluation:

$$R = \begin{pmatrix} b_{11} & b_{12} & \cdots & b_{1n} \\ b_{21} & b_{22} & \cdots & b_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{s1} & b_{s2} & \cdots & b_{sn} \end{pmatrix} \tag{22}$$

Calculate the overall evaluation results from the weight vector A and the evaluation matrix R in a similar way to the primary evaluation:

$$B = A \times R = (b_1 \quad b_2 \quad \cdots \quad b_n) \tag{23}$$

Where, b_i is the membership value of the first-level indicator.

C. EVALUATION INDICATOR SYSTEM

The effective implementation of blended practical training relies on three core elements: online learning resources, offline training facilities, and the active engagement of industry mentors. This model flexibly accommodates students‘ individualized learning needs. In engineering electromagnetic measurement (EEM) education, blended training is particularly critical—EEM involves precision instrumentation operation, complex parameter configuration, and data interpretation, which are difficult for students to master through theory alone. The blended model, combining step-by-step video instruction with hands-on guided practice, effectively enhances students' comprehension of EEM techniques. In practice, the online component provides digital resources including e-textbooks, instructional videos, and online quizzes, allowing students to progress at their own pace; the offline component reinforces hands-on skills through instructor-led demonstrations, equipment operation, and group tasks; and industry mentors participate via the online platform by assigning tasks, providing field operation videos, and evaluating training outcomes, thereby facilitating lightweight and sustainable industry-school collaboration.

Taking Ground Penetrating Radar (GPR) practical training—a representative EEM application—as an example, the blended teaching process is organized into three stages:

(1) Pre-class preparation: Instructors release GPR-based engineering inspection tasks through the platform, disseminating instructional videos covering electromagnetic wave propagation theory, the influence of dielectric permittivity on detection depth, and antenna frequency selection principles, together with radar image cases of typical engineering defects (voids, reinforcement distribution). Industry mentors record field operation videos,

focusing on critical procedures such as installation and switching of antennas of different frequencies, parameter configuration, and radar image interpretation.

(2) In-class implementation: Training is conducted primarily in the on-campus EEM laboratory, where instructors explain instrument composition and working principles on-site, demonstrate survey line layout and data acquisition procedures, and provide roving guidance. Students work in groups to complete hands-on tasks including line layout, parameter setting, and data collection. They may access key procedural videos via mobile devices at any time to reinforce memory. Industry mentors observe student operations in real time through video conferencing, providing immediate feedback on anomalous signals encountered during data acquisition (e.g., noise caused by environmental electromagnetic interference), assisting students in identifying and eliminating interference sources and correcting non-standard practices.

(3) Post-class consolidation and extension: Instructors and industry mentors jointly evaluate learning outcomes based on the radar survey reports submitted by students, and formulate targeted improvement recommendations. Students consolidate their learning by reviewing instructional videos, participating in online discussions, and undertaking supplementary practice in open laboratory sessions. They are also encouraged to complete advanced extension projects—such as tunnel lining thickness detection and underground utility positioning—to further strengthen their comprehensive capabilities in electromagnetic measurement applications.

The evaluation of the learning outcomes of blended practical training necessitates a comprehensive assessment of students' competencies across multiple dimensions. This includes not only the acquisition of knowledge and skills but also essential attributes such as innovative thinking and teamwork. The assessment framework employs a hybrid approach that integrates both process and summative evaluations, focusing on the entirety of the learning experience. This encompasses the pre-class, in-class, post-class stages, and the final summative assessment, as illustrated in Figure 1.

The evaluation framework incorporates multiple assessors, including instructors, industry mentors, peers, and students themselves. Instructors evaluate based on classroom observation, training reports, and project outcomes. Industry mentors assess the standardization and professionalism of training deliverables through the online platform, providing feedback from an industry perspective. Peer evaluation focuses on collaboration and contribution within group tasks, while self-assessment guides students to reflect on their learning gains and areas for improvement. In addition, online platform data serve as an objective source of learning behavioral records. The integration of these multi-source evaluation results ensures an objective and comprehensive assessment of students' learning outcomes in EEM practical training. The evaluation indicators and their corresponding data sources are presented in Table 1.

