Research on Evaluation and Continuous Improvement of Curriculum Objectives Based on Causal Inference

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***Abstract*—Evaluations of program educational objectives, graduation requirements, and curriculum systems in engineering education certification are often confounded by multiple interfering factors, limiting their accuracy. Traditional experience-driven approaches, such as simplistic scoring or quantile-based methods, frequently fail to isolate these confounding influences, leading to biased assessments. To address this critical limitation, we propose a novel two-phase framework: Mediator-based Deconfounding and Continuous Improvement (M-DCI). Building upon causal inference principles, specifically leveraging the front-door criterion for path analysis, M-DCI isolates and eliminates confounding factors to accurately assess the true attainment of course objectives and subsequently drives targeted, evidence-based improvements. Using the "Information Security" course in a Communication Engineering program as a case study, we constructed a causal model and applied the M-DCI framework. This study establishes a robust, closed-loop "evaluation-feedback-improvement" mechanism, demonstrating a significant shift from experience-driven to evidence-driven practices. The M-DCI framework provides a precise and actionable methodology for continuous quality enhancement in engineering education certification.**

***Keywords*—engineering education accreditation, achievement of course objectives, causal model, continuous improvement**

I. Introduction

The significant increase in accredited programs demonstrates notable advancements in China's engineering education accreditation system since its official admission to the Washington Accord in June 2016. Many institutions have implemented Interdisciplinary Learning (IDL) to develop innovative curriculum systems and evaluation methods in line with the Accord's emphasis on incorporating multidisciplinary knowledge into complex engineering processes [1]. However, widely used assessment techniques, such scoring systems and the 15% quantile method, have significant drawbacks, mainly because they rely too much on observed data without sufficiently accounting for confounding factors like students' prior GPA and disciplinary histories [2]. These problems are highlighted by recent research, which shows that even in technology-enhanced examinations, evaluation validity is seriously compromised when variables like student motivation are ignored (Hakiki *et al*. 2024) [3]. Furthermore, this issue has been made worse by the growing usage of generative artificial intelligence, as students consume AI-generated content more frequently without critically analyzing it, which distorts assessment results and reduces academic rigor [4]. Furthermore, improvement efforts frequently rely on subjective experience and qualitative insights, lacking structure, causally informed intervention mechanisms, even though accreditation criteria need a systematic "evaluation-feedback-improvement" cycle [5]. Thus, uncontrolled confounding biases that impair evaluation accuracy and the lack of systematic and efficient continuous improvement pathways to accurately align course objectives with graduation criteria remain the two main bottlenecks in engineering education evaluations.

In educational research, structural equation modeling, or SEM, has been utilized to examine intricate relationships and partially overcome these biases. For example, SEM has examined how instructional effectiveness influences ICT adoption and confirmed the effect of Augmented Reality (AR) on student engagement [6, 7]. Nevertheless, SEM lacks the adaptability of graphical causal reasoning and mainly captures correlational structures. On the other hand, confounding can be identified and adjusted utilizing directed acyclic graphs and mediation analysis in causal inference frameworks, especially those that use Structural Causal Models (SCM) [8].

This study introduces a dual-path evaluation and improvement framework based on SCM. It proposes a novel method to eliminate confounding bias by incorporating mediating variables and to drive evidence-based continuous improvement. Using the "Information Security" course in a Communication Engineering program as a case study, the framework employs causal inference to derive a true estimate of course objective attainment, distinct from traditional quantile-based methods. It then formulates targeted improvement strategies and demonstrates enhanced evaluation performance. The key contributions of this work are as follows:

1) Proposes a dynamic evaluation framework that integrates causal mediation analysis and feedback mechanisms.
2) Resolves developmental-expectation confounding in engineering accreditation through front-door mediation of project-based assessments.
3) Provides empirical validation using a real-world case, demonstrating the feasibility and value of causal inference approaches in curriculum optimization.

