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ARTICLE

From Behavioral Assessment to Cognitive Attribution: Explainable AI-Enabled Reform in Electrical Machines Laboratory Instruction

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Abstract

Laboratory courses in electrical machines have long been constrained by unidimensional process assessment, ambiguous attribution of learning difficulties, and the absence of personalized feedback. This study proposes an intelligent teaching evaluation and feedback framework grounded in explainable AI. The framework first constructs a multidimensional set of explicit features spanning cognitive foundations, affective attitudes, and operational behaviors. A differentiable causal discovery algorithm then extracts latent causal relationships from these explicit features that influence experiment completion. Finally, the TabNet attentive interpretable model builds a personalized prediction and attribution model for learning performance. This mechanism shifts laboratory evaluation from an outcome-oriented paradigm toward cognitive attribution, offering a computational pathway to address the diagnostic blind spot wherein traditional evaluation identifies surface problems but fails to trace their cognitive origins. The framework can inform the transition from experience-driven teaching evaluation to data-driven cognitive attribution in core electrical engineering laboratory courses.

Keywords: electrical machines laboratory; cognitive attribution; causal discovery; personalized feedback; teaching assessment reform

1. INTRODUCTION

The electrical machines laboratory course translates electromagnetic field theory into intuitive engineering cognition. Experiments such as measuring the speed regulation characteristics of a DC motor, determining three-phase transformer connection groups, and plotting the torque-slip curve of an induction motor demand a solid grounding in circuit and magnetic circuit theory, spatial imagination, sequential operational logic, and multivariable coordination. A recurring puzzle in teaching practice is that some students who excel in theoretical examinations perform poorly in experiments involving transformer polarity identification and connection group verification, whereas others with modest theoretical scores but strong hands-on interest operate fluently in complex wiring tasks. This pattern suggests that the core determinants of experiment completion may not be fully visible in conventional preparatory and theoretical achievement indicators. They may instead reside in spatial cognitive patterns, error sensitivity, or the allocation of attentional resources during operational feedback.

Current evaluation and feedback rely primarily on final data and conclusions presented in laboratory reports. Students receive only surface-level information, such as a poor curve fit or an incorrect connection group judgment. They cannot determine whether the root cause is a weak theoretical foundation, mistaken spatial polarity reasoning, or inadequate attention distribution during operations. The delayed and vague nature of this feedback severely limits the formative function of laboratory courses.

Existing research on reforming electrical machines teaching follows two broad directions. The first emphasizes the improvement of instructional organization and technical tools. Cui et al. [1] proposed a

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visual teaching method combining virtual simulation based on finite element models with waveform verification using on-site measurements, effectively lowering the cognitive threshold for abstract electromagnetic field concepts. Ren et al. [2] systematically reformed the laboratory course across syllabus, content, organization, methods, and extension activities. They proposed an intensive teaching model of combined lectures and grouped experiments together with a training mechanism integrating teaching, research, and competition. Zhang et al. [3] introduced a cloud-based classroom platform for course informatization and upgraded the laboratory benches with data acquisition and video monitoring systems. Ji et al. [4] presented a progressive project-based practice pathway advancing through key technology simulation, theory verification, comprehensive experimental simulation, and extended dynamic model experiments. Kan et al. [5] explored a hierarchical, progressively advancing teaching method blending virtual and physical experiments within the electrical engineering training course, establishing an intelligent experimental platform and a university–enterprise collaborative education mechanism. Li et al. [6] constructed a diversified experimental teaching system for electromechanical system control that strengthens foundations, emphasizes analysis, facilitates knowledge transition, and encourages innovative design. Lu and Li [7] integrated 3D-printed models, multiple intelligences theory, and gamification strategies into electrical machinery instruction and observed significant improvements in knowledge construction and learning motivation. Badreddine et al. [8] developed an immersive motor laboratory system using co-simulation with Unity and Simulink and confirmed through the System Usability Scale that the system enhanced students' practical confidence and operational proficiency. Shao et al. [9] designed an open linear motor drive experimental platform with an adjustable air gap that supports switching among synchronous, asynchronous, and doubly-fed operation modes, offering a flexible teaching resource for motor drive experiments. Duan et al. [10] discussed a teacher training model based on virtual simulation of engineering cases and proposed collaborative university–enterprise pathways such as co-building dual-qualification teacher workstations and jointly developing virtual–real training courses. Liu [11] proposed a creative thinking cultivation strategy driven by a three-level task chain: basic perception, comprehensive application, and innovative breakthrough.

