Course Quality Evaluation and Continuous Improvement Method Based on Causal Inference

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Abstract. Courses are crucial carriers for achieving talent training goals of higher education universities. Current evaluations of courses quality often rely on intuition rather than scientific methods, leading to less reliable results and hindering continuous improvement. To address this, we propose a causal inference-based evaluation method. First, a structural causal model for course quality evaluation is constructed based on causal inference theory. Then, taking '*Electromechanics (Part 1)*', an important foundational course in the major of Electrical Engineering and Automation, as an example, a structural causal model for the course quality evaluation system is constructed. The *do-operator* is introduced to determine the average causal effect of various instructional intervention measures, such as course assignments, chapter tests, and final exams on the course objectives. Finally, by analyzing the differences in the average causal effects of these interventions on the course objectives over two academic years, the causes of these differences are identified, which will be used for the continuous improvement of the course in the following academic year. Although initially applied in electrical engineering, this method is adaptable to other disciplines.

Keywords: Course quality, course objectives, causal inference, structural causal model, engineering education professional accreditation.

1 Introduction

The Washington Accord, established in 1989, is a mutual recognition agreement that serves as the basis for evaluating educational credentials [1]. In 2016, China formally joined this international engineering alliance, indicating that its engineering education has achieved international equivalence. Education 4.0, integrating technology with experience-based learning, addresses modern needs and personalizes education [2]. It aligns with innovative society requirements, bridges educational gaps, and uses AI to enhance and digitalize teaching [3]. Using Cite Space to analyze literature on higher education quality assurance from Web of Science, the research identifies key hotspots in quality assurance, sustainable development, and medical education, with trends focusing on frameworks and knowledge [4]. Effective and scientific methods for evaluating course quality can reflect teaching effectiveness, student achievement of course

D. Hu et al. (eds.),
Management (ICMEIM 2024), Atlantis Highlights in Social Sciences, Education and Humanities 29,
https://doi.org/10.2991/978-94-6463-568-3_23

objectives, and the fulfillment of graduation requirements. Indicators for evaluating course quality can be categorized into three areas: the course itself, the course implementation process, and the effects of course teaching.

Currently, there are the following problems in course quality evaluation: (1) uniformity in evaluation methods. course quality evaluation mainly relies on students' final exam scores to calculate the achievement of course objectives. The results are often a single score, making it difficult to identify teaching problems from this single outcome. (2) Lack of a psychological model in the evaluation process. Continuous improvement of course quality relies on causal intuition rather than assessment results. Without psychological models and methodologies, it's challenging to identify teaching problems, and improvement measures are often too vague and impractical.

Recent advances in cognitive science and neuroscience have highlighted that human learning and thinking revolve around causality, composability, and transferability [5]. Causality is now a crucial cognitive tool with applications in medicine, economics, materials science, computer science, education, and artificial intelligence [6]. In education, causal inference methods add mathematical rigor to teachers' intuitive understanding, aligning with the field's dual focus on humanistic care and scientific rationality [7]. Revising the curriculum system should rely on scientific evidence that provides rich causal information for informed decision-making.

The paper uses Judea Pearl's structural causal model (SCM) to analyze the relationships between assessment methods, course objectives, and graduate attributes in the '*Electromechanics (Part 1)*' course. It employs the *do-operator* to calculate the average causal effect (ACE) of various interventions—assignments, chapter tests, and final exams--on course objectives. By comparing the ACE of these interventions over two academic years, the paper identifies reasons for differences and offers recommendations for course improvement. The SCM formalization and mathematical expressions enhance understanding of causal relationships and improve course quality assessment.

2 Course Quality Evaluation Based on Structural Causal Model

The structural causal model is a method that visualizes the causal assumptions behind data. It is used to describe real-world associations and their interactions. It is a causal inference method based on graph theory that divides events into three levels: observation, intervention, and counterfactual [8]. With *do-operations*, it reduces the causal relationships at the intervention and counterfactual levels to problems that can be addressed through statistical methods. The structural causal model for course quality evaluation is depicted in Figure 1. Teaching activities have a causal effect on the achievement of course objectives, and the attainment of course objectives have a causal effect on the achievement of graduate attributes.