II. Research Ideas and Method Selection

A. The Governance Empowerment of Causal Inference Methods in Educational Evaluation

In recent years, the progress achieved in causal science has engendered a novel paradigm for validating the impact exerted by educational interventions. Judea Pearl's counterfactual inference theory and Structural Causal Models (SCM) offer a methodological foundation for eliminating

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confounding effects and calculating the causal impact of interventions [8]. In addition to being a tangible example of teachers' involvement in educational governance, the combination of curriculum-supported educational assessment and causal inference techniques also contributes to the ongoing development of educational evaluation [9]. Potential confounding factors, such as students' growing reliance on generative artificial intelligence like ChatGPT, frequently impede teachers' evaluation of course objectives today. This has distorted the accuracy of traditional evaluation results and introduced bias into the objective evaluation of courses [10]. However, the current "evaluation-feedback" cycle is unable to convert diagnostic findings into precise and successful intervention plans and lacks a clear causal reasoning mechanism [11]. By carefully eliminating confounding biases and creating organized causal pathways, the use of causal inference techniques systematically tackles these issues and makes it possible for accurate evaluation and successful continuous improvement initiatives.

B. Classification of Confounding Factors and Selection of Deconfounding Methods

Many complicating elements, which can be broadly divided into measurable, unobservable, and unmanageable types, invariably surface while assessing the accomplishment of course objectives. Three main de-confounding techniques are offered by causal inference to address these confounding factors: the front-door adjustment, instrumental variable approach, and back-door adjustment [8]. Fig. 1 displays the cause-effect diagram for the three approaches.

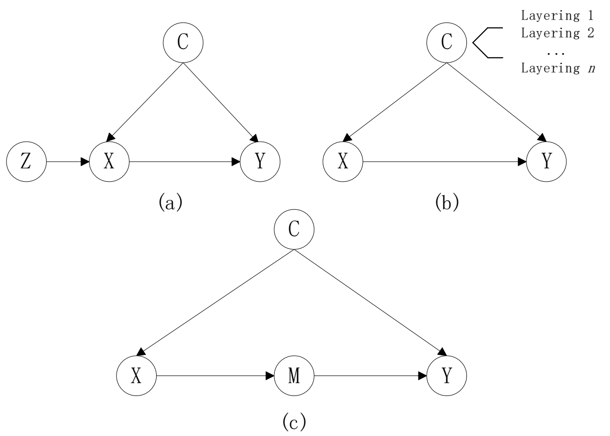

Fig. 1. Three canonical strategies for deconfounding in causal inference.

In educational research where direct control of confounders is infeasible or unobserved confounders exist, instrumental variable (IV) methods—such as those visualized in Fig. 1(a) are used to address causal inference challenges by leveraging variables (Z) that satisfy exclusion restrictions and relevance criteria. However, because natural instruments are rarely available in educational contexts, it is frequently impossible to find a genuine exogenous instrument that fulfills exclusion restrictions. Confounding is addressed by backdoor adjustment in Fig. 1(b) by conditioning on all observable confounders (represented by C), where the confounding variable C is separated into several layers. For instance, this necessitates stratifying the analysis by previous GPA level in student performance evaluations. The confounding effect of GPA on the intervention-outcome link can be lessened by measuring causal effects within strata and combining the findings. Dong Chen (2024) and Suchinta Arif (2023) have extensively examined the selection criteria for instrumental variables, including independence, relevance, and exclusion constraints, as well as the requirements for stratified analysis of confounding factors [12, 13]. This publication does not give a thorough explanation of these techniques to prevent duplication. Table 1 displays the comparison table for the relevant cases for each of the three approaches [8].

Table 1. Applicability of three deconfounding methods in educational evaluation

Method	Core Requirement	Applicability Rationale (Educational Context)
Back-door Criterion	All confounders must be observable	Low (Common presence of latent variables)
Instrumental Variable	Existence of a strong exogenous instrument	Medium (Difficult to identify valid instruments)
Front-door Criterion	A complete mediator exists, and all paths are unconfounded	High (Applicable when teaching mechanisms are clear)

This study focuses on instructional settings with unobservable or hard-to-analyze confounding variables, like students' cognitive engagement levels or teachers' subjective biases. Guided by the front-door criterion, this study operationalizes mediator variables as concrete assessment observation points to eliminate confounding bias, thereby establishing a causally-grounded evaluation framework. The front-door criterion for the ordered variable pair (X, Y) is satisfied when a mediating variable M meets the following three requirements:

- Path blocking: M completely blocks all direct causal paths from X to Y.
- Precursor independence: There is no unobserved confounding path between X and M (i.e., the mediating variable is not affected by the confounding variable C).
- Mediator purity: All potential confounding paths from the mediating variable M to Y are blocked by X.