The second direction focuses on data-driven learning outcome evaluation. Ruiz-Sarrio et al. [12] designed a finite-element-assisted experimental teaching platform combining finite element simulation of the motor air-gap magnetic field with on-site vibration measurement to help students understand the electromechanical coupling between stator current and mechanical vibration. Their Delphi expert survey yielded mean scores between 4.32 and 4.64 across various teaching dimensions. Lu and Zhang [13] developed a dynamic teaching decision support framework for motor and drive courses that integrates a sliding-window entropy weight method, Mahalanobis-distance TOPSIS, and a Markov prediction model, achieving a shift from static assessment to dynamic prediction.

Both lines of research have distinct emphases. The former starts from the organization of teaching activities and attempts to improve learning outcomes by optimizing external conditions; the latter begins with evaluation techniques and seeks to make assessment more precise. Neither approach, however, effectively addresses a core problem: when students make mistakes during experiments, they are not informed precisely about the cognitive origins of those mistakes. Data collection can record where an error occurred but cannot explain why it occurred. Although Zhang et al. [3] automated data acquisition through laboratory bench modifications, evaluation still relied mainly on instructors' subjective judgment. Ren et al. [2] introduced inter-group peer assessment and intra-group self-assessment, yet the criteria remained based on observable behavioral performance without reaching the level of cognitive diagnosis. The dynamic evaluation framework of Lu and Zhang [13] served course administrators rather than providing individualized diagnostic feedback to students.

The fundamental reason for these shortcomings is that existing methods depend primarily on statistical correlation analysis. They can indicate which factors are associated with learning outcomes but cannot identify which factors are root causes. Association does not imply causation, and this limitation makes it difficult for teachers to distinguish surface symptoms from deep-seated problems. It also prevents students from developing the capacity to self-diagnose from behavioral performance to cognitive structure. Ruiz-Sarrio et al. [12] noted that the teaching of electrical machines involves multiphysics coupling among electromagnetics, thermodynamics, mechanics, and fluids. The pedagogical difficulties essentially arise from cognitive barriers of abstraction, invisibility, dynamic unrepeatability, and internal unmeasurability. Overcoming these barriers requires extending the evaluation perspective from the behavioral level to the cognitive level.

Advances in explainable artificial intelligence offer a new technical pathway for addressing these challenges. The differentiable causal discovery algorithm proposed by Bhattacharya et al. [14] can recover causal network structures among variables from observational data even in the presence of unobserved confounders, making it suitable for mining causal relationships of latent cognitive features from explicit behavioral data. The TabNet model proposed by Arık and Pfister [15] achieves high-precision fitting and intrinsic interpretability through a sequential attention mechanism. Specifically, TabNet employs a sequential attention mechanism that selects the most relevant features at each decision step and outputs feature contribution weights that can be directly used to understand the basis of model decisions. This paper adopts these two techniques to construct an intelligent teaching evaluation and feedback framework based on explainable AI. The framework goes beyond predicting experiment scores. It uses causal discovery to search for latent implicit features behind explicit ones, establishes causal links between students' unrecognized cognitive blind spots and critical error nodes in experiments, and provides theoretical support for constructing deeply personalized feedback.

The remainder of the paper is organized as follows. Section 2 introduces the multidimensional feature system of the electrical machines laboratory course. Section 3 analyzes the principle of implicit cognitive diagnosis based on differentiable causal discovery. Section 4 presents the intelligent evaluation and feedback mechanism for personalized intervention. Section 5 details the implementation pathway and discussion. Section 6 concludes the paper.