III. RESULTS AND DISCUSSION

A. MODEL WEIGHT ANALYSIS

This study focuses on the Engineering Testing course within the Urban Railway Transportation Engineering Program at Chongqing Open University, China. This course primarily encompasses electromagnetic testing techniques—including Ground Penetrating Radar (GPR) surveying, Transient Electromagnetic Method (TEM) exploration, electromagnetic wave ranging, and electromagnetic induction detection of steel reinforcement, among others—which are core competencies in engineering non-destructive testing (NDT). In this course, a hybrid online and offline blended practical training model was implemented for Class 1 of 2023, which served as the experimental group. In contrast, Class 2 followed the traditional face-to-face practical training model, serving as the control group. Both groups were taught by the same instructor. The final outcomes of the comprehensive skills assessment and the written theoretical knowledge test are presented in Figure 2.

Based on the summative assessment data from both the experimental and control groups, the experimental group demonstrated superior performance in both the summative skill assessment and the written test compared to the control group. Specifically, the experimental group exhibited an improvement of approximately 12.87% in the skill assessment and an 11.47% enhancement in the written test performance. These results indicate that the blended teaching model possesses distinct advantages in fostering students' practical skills and the acquisition of theoretical knowledge in electromagnetic testing training. This effectiveness can be attributed to key features of blended teaching, including the use of segmented video resources for demonstrating electromagnetic instrumentation procedures, mentorship from industry professionals providing practical insights into field measurements, and opportunities for repeated targeted practice on specific operational steps.

It is important to note, however, that summative evaluations primarily reflect final outcomes and do not fully capture the intricacies of the learning process. To further identify the shortcomings of blended teaching and optimize instructional design, the introduction of a fuzzy comprehensive evaluation model is warranted. This model enables a systematic assessment of the entire blended practical training process for this course. By integrating data from online learning, offline practical operations, instructor evaluations, and peer assessments, a multi-dimensional evaluation system can be established. Such a system facilitates a quantitative analysis of the contributions from each component, accurately pinpoints areas for improvement, and provides data-driven insights to enhance the design of blended learning experiences for electromagnetic testing training.

Utilizing the framework of formative evaluation and summative evaluation indices, the EWM-AHP-DEMATEL method is employed to determine the comprehensive