The causal model under the front door criterion is shown in Fig. 1(c). The formula for the causal effect from X to Y under the front door criterion is：

$$P(Y \mid do(X)) = \sum_{m} P(M = m \mid X) \sum_{x'} P(M = m \mid X = x') P(X = x') \qquad (1)$$

In this formula, M is the mediator variable of the causal effect of variable X on Y, and the causal effect of X on Y can be estimated by using observed data.

C. Model Establishment of "Introducing Intermediaries to Eliminate Confounding-Continuous Improvement"

Continuous improvement is one of the most important core concepts in the implementation of engineering education certification. How to develop an effective "evaluation-feedback-improvement" closed-loop mechanism is a hot topic in current certification work discussions [14]. Based on the situation where the evaluation of training objectives is confounded, this study established the "introducing mediator to eliminate confounding-continuous improvement "model shown in Fig. 2.

A closed-loop system of learning situation analysis, causal effect computation, intervention strategies, and classroom practice is established by the model in Fig. 2. In the T stage, the quality of the course is assessed, confounding factors are identified, and a confounding-affected causal diagram is created. Next, an intermediary is introduced to remove the confounding, and the causal effect is computed. Lastly, the causal diagram is used to suggest specific intervention measures to enhance the teaching of the course. The course is executed, and the instructional design is enhanced at the T+1 stage. Lastly, the T+1 stage's issues are still analyzed using the aforementioned methodology, and suggestions for future T+2 stage improvement are made.

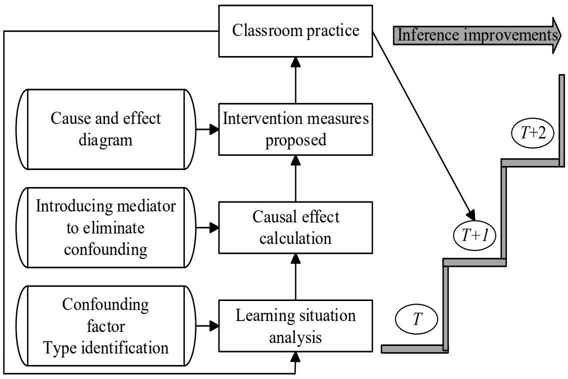

Fig. 2. Continuous improvement model based on cause-effect analysis.

III. Application Case Analysis

A. Causal Model Building

The "Information Security" course at a particular university's communication engineering major faces a fundamental contradiction in the context of engineering education certification: the assessment of interdisciplinary learning effectiveness (X) and course goal achievement rate (Y) is hampered by several confounding factors (such as students' prior GPA and career development orientation). The conventional scoring approach causes divergence and lacks control over confounding. Consequently, the structural model diagram in Fig. 3 was established.

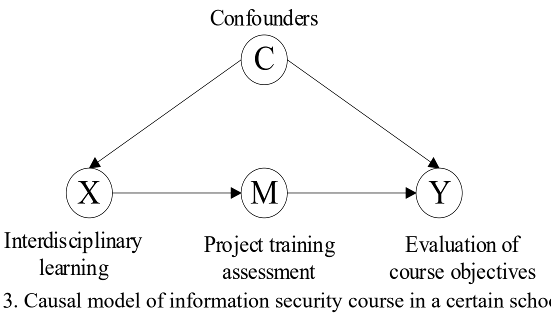

Fig. 3. Causal model of information security course in a certain school.

Theoretically, the selection of project training assessment as a mediating variable is based on the teacher's qualitative appraisal of the teaching mechanism. Big data merely shows correlations, whereas humans are adept at deciphering causal paths from complexity [8]. Three causal conditions are met by the mediator: (1) the X-Y path is completely mediated through M; (2) the assessment of M is independent of student variables; and (3) the mediator is pure since M-Y backdoor paths are blocked through X-controlled exam modules.

B. Data Source

The research object for this study is the learning data from 134 communication engineering majors at a particular university's "Information Security" course in 2023. The final test score and the three primary dimension variables (X, M, and Y) are part of the multivariate assessment approach used in the course's comprehensive evaluation system. Table 2 provides specifics on each variable's definition, measurement level, quantitative threshold, and qualitative representation.