2. MULTIDIMENSIONAL FEATURE SYSTEM FOR THE ELECTRICAL MACHINES LABORATORY COURSE

2.1. Composition of Explicit Features

Learning outcomes in electrical machines experiments are influenced by multiple factors. Liu [11] identified five constraints on cultivating creative thinking: teaching objectives that overemphasize knowledge mastery, rigid teaching methods, outdated content, instructors' insufficient engineering innovation experience, and weak practical components. A meta-analysis by Li and Liang [16] further confirmed that learning motivation and engagement are key mediating variables through which virtual laboratories affect learning outcomes, with effect sizes considerably larger than those of traditional indicators such as academic achievement. Drawing on these theoretical foundations, this paper constructs an explicit feature system across three dimensions.

(1) The cognitive and knowledge dimension includes the prerequisite course grade in Circuit Principles, reflecting mastery of Kirchhoff's laws and phasor analysis; the score on the current chapter quiz in the electrical machines theory course, capturing immediate understanding of specific principles; and the accuracy rate on a pre-lab self-test designed for a particular experiment, indicating the adequacy of preparation. These three indicators form the basic framework for evaluating students' cognitive starting points.

(2) The affective and behavioral engagement dimension includes the score on a learning interest scale assessing professional interest in power engineering; the completeness and quality of the pre-lab report, reflecting learning attitude and self-management; and the number of active questions raised during previous experiments, measuring participation depth and proactive learning tendencies.

(3) The operational and process dimension includes the total time spent on the experiment, the accuracy rate of initial instrument range selection, and the rate of standardized execution of critical steps. Critical steps involve operational norms such as returning the voltage regulator to zero and adjusting the excitation current in a single direction. Ji et al. [4] observed that traditional experiments follow fixed procedures and overemphasize simple verification, making it difficult to effectively assess students' operational standards and process thinking, which provides a problem-oriented rationale for the design of this dimension.

2.2. Definition of Challenging Experiments and Quantification of Completion

This study selects two types of experimental modules characterized by typical cognitive challenges as research objects.

(1) The three-phase transformer connection group identification experiment requires students to determine the polarity of the primary and secondary windings and then ascertain connection groups such as Y/Y-12 or Y/Δ-11 based on voltage phasor relationships. The main cognitive challenge is to construct the phase rotation relationship between high-voltage and low-voltage windings through three-dimensional spatial imagination. This goes beyond memorizing formulas. Experiment completion is quantified by the first-attempt accuracy of connection group identification and the consistency between the phasor diagram drawn and the measured voltage values.

(2) The speed regulation characteristic experiment of a DC separately excited motor involves simultaneously adjusting three physical quantities, namely armature voltage, field current, and load torque, so as to obtain the mechanical characteristic curve. The main cognitive challenge is to coordinate multiple variables while grasping the physical concept of constant torque load in real time. Completion is quantified by the goodness-of-fit of the slope of the plotted torque-speed curve near the rated operating point.

Figure 1 illustrates the multidimensional feature schematic of the electrical machines laboratory course studied in this paper. These features serve as the input to the proposed intelligent teaching evaluation and feedback framework.