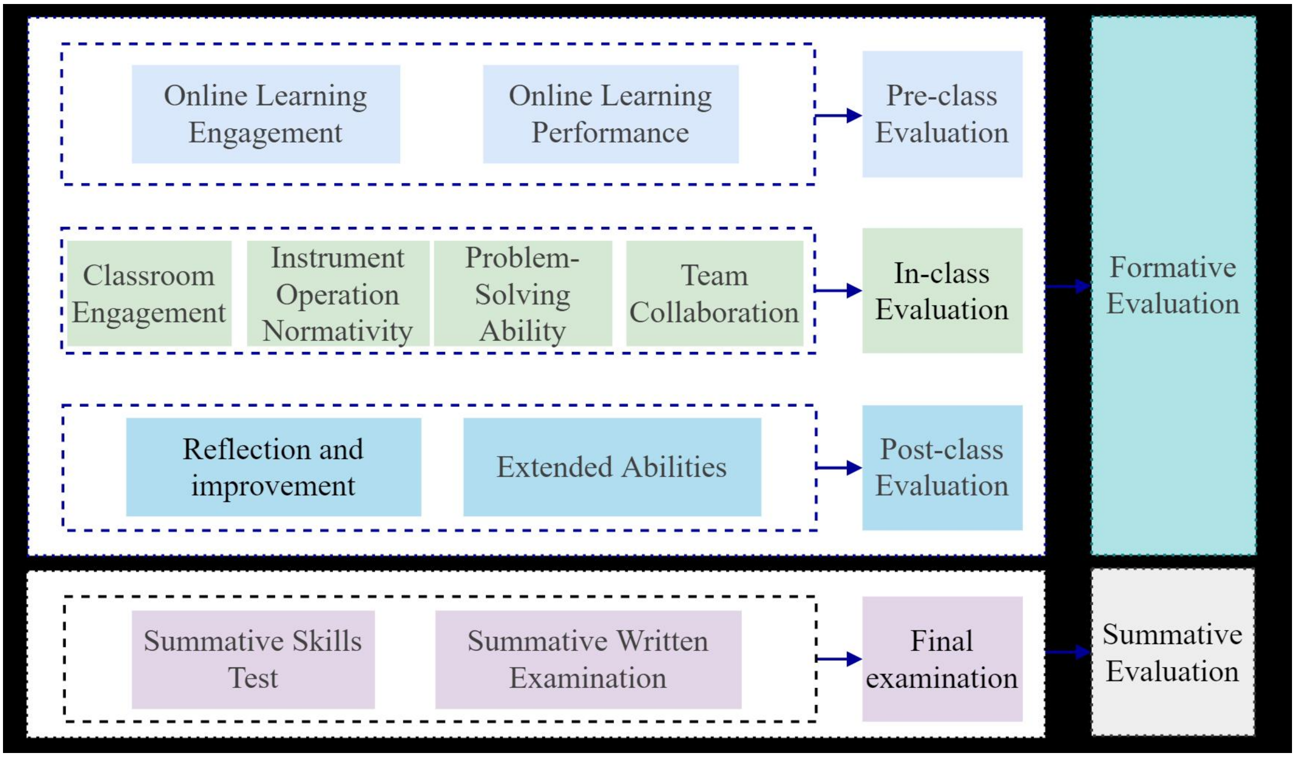

FIGURE 1. Evaluation index system

TABLE 1. Content of Evaluation Indicators

Objective Layer	Primary indicators	Secondary indicators	Tertiary indicators	Content	Evaluator
Blended EEM Practical Training Learning Effectiveness Evaluation	Formative Evaluation (A1)	Pre-class Evaluation (B1)	Online Learning Engagement (C1)	Platform login frequency, video viewing time, and completion rate	Online platform statistics
			Online Learning Performance (C2)	Online test scores	Online platform statistics
		In-class Evaluation (B2)	Classroom Engagement (C3)	Attendance, active participation in hands-on sessions, and frequency of key procedural video reviews	Instructors
			Instrument Operation Normativity (C4)	Correct installation and commissioning of electromagnetic measurement equipment, proper configuration of critical measurement parameters, and adherence to system calibration protocols	Instructors and Industry Mentors
			Problem-Solving Ability (C5)	Rationality of survey line/point layout, identification and elimination of anomalous signals, and on-site troubleshooting capability	Industry Mentors
			Team Collaboration (C6)	Contribution of group members	Instructors and students
		Post-class evaluation (B3)	Reflection and improvement (C7)	Frequency of extracurricular supplementary exercises	Course report, open record of training room
			Extended Abilities (C8)	Completion rate of extended projects	Industry Mentors
	Summative Evaluation (A2)	Summative Skills Assessment (B4)	Summative Skills Test (C9)	Completion of authentic engineering projects	Instructors and Industry Mentors
		Summative knowledge assessment (B5)	Summative written examination (C10)	Closed-book examination covering fundamental EEM principles, measurement parameter selection criteria, and typical measurement data interpretation and analysis	Instructors

weights of the indicators. The calculated weights for the tertiary indicators are presented in Table 2, while the weights for the primary and secondary indicators are illustrated in Figures 3 and 4.

Comparison of comprehensive and single assignment results reveals that the comprehensive assignment model effectively optimizes weight allocation by integrating both subjective and objective information. For instance, the comprehensive weight for "Instrumentation Operation Standardization (C4)" is 0.155, which represents a slight decrease from the AHP weight of 0.194; however, it remains a pivotal component. This outcome suggests that the comprehensive approach mitigates excessive subjectivity by incorporating EWM objective data while still valuing expert judgment. The consistently high weight assigned to C4 across all weighting models underscores the critical importance of procedural precision in electromagnetic testing—where even minor configuration errors in antenna selection, parameter settings, or system calibration can propagate into significant measurement deviations and compromise

TABLE 2. Model Weight Calculation Results

Primary indicators	Secondary indicators	Tertiary indicators	AHP weight	AHP-DEMATEL Weight	EWM weight	Combined Weights
Formative Evaluation (A1)	Pre-class evaluation (B1)	C1	0.047	0.057	0.098	0.071
		C2	0.094	0.115	0.106	0.112
	In-class evaluation (B2)	C3	0.049	0.026	0.105	0.052
		C4	0.194	0.177	0.111	0.155
		C5	0.081	0.081	0.104	0.089
		C6	0.042	0.014	0.083	0.037
	Post-class evaluation (B3)	C7	0.071	0.087	0.074	0.083
		C8	0.089	0.109	0.105	0.108
Summative evaluation (A2)	Summative Skills Assessment (B4)	C9	0.222	0.222	0.110	0.185
	Summative knowledge assessment (B5)	C10	0.111	0.111	0.104	0.109