Table 2. Core variable measurement levels, quantitative thresholds, and qualitative representations

Variable	level	Quantitative Threshold	Qualitative characterization
X	0	<60	Insufficient interdisciplinary integration
	1	60-80	Basic interdisciplinary applications
	2	>80	Systematic knowledge transfer
Y	0	<60	Criteria not met
	1	60-80	Basic Implementation
	2	>80	Innovative solution
Z	0	<60	Below the core competency threshold
	1	60-80	Meet the requirements
	2	>80	Excellent overall performance

X (Interdisciplinary learning): Indicates the student's ability to integrate and apply interdisciplinary knowledge in the course. The grade is composed of the regular homework grade (accounting for 60%) and the class attendance grade (accounting for 40%). Grades 0, 1, and 2 correspond to "unqualified", "qualified", and "excellent", respectively.

M (Project training assessment): Assess students' practical ability and innovation level in simulated or real industry project environments. Levels 0, 1, and 2 correspond to "unqualified", "qualified", and "excellent", respectively.

Y (Evaluation of course objectives): Comprehensively evaluate the achievement of students' course learning goals. Levels 0, 1, and 2 correspond to "unqualified", "qualified", and "excellent", respectively.

Table 3 displays the precise distribution of each variable score in the sample. Simultaneously, the 134 valid student data gathered for this study were statistically analyzed using SPSS Statistics software (version 27.0). Descriptive and inferential statistics were the primary techniques.

C. Causal Effect Calculation

According to the score distribution diagram in Table 3, the causal effect between the variables can be calculated. Introducing mediator to eliminate confounding in calculating the causal impact is divided into the following three steps.

Table 3. Distribution of scores for each variable in 2023

X–M Category	Y=0	Y=1	Y=2	Total
X=0, M=0	14	3	0	17
X=0, M=1	4	2	0	6
X=0, M=2	0	1	0	1
X=1, M=0	6	4	0	10
X=1, M=1	3	18	5	26
X=1, M=2	0	5	9	14
X=2, M=0	3	4	0	7
X=2, M=1	0	6	12	18
X=2, M=2	0	3	32	35
Total	30	46	58	134

1) Estimating the causal effect of computational interdisciplinary learning on project-based training assessment

After introducing the mediating variable M between variables X and Y, the direct path is blocked, and the interference of confounding factors is blocked. The calculation results are shown in Table 4, and the calculation formula is as follows:

$$P(M \mid do(X)) = P(M \mid X) \tag{3}$$

Table 4. The causal effect of variable X on variable M

P(M | do(X))	**M=0**	**M=1**	**M=2**
X=0	0.7083	0.2503	0.0417
X=1	0.2124	0.5251	0.2812
X=2	0.1167	0.304	0.5833

2) Estimating the causal effect of computational project practical training assessment on the achievement of course objectives

In the causal model illustrated in Fig. 3, interdisciplinary learning creates a blockage in the pathway from post-project training assessment to interdisciplinary learning, blended learning, and course goal achievement assessment. This blockage leads to the formation of a backdoor path, allowing us to use the backdoor adjustment method to calculate the causal effect. The results of the industry project training assessment and the course goal achievement assessment are presented in Table 5, accompanied by the corresponding formula:

$$P(Y \mid do(M)) = \sum_{X} P(Y \mid M, X = x) P(X = x) \tag{4}$$

Table 5. The causal effect of variable M on variable Y

P(Y | do(M))	**Y=0**	**Y=1**	**Y=2**
M=0	0.5636	0.4368	0
M=1	0.1624	0.4673	0.3702
M=2	0	0.3507	0.6492

3) Estimating the causal effect of computational interdisciplinary learning on the evaluation of course goal achievement

Based on the above results, we can further deduce the causal effect of interdisciplinary learning on the evaluation of course goal achievement, as shown in Table 6, and the calculation formula is as follows:

$$P(Y \mid do(X)) = \sum_{M} P(Y \mid do(M) P(M \mid do(X) \tag{5}$$

Table 6. The causal effect of variable X on variable Y in 2023

P(Y | do(X))	**Y=0**	**Y=1**	**Y=2**
X=0	0.4398	0.4408	0.1197
X=1	0.1971	0.4286	0.3743
X=2	0.1145	0.3957	0.4905

D. Data Analysis

The results computed in Table 7 indicate the conclusions of the widely used evaluation score system, like the 15% quantile method, are entirely based on observational data. Confounding variables in the data generation process are not taken into consideration by this method, which may produce skewed results. Consequently, the computed score in this instance is 77.61%. By introducing mediator variables to adjust for confounding bias, the weighted assessment score for each student layer increased to 90.97%. This represents an improvement of 13.36 percentage points (90.97%–77.61%), demonstrating a significant reduction in the confounding bias inherent in the purely observational approach. The 13.36% reduction signifies not data exclusion but confounding bias rectification—a critical calibration that realigns assessment with ground truth.