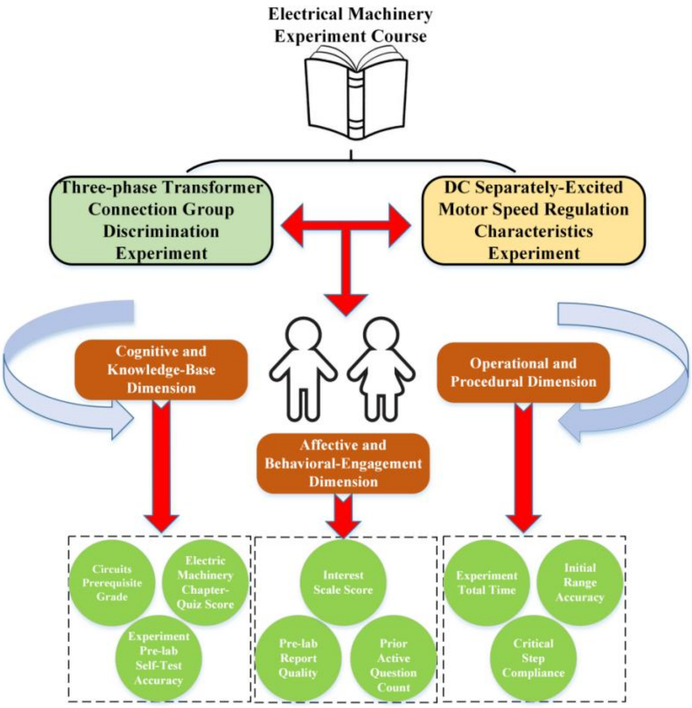

Figure 1. Schematic diagram of multidimensional features of the electrical machines laboratory course

3. DIAGNOSING IMPLICIT COGNITIVE BOTTLENECKS VIA DIFFERENTIABLE CAUSAL DISCOVERY

3.1. Method Principle and Logic of Implicit Feature Discovery

A foundational clarification is necessary before presenting the methodology. Causal inference involves three distinct tasks: structure discovery, effect estimation, and counterfactual prediction. Structure discovery identifies which variables are causally connected. Effect estimation quantifies the magnitude of causal effects. Counterfactual prediction estimates outcomes under hypothetical interventions. These tasks require different modeling components and rely on different identification assumptions.

The proposed framework performs the first of these tasks. It discovers causal structure among observed explicit features and latent variables using the differentiable causal discovery algorithm [14]. The algorithm outputs a directed acyclic graph indicating causal connectivity patterns. It does not estimate effect sizes or produce counterfactual predictions. The discussions in Section 3.2 should be understood as interpretations of the graphical structure, not as quantitative estimates of causal effects.

The projections in Section 4.2 are illustrative scenarios for teaching purposes. They are not rigorous counterfactual predictions, which would require additional methodological components.

Conventional regression analysis captures only statistical correlations between explicit features and learning outcomes. It indicates whether two variables change together in a statistical sense. In educational practice, however, numerous factors profoundly affect learning yet cannot be directly observed. For instance, an unmeasured latent trait may be strongly affected by explicit features and may strongly affect performance in the connection group identification experiment. Yet this trait has never been directly recorded by any examination or questionnaire. Traditional evaluation methods lack the means to identify such implicit factors. This gap is precisely the source of ambiguous attribution.

The differentiable causal discovery algorithm attributes information to latent variable nodes. This information cannot be directly explained by explicit features but exerts a significant and stable influence on learning outcomes. The algorithm learns a graphical structure specifying which variables are causally connected and whether latent confounders exist. It does not estimate the magnitude of causal effects nor produce valid counterfactual predictions on its own. By analyzing the strength of associations between these latent nodes and various explicit features, the algorithm endows them with interpretable educational semantics. Figure 2 depicts the mechanism of implicit feature extraction and causal relationship mining. Explicit features serve as inputs, and the algorithm outputs a causal structure graph. A unidirectional causal edge between nodes indicates a direct causal relationship in the graphical sense. A bidirectional edge signals the existence of a common parent node rather than mutual influence. This common parent node simultaneously affects both nodes directly and represents an implicit feature excavated from explicit data. The causal graph should be interpreted as a hypothesis about the underlying causal structure. It requires validation through additional analyses, such as sensitivity testing for latent confounding.