To represent the overall causal effect of teaching activity X_i on course objective O_j, the average causal effect (ACE) is used. The ACE refers to the average of all individual causal effects, which means calculating the average difference between the potential outcomes when the teaching activity X_i is implemented as an intervention and when it is not implemented as an intervention across all samples. In other words:

$$ACE = E[O_j \mid do(X_i = 1)] - E[O_j \mid do(X_i = 0)] \tag{1}$$

where, $do(X_i)$ represents the intervention operator, indicating the manipulation of X_i alone, without affecting the manipulation of other variables in the model [9]. Similarly, to obtain the ACE of course objective O_k on course objective O_1, the following calculation should be performed:

$$ACE = E[O_l \mid do(O_k = 1)] - E[O_l \mid do(O_k = 0)] \tag{2}$$

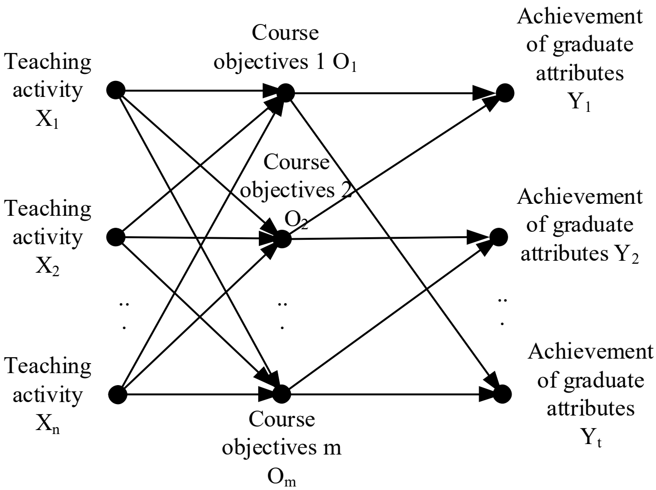

Fig. 1. SCM for course quality assessment.

3 Case Study

3.1 SCM for the 'Electromechanics (Part 1)' Course

In the '*Electromechanics (Part 1)*' course at the School of Mechanical and Electrical Engineering, electrical engineering and automation students engage in classroom lectures and online learning through platforms like Rain Classroom [10]. The course uses assignments, chapter tests, and final exams to evaluate course objectives and graduate attributes. The instructional SCM for this course is shown in Figure 2.

Students are expected to master fundamental theories in electromagnetism, magnetic circuits, and electromechanics (course objective 1, denoted as O_1), and skillfully apply these theories to analyze electric machines (course objective 2, denoted as O_2). They should demonstrate a solid grasp of electrical engineering knowledge (graduate attribute observation point 1-4), analyze and model related problems, and effectively research and present solutions (graduate attribute observation point 2-2).

Data for the '*Electromechanics (Part 1)*' course were collected from 75 students in 2018 and 156 in 2019, including scores from assignments (A_1, A_2), chapter tests (B_1, B_2), and final exams (C_1, C_2) related to course objectives O_1 and O_2. Traditional assessment methods average these scores against preset targets, but this approach does not reveal which teaching activities may be lacking, complicating targeted improvements.

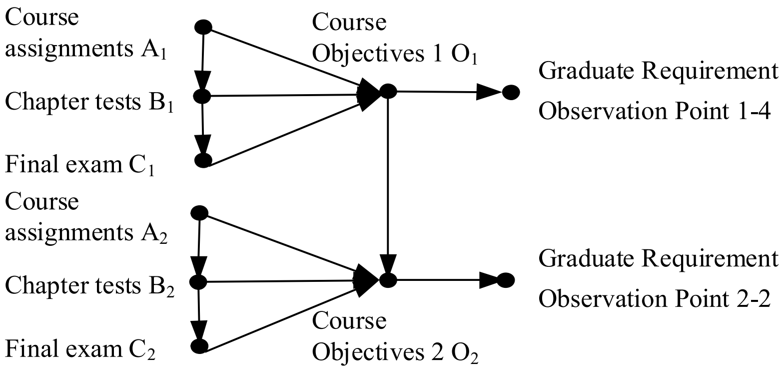

Fig. 2. SCM for the course '*Electromechanics* (*Part* 1)' evaluation.