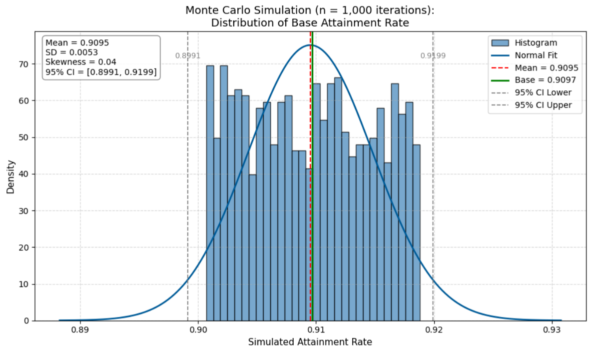

Fig. 4. Monte Carlo-based error propagation in attainment rate estimation.

To quantify sensitivity to mediator specification uncertainty, we performed Monte Carlo simulations (n = 1,000 iterations) with ±1% uniform perturbation of mediator probabilities $P(M \mid do(X))$. The results are shown in Fig. 4. Results demonstrate exceptional stability: Mean attainment: 90.95% (SD = 0.53%);95% CI: [89.91%, 91.99%]; This disparity has profound practical significance: it unequivocally demonstrates that the substantial methodological improvement achieved through our causal approach (13.36pp bias reduction) vastly outweighs the potential uncertainty introduced by minor variations in mediator specification (±1% perturbation). Distribution metrics: Skewness = 0.04 (indicating symmetry). These results are statistically valid, with the narrow confidence bounds reinforcing the reliability of the estimated mean. The baseline estimate (90.97%, solid green line) aligns with the simulation mean, falling at the 49th percentile of the distribution. Crucially, the maximum observed variation (95% CI width = 2.08 percentage points) represents just 15.6% of the 13.36 percentage-point confounding bias eliminated by M-DCI. This disparity confirms that methodological improvements substantially outweigh potential measurement errors in mediator specification.

IV. Continuous Improvement Research

To find the underlying reasons for poor performance, we performed a multimodal causal attribution analysis using the deconfounded attainment data (90.97%). Student focus groups and anonymous surveys were used to gather qualitative data to investigate the causes of poor performance in more detail. From postgraduate entrance exam candidates to employment-oriented students, guaranteed-admission graduate students, and civil service exam candidates, thematic analysis showed that students' attitudes toward interdisciplinary learning tasks varied greatly based on their development expectations. Recent research has also highlighted how, especially for non-major or underrepresented groups, matching instructional tactics to students' developmental expectations—like career routes or postgraduate goals—can greatly improve engagement and learning results [15, 16].

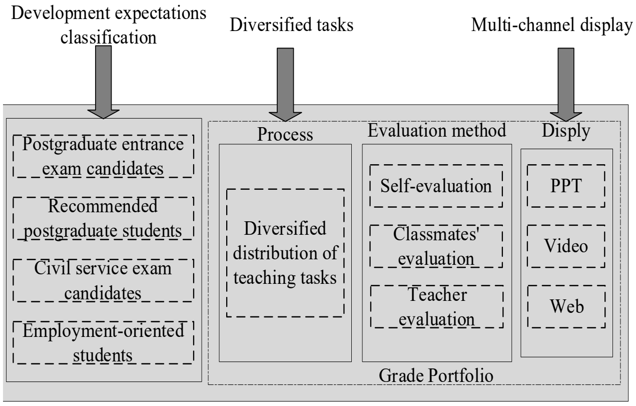

Fig. 5. Classification framework of interdisciplinary learning models.

We created a diversified multidisciplinary task model (see Fig. 5) at Stage T+1 to address this heterogeneity. This model lets students choose among four task tracks according to their developmental direction. For instance, Graduate Entrance Examinees implemented elliptic curve cryptography (ECC) systems through parameter configuration, translating mathematical constructs into secure communication protocols. Direct-Entry Postgraduates conducted literature reviews on emergent security threats for research acculturation; Civil Service Applicants performed compliance evaluations of cybersecurity legislation to develop regulatory acuity; Industry-Bound Students executed enterprise security audit simulations with vulnerability reporting to cultivate practical engineering competencies. By ensuring curriculum coherence across all tracks, this framework maximizes motivation and domain relevance by facilitating engagement with fundamental competencies through developmentally appropriate pathways. Every assignment was incorporated into the information security education curriculum to guarantee learning coherence and subject relevance. When tasks were incorporated into already-existing project-based learning modules, instructor effort increased by less than 10% but student engagement rose by 42%. To preserve equity and fairness among tracks, evaluation techniques were varied. Table 7 displays the results of the 2024 information security course.