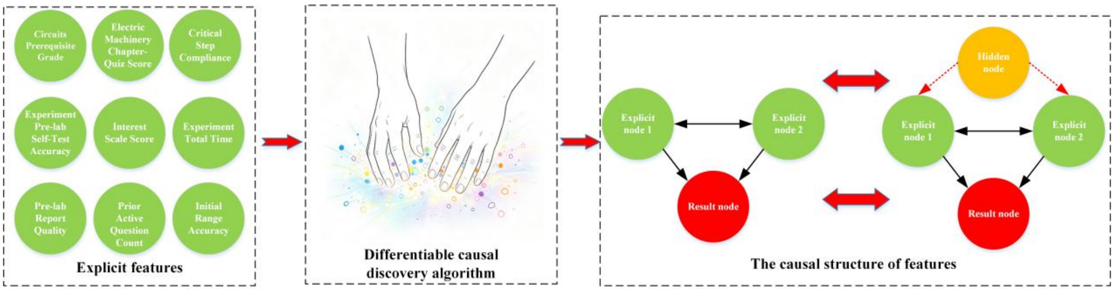

Figure 2. Mechanism of latent feature and causality mining based on differentiable causal discovery

From the perspective of teaching diagnosis, this process resembles a physician identifying the root cause of an illness. Students' external manifestations are analogous to symptoms. Explicit features resemble medical history records. The implicit features mined by the algorithm correspond to the root cause, namely cognitive bottlenecks that students themselves may not even recognize. This inferential capacity from surface phenomena to deep structure is what traditional educational statistical methods lack.

3.2. Causal Inference Analysis for Electrical Machines Experiments

Integrating the characteristic analysis of the electrical machines laboratory course with the inferential logic of the causal discovery algorithm, two explicit-implicit causal chains with pedagogical significance can be identified. These interpretations represent plausible causal narratives derived from the graphical structure. They are not quantitative estimates of causal effects.

(1) For the transformer connection group experiment, the explicit features of prerequisite circuit course grades and pre-lab report scores are not the direct main causes of variations in connection group identification accuracy. The algorithm identifies a strong mediating latent variable. In the causal graph, this latent variable is directly connected to identification accuracy. This means it serves as an immediate prior cause in the graphical sense. This implicit feature is influenced by prior factors such as secondary school solid geometry learning experience. The graphical pattern suggests that students who perform poorly in the transformer experiment may not lack effort. Rather, they may lack the cognitive tools to convert planar circuit diagrams into the three-dimensional spatial distribution of windings. Based on this hypothesis, instructors can recommend targeted remedial

resources. These include dynamic rotation demonstrations of spatial phasors, instead of simply asking students to review the textbook or solve more exercises.

(2) For the DC speed regulation experiment, the explicit features of theoretical learning interest and experiment operation duration jointly point to a latent variable. In the causal graph, this latent variable is directly connected to the smoothness of the mechanical characteristic curve. This implicit feature can be interpreted as real-time feedback attention allocation ability. The graphical pattern suggests that seemingly diligent students may achieve unsatisfactory operational results because they cannot appropriately distribute visual attention among multiple instruments. Ruiz-Sarrio et al. [12] observed a similar phenomenon in vibration monitoring experiments. Students commonly experienced attention allocation difficulties during parallel acquisition of multiple signals.

It is important to emphasize that the causal directions and chains described above are derived from the graphical structure of the causal discovery algorithm. They represent hypotheses about causal relationships. These should be validated through additional experimental or quasi-experimental designs. For the purpose of this teaching reform framework, these graphical patterns provide valuable diagnostic hypotheses. They can inform instructional interventions and guide further investigation.