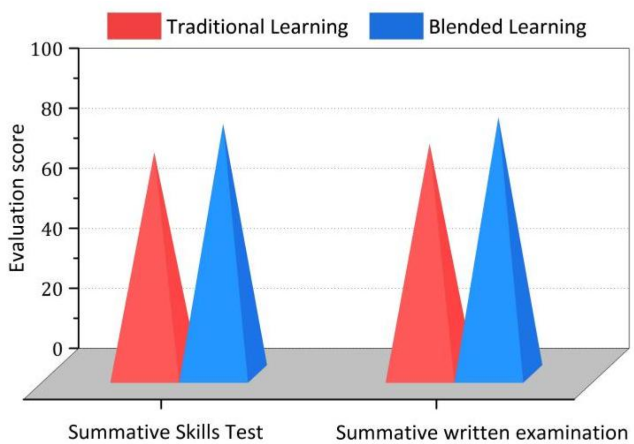

FIGURE 2. Comparative analysis of summative assessment

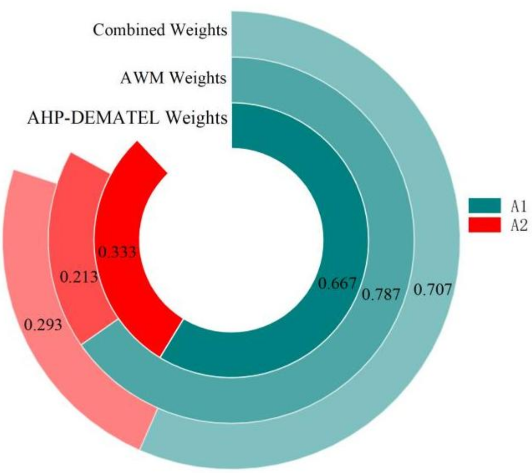

FIGURE 3. Primary indicator weights

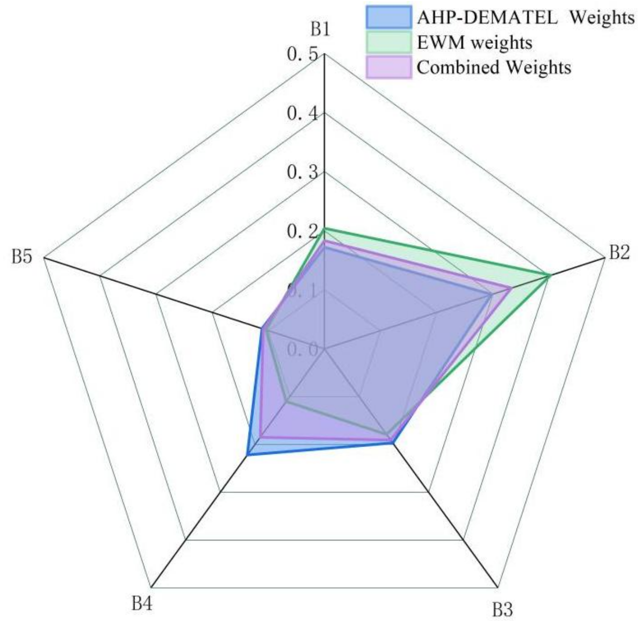

FIGURE 4. Secondary indicator weights

detection reliability.

The weight for "Comprehensive Practical Skills (C9)" decreases from 0.222 in the AHP-DEMATEL model to 0.185 in the composite model, indicating a moderate adjustment of subjective weights through the application of information entropy derived from objective data. Nevertheless, C9 retains the highest weight among all tertiary indicators, reflecting the emphasis placed on students' ability to execute complete electromagnetic testing workflows—from equipment setup and calibration to data acquisition, processing, and interpretation—which is essential for professional competence in electromagnetic measurement applications.

In contrast, the weight for "Classroom Engagement (C3)" rises from 0.026 in the AHP model to 0.052 in the composite model, while the weight for "Team Collaboration (C6)" increases from 0.014 to 0.037. These changes suggest that the composite method compensates for the underestimation of process indicators that may result from subjective evaluations by integrating objective data. This adjustment effectively reconciles the discrepancies between subjective preferences and objective data, leading to a more rational weight distribution.