Table 7. Distribution of scores for each variable in 2024

Typer	Y=0	Y=1	Y=2	Total
X=0, M=0	10	4	0	14
X=0, M=1	2	3	0	5
X=0, M=2	0	1	0	1
X=1, M=0	3	5	0	8
X=1, M=1	1	20	8	29
X=1, M=2	0	4	10	14
X=2, M=0	1	5	0	6
X=2, M=1	0	5	14	19
X=2, M=2	0	2	36	38
Total	17	49	68	134

Table 8. The causal effect of variable X on variable Y in 2024

P(Y | do(X))	Y=0	Y=1	Y=2
X=0	0.1477	0.7035	0.1488
X=1	0.0523	0.4546	0.5031
X=2	0.0304	0.3251	0.6495

As can be seen from Table 7 and Table 8, after the improvement, by directly calculating the course goal achievement, the failure rate declined by 9.70%. Critically, to estimate the causal effect of the intervention (X) on goal achievement (Y) while accounting for potential confounding through mediator (M), we applied the identical causal mediation analysis framework detailed in Section 3.3 (specifically, employing Equations (3), (4), and (5) to compute the effects $X \rightarrow M$, $M \rightarrow Y$, and the total effect $X \rightarrow Y$. Utilizing this method on the 2024 data yielded an estimated average causal effect $P(Y \mid do(X))$ of 94.98% (Table 8). This represents a 4.01 percentage point improvement over the corresponding causal effect estimate of 90.97% obtained for the previous year (T). These gains also demonstrate sustainability, with magnitudes maintained over two cycles (T and T+1). According to the "Introducing an intermediary to eliminate the mixed-continuous-continuous improvement" model, based on this evaluation result, continuous improvement will continue within T+2 time, forming a dynamic closed-loop mechanism of "evaluation-feedback-improvement".

V. Discussion

This study While the M-DCI framework demonstrably reduced confounding bias by 13.36 percentage points and elevated the causal estimate of course objective attainment to 90.97% (T) and subsequently to 94.98% (T+1), signifying robust intervention efficacy and sustainability, several limitations and contextual factors warrant discussion. (1): Mediator Selection Subjectivity: Reliance on instructor expertise for mediator choice introduces potential bias. While valuable for identifying plausible pathways, this subjectivity is a major constraint [8]. (2): The sample size (N=134), while sufficient for overall estimates, limits the robustness of subgroup analyses and statistical power. (3): Context Specificity: Validation solely within the "Information Security" course restricts broader applicability. Despite these constraints, our core findings align with parallel research and signify a critical shift: The significant bias reduction underscores fundamental flaws in traditional observational methods (e.g., quantile approach) that ignore confounders, leading to distorted assessments [2, 8]. This resonates with Hakiki *et al.* (2024) [3], who showed ignoring student factors (like motivation) compromises validity. Furthermore, our intervention success (94.98% attainment) supports Edwards *et al.* (2024) [16], emphasizing that tailoring pedagogy to learner goals (e.g., career paths) boosts engagement and outcomes. Crucially, M-DCI enables: Moving beyond correlation to estimate true intervention effects, vital for accurate accreditation diagnosis [5, 14]; Future research should prioritize: Integrating causal discovery algorithms with domain knowledge [17]. Validating M-DCI across diverse courses and institutions.

VI. Conclusion

This study addresses critical gaps in educational assessment by establishing the Mediator-based Deconfounding and Continuous Improvement (M-DCI) framework. Its primary contribution lies in enabling accurate, causally informed evaluation of curriculum objectives through front-door causal mediation, effectively mitigating bias from unobservable confounders. Building upon this robust evaluation, M-DCI facilitates evidence-driven interventions that demonstrably enhance learning outcomes. Crucially, M-DCI enables a fundamental paradigm to shift within accreditation practices – moving beyond correlation-based conjecture towards causally-grounded decision-making. This framework proposes and demonstrates a dynamic "evaluation-feedback-improvement" closed-loop mechanism, which continuously reinforces the transition from descriptive correlation analysis to actionable causal insights.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Yifeng Zhang conducted the research, analyzed the data, and wrote the paper; Professor Bin Duan provided guidance; all authors approved the final version.