3.2 ACE of Intervention Measures on Course Objectives

In the 'Electromechanics (Part 1)' course, interventions include assignments, chapter tests, and final exams. The causal effect of course assignment A on the *i*th course objective O_i (i=1,2) is P(O_i| do(A=1)), with the correction formula given by formula (3).

$$P\left(O_i \mid do\left(A_i = a\right)\right) = P\left(O_i \mid A_i = a\right) \tag{3}$$

where, '*a*' represents whether the objective is achieved or not, with 1 indicating achievement and 0 indicating non-achievement.

The causal effect of chapter test B on O_i(i=1,2) is $P(O_i|do(B=1))$, and the causal model after the B_1 intervention is shown in Figure 3, with the correction formula in formula (4). For the final exam C, the correction formula is shown in formula (5).

$$\begin{aligned} &P\left(O_i = o \mid do\left(B_i\right)\right) \\ &= \sum_a P\left(O_i = o \mid B_i = b, A_i = a\right) P\left(A_i = a\right) \end{aligned} \tag{4}$$

where, *a*, *b*, *o* represents whether the objective is achieved or not, with 1 indicating achievement and 0 indicating non-achievement.

$$\begin{aligned} &P\left(O_i = o \mid do\left(C_i\right)\right) \\ &= \sum_b P\left(O_i = o \mid C_i = c, B_i = b\right) P\left(B_i = b\right) \end{aligned} \tag{5}$$

where, *b*, *c*, and *o* represent whether the objective is achieved or not, with 1 indicating achievement and 0 indicating non-achievement.

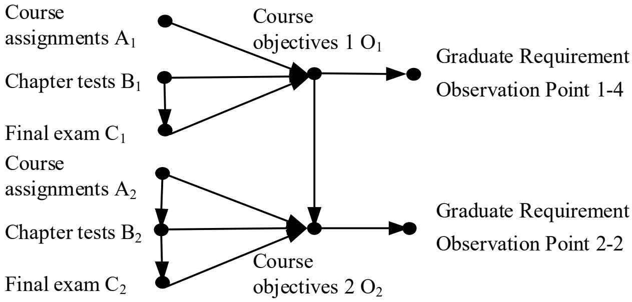

Fig. 3. Teaching causal model of the '*Electromechanics* (*Part* 1)' course after the intervention of chapter test B_1.

Combining formulas (1), (3) ~ (5), the ACE of teaching activities on course objectives can be obtained, as shown in Table 1. Table 1 shows that for the 2018 and 2019 classes, course assignments, chapter tests, and final exams all have an ACE greater than 0 for course objectives O_1 and O_2, indicating a positive contribution to achieving these objectives. In the 2019 class, the ACE for course assignments A_1 and A_2 is above 0.9, suggesting students have effectively mastered the course content.

Table 1. ACE of Teaching Activities on Course Objectives for the '*Electromechanics* (*Part* 1)' Course in Electrical Engineering and Automation Major of the classes of 2018 and 2019.

Course objectives / Assessment grades	Class of 2018		Class of 2019		Average magnitude changes in the causal effect
	O_1	O_2	O_1	O_2	
A_1	0.6245	-	0.9577	-	+53.35%
B_1	0.3893	-	0.3156	-	-18.93%
C_1	0.3339	-	0.1620	-	-51.48%
A_2	-	0.6910	-	0.9143	+24.42%
B_2	-	0.4548	-	0.3728	-18.03%
C_2	-	0.2618	-	0.2600	-0.69%

The ACE of chapter tests B_1 and B_2 on course objectives O_1 and O_2 are 0.3156 and 0.3728, respectively. The ACE of the final exam C_1 and C_2 on course objectives O_1 and O_2 are 0.1620 and 0.2620, respectively. It can be observed that although students have mastered basic knowledge about the circuit and magnetic structures of transformers and rotating motors, there are still deficiencies in understanding motor operating principles and analyzing internal electromagnetic processes in motors. In future classroom teaching, teachers can use project-based learning, guiding students through problem-oriented approaches to actively engage in class discussions, encouraging proactive thinking, and enhancing their ability to analyze and calculate aspects related to motor principles, the electromagnetic processes within motors based on foundational knowledge, such as magnetic circuits and transformers.