At the secondary indicator level, "In-Class Evaluation

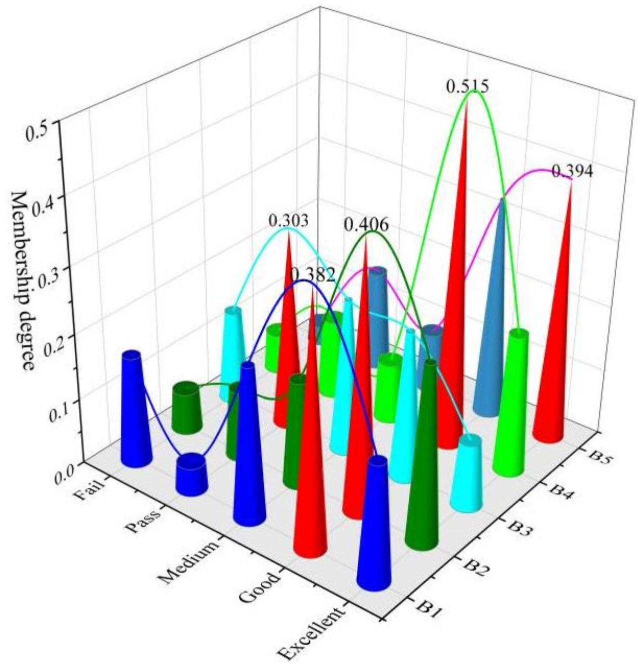

FIGURE 5. Membership values of secondary indicators

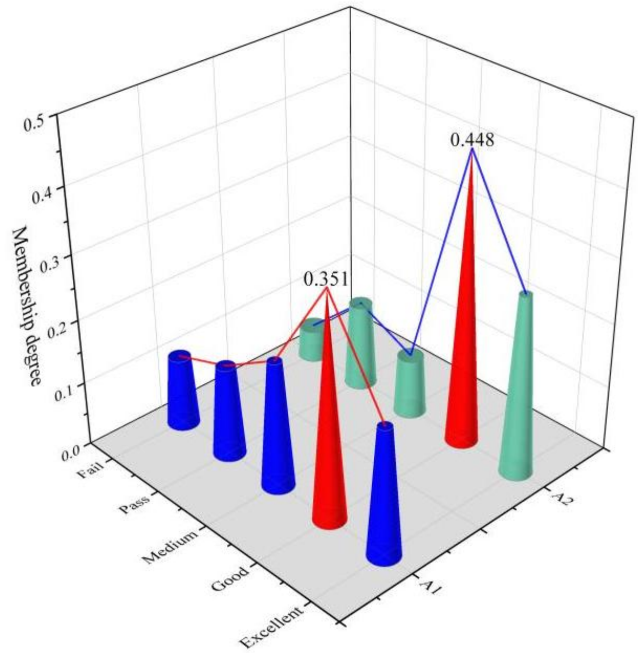

FIGURE 6. Membership values of primary indicators

(B2)" with a weight of 0.333 emerges as the dominant factor in formative evaluation, underscoring the significance of face-to-face practical sessions within the blended teaching framework. Furthermore, the weight for "Formative Evaluation (A1)" (0.707) notably exceeds that of "Summative Evaluation (A2)" (0.293), indicating a greater emphasis on dynamic processes within the evaluation system. This judicious allocation of weights, which prioritizes continuous assessment of operational skills development and real-time problem-solving over end-of-course testing, is particularly well-suited to the progressive skill acquisition model inherent in electromagnetic testing training, where competencies are built incrementally through repeated practice. This framework provides a robust foundation for subsequent data analysis.

B. FUZZY COMPREHENSIVE EVALUATION RESULTS

Based on the assigned weights of the indicators, the FCEM is employed to assess the effectiveness of blended learning in Engineering Measurement Practical Training. Each indicator is categorized into five assessment levels: excellent, good, medium, pass, and fail. According to the learning data and assessment levels, an evaluation matrix is established to perform a multi-level FCEM for evaluating blended practical training effectiveness, and the evaluation results are analyzed based on the principle of maximum membership. The membership value of each evaluation index is shown in Figures 5-7.