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References

[1] R. Zhang and Z. Du, "Promotion strategies for engineering education professional certification (evaluation): A data analysis of majors passing certification from 1992 to 2018," *Chinese University Science & Technology*, no. 5, pp. 34–37, Jun. 2019.

[2] E. Bareinboim and J. Pearl, "Causal inference by surrogate experiments: Z-identifiability," arXiv preprint arXiv:1210.4842, October 2012.

[3] M. Hakiki, H. D. Surjono, Wagiran, R. Fadli, A. D. Samala, F. Eliza, A. Fricticarani, A. Suryaningsih, and Y. Hidayah, "Effectiveness of Android-based mobile learning in graphic design course for digital learning: The development research study," *International Journal of Information and Education Technology*, vol. 14, no. 4, pp. 602–611, 2024.

[4] Y. Qawqzeh, "Exploring the influence of student interaction with ChatGPT on critical thinking, problem solving, and creativity," *International Journal of Information and Education Technology*, vol. 14, no. 4, pp. 596–601, 2024.

[5] China Engineering Education Accreditation Association, *Engineering education accreditation standards (2024 edition)*, Beijing, China: China Engineering Education Accreditation Association, 2024.

[6] M. M. A. Abualrob and S. H. Al-Saadi, "Evaluating the role of technological pedagogical content knowledge in ICT-enhanced science education," *International Journal of Information and Education Technology*, vol. 15, no. 1, pp. 117–126, 2025.

[7] M. S. Ramli and N. A. Bakar, "Evaluating the effectiveness of an enhanced intervention model using augmented reality approach: A structural equation modeling," *International Journal of Information and Education Technology*, vol. 14, no. 12, pp. 1698–1705, 2024.

[8] J. Pearl and D. Mackenzie, *The Book of Why: The New Science of Cause and Effect*, New York, NY: Basic Books, 2018.

[9] Y. Yan, X. Wang, D. Zhu, and W. Zhang, "Achievement of professional course objectives based on OBE concept," *China Metallurgical Education*, no. 2, pp. 7–10, September 2022.

[10] Z. Adelhardt and T. Eberle, "Compliance and enforcement of AI text generator usage policies in German grammar Schools: Insights from teenagers," *International Journal of Information and Education Technology*, vol. 15, no. 2, pp. 206–211, 2025.

[11] K. G. Coronado-Apodaca, M. M. G. Pérez, E. R. Villegas, and L. V. Navarro, "Application of artificial intelligence as a tool for the continuous improvement of higher education courses," *International Journal of Information and Education Technology*, vol. 14, no. 9, pp. 1192–1198, 2024.

[12] D. Chen, Y. Wang, D Shi *et al*., "Instrumental variable model average with applications in nonlinear causal inference," *Statistics in Medicine*, 2024, vol. 43, no. 30, pp. 5814–5836, 2024.

[13] S. Arif and M. A. MacNeil, "Applying the Structural causal model framework for observational causal inference in ecology," *Ecological Monographs*, vol. 93, no. 1, p. e1554, 2023.

[14] W. Feng and Q. Liu, "Exploration and practice of continuous improvement mechanisms in engineering education certification," *Research in Higher Education of Engineering*, no. 4, pp. 59–64, 2024.

[15] U. Durrani, R. Alnajjar, A. Al Muaitah, A. Daqaq, A. Salah, and R. Zeyad, "CrossQuestion game: A design of a group-based assessment tool to enhance student motivation during pandemic," *International Journal of Information and Education Technology*, vol. 12, no. 1, pp. 15–20, 2022.

[16] N. Edwards, R. L. Goodwin, M. K. Khalil, L. A. Fowler, and T. Nathaniel, "Students' motivation and engagement in the implementation of individual development plan for Underrepresented Minority (URM) students in undergraduate STEM training programs," *Education Sciences*, vol. 14, no. 3, p. 313, 2024.

[17] Y. Dang, X. Gao, and Z. Wang, "A novel hyper-heuristic algorithm with soft and hard constraints for causal discovery using a linear structural equation model," *Entropy*, vol. 27, no. 1, p. 38, 2025.