4. CONSTRUCTION OF AN INTELLIGENT EVALUATION AND FEEDBACK MECHANISM FOR PERSONALIZED INTERVENTION

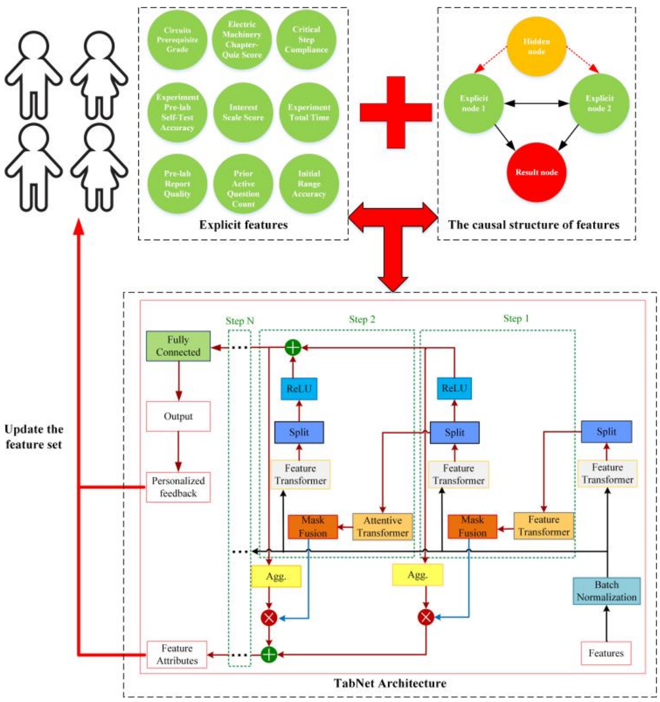

Figure 3. Intelligent Teaching Evaluation and Feedback Framework Based on Explainable AI

This paper aims to build an intelligent teaching evaluation and feedback framework grounded in explainable AI. The framework supports personalized intervention for both instructors and students. It facilitates the reform of electrical machines laboratory teaching. Figure 3 illustrates the framework. After students' important feature information is input into the TabNet prediction model, the model generates a personalized feedback report and a feature contribution analysis report. These two reports prompt students to reflect and revise their learning plans. This updates the explicit feature set and provides new input to the TabNet model, which continuously improves learning outcomes. Due to the ongoing data collection process, the framework is currently presented as a methodological design with illustrative examples rather than validated empirical results. The detailed mechanisms are presented in Sections 4.1 and 4.2.

4.1. Learning Performance Prediction Modeling with Causal Priors

Using the causal structure output from the causal discovery stage as a feature selection constraint, both the explicit features and the extracted implicit causal relationships are fed into the TabNet model, as shown in Figure 3. TabNet employs a sequential attention mechanism to progressively filter input features. It outputs the marginal contribution of each feature to the prediction result. This provides an interpretable basis for decisions while completing the prediction [15]. A brief explanation of TabNet's core mechanism is warranted here. TabNet uses a sequential attention mechanism that selects the most relevant features at each decision step. It builds predictions through a series of decision steps. This architecture enables the model to output feature contribution masks. These masks reveal which features were most influential for each individual prediction. This provides a degree of interpretability that is absent in many alternative deep learning approaches.

In the specific implementation, the explicit features affecting experiment learning outcomes and their positions in the causal graph are taken as input to TabNet. This ensures that the model's prediction paths conform to the prior causal structure and avoids confounding statistical associations with causal directions. Unlike traditional black-box deep learning models, TabNet's attention weights can be directly mapped to individual students' feature contribution analysis. Feature contribution refers to the degree of influence on the prediction result of learning performance, which TabNet quantifies. This allows students to intuitively understand the key factors affecting their learning outcomes and to identify specific shortcomings in their cognitive structure or operational habits.

4.2. Three-Tier Progressive Personalized Feedback Mechanism

Based on the prediction results and feature contribution weights output by TabNet, a systematic three-tier structural academic feedback report can be generated for each student.

Taking the transformer connection group experiment as an example, the first tier is explicit factor diagnosis. The system might indicate that a student's pre-lab quiz accuracy and prerequisite circuit course grade both rank in the upper-middle range of the class, yet the predicted completion is low. The system presents this data contradiction captured by TabNet to the student. This induces cognitive conflict. It makes the student aware that the root of the problem may lie beyond surface factors.

The second tier is implicit bottleneck revelation. The system further points out that, based on causal inference, the student's spatial phase rotation cognitive ability has a substantial negative contribution. This feedback transforms a vague attribution of carelessness into a concrete judgment. It identifies a cognitive obstacle at the level of spatial imagination. It simultaneously recommends targeted learning resources, such as a dynamic rotation demonstration of three-phase voltage phasors.