Compared to the class of 2018, the class of 2019 electrical engineering and automation A_1 and A_2 showed an increased causal effect on O_1 and O_2 by 53.35% and 24.42%, respectively. This is because the teacher increased the frequency and intensity of in-class and after-class exercises in their classes of 2019.

From Table 1, it is evident that in the chapter tests of the 2019 class for the 'Electromechanics (Part 1)' course, the proportion of subjective questions involving analysis and computation of magnetic circuits and transformers was reduced in the transformer tests. This reduction meant that students did not effectively practice their analysis and computation skills for this part, leading to a decrease in the causal effect of chapter test B_1 on course objective O_1.

Compared to the 2018 class, the 2019 class in electrical engineering and automation A_1 and A_2 saw a 53.35% and 24.42% increase in the causal effect on O_1 and O_2, respectively, due to more frequent and intense exercises. Table 2 shows the chapter tests for 'Electromechanics (Part 1)' for the class of 2019, the proportion of subjective questions on magnetic circuits and transformers was reduced. This led to less effective practice in these areas, decreasing the causal effect of chapter test B_1 on course objective O_1.

Table 2. Number and Proportion of Question Types in the Chapter Tests for the '*Electromechanics* (*Part* 1)' Course in the classes of 2018 and 2019.

	Class of 2018		Class of 2019	
	Objective Questions (supporting O_1)	Subjective Questions (supporting O_2)	Objective Questions (supporting O_1)	Subjective Questions (supporting O_2)
Transformer Test	0%	100.0%	63.6%	36.4%
DC Motor Test	100%	0%	84.0%	16.0%

Table 3. Mean causal effects of teaching activities on course objectives of '*Electromechanics* (*Part* 1)' course for the classes of 2018 and 2019.

	Class of 2018		Class of 2019		Magnitude changes in the causal effect
	O_1	O_2	O_1	O_2	
O_1	-	0.2867	-	0.7836	173.3%

According to formula (4), the ACE of course objective O_1 on O_2 for the '*Electromechanics (Part 1)*' course in 2018 and 2019 is shown in Table 3. The ACE values indicate a significantly positive impact of O_1 on O_2. For the 2019 class, the benefits include: (1) Increased frequency and intensity of exercises positively impacted course assignments; (2) A more balanced distribution of question types in chapter tests made the effect of O_1 on O_2 more apparent. Future improvements could include: (1) Using project-based and problem-guided learning to enhance students' analytical and computational skills in transformers and motors; (2) Increasing subjective questions in transformer chapter tests to intensify training in analysis and computation.

4 Conclusions

To address the overly simplistic course quality evaluations, lack of a psychological model, and difficulties in obtaining actionable results, this paper uses the 'Electromechanics (Part 1)' course as a case study. It proposes an SCM for course quality assessment based on course assessment methods, objectives, and graduate attributes. The do-operator calculates the ACE of interventions like assignments, tests, and exams on course objectives. By analyzing ACE differences over two academic years, the paper identifies reasons for changes in causal effects and suggests continuous improvement measures. The formalized SCM and symbolic causal mathematics enhance the rigor and effectiveness of course evaluations, uncovering specific measures for continuous improvement.

Although the strategy is applied to 'Electromechanics (Part 1)' in electrical engineering and automation, it could be adapted to other courses. Future work could involve using data from assessments of 'Electromechanics (Part 2)' for a longitudinal evaluation to achieve more effective quality evaluation and improvement of 'Electromechanics (Part 1)'.

Acknowledgment

This work was funded by the Key Program of the Teaching Reform Research in Colleges and Universities of Hunan Province (HNJG-2022-0079).

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