The overall effectiveness of blended learning in engineering electromagnetic measurement practical training has a maximum membership degree of 0.365, which corresponds to a rating of "good," indicating that the course design is

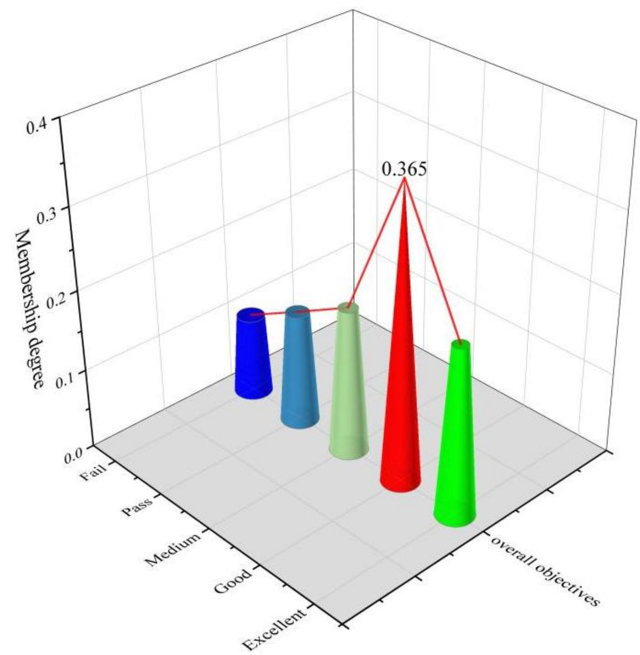

FIGURE 7. Membership values of overall objectives

fundamentally effective. Among the primary indicators, both the formative evaluation (A1) and the summative evaluation (A2) predominantly receive "good" ratings, with membership values of 0.351 and 0.448, respectively. This suggests notable effectiveness in teaching implementation and assessment. However, the formative evaluation also yields membership degrees of 0.142 and 0.110 for the "pass" and "fail" levels, respectively. These lower-tier ratings indicate potential deficiencies within the formative evaluation (A1), which warrants further investigation through its secondary indicators.

In the secondary indicators, the maximum membership degrees for pre-class evaluation (B1), in-class evaluation (B2), and summative skills assessment (B4) are 0.382, 0.406, and 0.515, respectively, all categorized as "good." In contrast, the maximum membership for the post-class evaluation (B3) is 0.303, corresponding to a "pass" evaluation grade, while the summative knowledge assessment (B5) achieves a maximum membership degree of 0.394, classified as "excellent." Overall, the performance during the in-class phase and the summative skills assessment is strong, with the summative written test yielding the highest membership value. Conversely, the post-class phase is relatively weaker, representing a critical area for improvement.

The relative weakness in the post-class stage (B3) can be attributed to two primary factors. First, the absence of an effective learning management system (LMS) impedes monitoring of out-of-class independent practice—a critical gap given that electromagnetic testing training requires extensive repetitive practice to master complex skills and internalize procedural standards. Second, the difficulty level of extended tasks is often misaligned with students' current proficiency, as these tasks demand integrated application of electromagnetic theory, instrumentation knowledge, and data processing skills that most learners have not yet fully developed.

To address these deficiencies, this study recommends three interventions:

(1) introducing an LMS for real-time progress tracking and timely instructor intervention;
(2) adopting a tiered task design to accommodate varying proficiency levels; and
(3) equipping instructors with targeted guidance strategies, such as annotated solution walkthroughs for complex data interpretation exercises and online discussion forums for peer-to-peer problem solving.

These measures would strengthen post-class learning outcomes and enhance the overall effectiveness of blended electromagnetic testing training.

IV. CONCLUSION

This study has developed a fuzzy comprehensive evaluation model based on the EWM-AHP-DEMATEL combined weighting approach to assess the learning effectiveness of blended practical training in the Engineering Testing course, which encompasses core electromagnetic testing techniques. The following conclusions can be drawn:

1) The blended practical training model offers significant advantages in enhancing students' practical skills and their ability to apply electromagnetic theory. The experimental group significantly outperformed the traditional control group in both the summative skills assessment and the theoretical written test, confirming the effectiveness of blended learning for electromagnetic testing instruction.
2) The comprehensive weighting method effectively reduces subjective bias, leading to a more rational weight distribution. The consistently high weight assigned to instrumentation operation standardization highlights the critical importance of procedural precision in electromagnetic testing, while the dominance of comprehensive practical skills reflects the emphasis on complete workflow competence.
3) The in-class sessions and summative skills assessment show strong effectiveness, whereas post-class consolidation remains weak due to the lack of supervision and a misalignment between task difficulty and student proficiency. Targeted interventions—including LMS adoption, tiered task design, and enhanced instructor guidance—are recommended.

This study provides a quantitative basis for optimizing blended electromagnetic testing instruction. Future research should extend the observation period and validate the model across broader contexts to establish its generalizability.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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