The third tier is improvement pathway prediction. The system provides a descriptive projection. This projection shows the student the expected improvement in predicted experiment completion. This assumes the student completes designated spatial phasor decomposition exercises before the next laboratory session. It should be noted that this projection is presented as an illustrative scenario based on the TabNet prediction model with causal structural constraints. It is not a rigorous counterfactual prediction. Valid counterfactual inference would require additional modeling assumptions and components. These are beyond the current scope of this study.

5. IMPLEMENTATION PATHWAY AND DISCUSSION

Two main points regarding the specific implementation pathway and complexity of the proposed reform framework for the electrical machines laboratory course are discussed below.

(1) The implementation of this framework requires no alteration to the hardware configuration of existing electrical machines laboratory benches. Only data acquisition and algorithm analysis modules need to be embedded in the teaching management system. The causal discovery algorithm runs once per semester and updates the causal graph structure every four to six weeks to accommodate variations in the cognitive feature distribution across different cohorts. The TabNet prediction model runs in real time after each experiment, and feedback results are pushed to students' terminals ten minutes before the end of the laboratory session. Furthermore, the extraction of implicit causal relationships relies entirely on algorithmic deep computation of teaching system logs. These logs include behavioral data such as pre-lab clickstreams, experiment operation timestamps, and instrument reading correction records. This imposes no additional testing burden.

(2) Boundary conditions that require attention include the following. The causal discovery algorithm has a certain sample size requirement. It is recommended that data from two consecutive cohorts, consisting of no fewer than 200 valid records, serve as the basis for model training. When class sizes are small, strategies such as data augmentation or transfer learning can be adopted. Duan et al. [10] pointed out that teachers' operational competence with virtual simulation and intelligent analysis tools is a key factor constraining technology adoption. Therefore, before promoting this framework, foundational training for course instructors should be conducted simultaneously.

It is important to acknowledge that the proposed framework is currently presented as a methodological design with illustrative analyses. The data collection process for empirical validation is ongoing and presents significant challenges. These include the integration of multi-source teaching logs, the alignment of cognitive scales with experimental outcomes, and the establishment of consistent data collection protocols across multiple cohorts. These challenges constitute a central direction for our future research. The framework's current value lies in providing a theoretically grounded and technically specified pathway. This pathway transforms laboratory evaluation from behavior-focused assessment to cognitive-attribution-based feedback. It can inform both instructional practice and further methodological development.

6. CONCLUSION

This study takes the electrical machines laboratory course as its setting and proposes an intelligent teaching support framework whose logical thread consists of explicit feature acquisition, latent causal mining, and explainable predictive feedback. The framework introduces causal discovery algorithms into the field of engineering experiment teaching evaluation. It extends the attribution perspective from observable surface behaviors to unobservable deep cognitive structures. It offers a computational technical solution to the persistent problem of vague attribution of learning difficulties in electrical machines experiments. The framework is not a replacement for the existing teaching system but a complement to and deepening of traditional outcome-oriented evaluation. In its current form, the work presents a methodological design illustrated by examples grounded in established teaching observations, and the absence of empirical validation is acknowledged as a limitation. Future research will collect real classroom data to empirically examine TabNet's prediction accuracy, the validity of the discovered causal structures, and the learning gains attributable to the feedback mechanism.

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AI Tool Usage Declaration: No AI tools were used in this study.

Author Contributions Statement: Wenxue Xie conceived the study, developed the methodology, conducted the investigation, wrote the original draft, and secured the funding. Xiyang Xue supervised the project, administered the project, and reviewed and edited the manuscript. Jia Hu contributed to methodology refinement and formal analysis. Qingkan Zhang contributed to investigation and visualization, and reviewed the manuscript. Ziwei Wu, Tingyu Li and Shaojun Zhang contributed to investigation and resources.

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