

Interdisciplinary Integrated Curriculum Design, Evaluation and Improvement Based on Causal Inference

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Abstract—To meet the demands of the information and intelligent era and cultivate students' ability to integrate diverse knowledge and skills to solve practical problems, interdisciplinary integrated curriculum design has become an important paradigm in education and teaching. However, due to challenges such as the interference of confounding factors, static evaluation systems, and the lack of dynamic optimization mechanisms, the design, assessment, and improvement of interdisciplinary integrated courses are difficult to be effectively supported. For this reason, based on the theory of causal science, this paper proposes the method of “introducing mediators to eliminate confounding”, adopts the structural equation model and combines counterfactual inference to calculate the causal effect, in order to analyze the intervention path. Taking the cognitive computing course as a case, a causal model including AI-enhanced research, the application of metacognitive strategies and higher-order abilities is constructed, and an empirical analysis is conducted through teaching data. The results show that the overall intervention effect is positive, and teaching intervention mainly acts on the improvement of students' abilities through mediating variables. The research provides a scientific path for the quantitative assessment of educational intervention effects and offers theoretical and methodological support for the dynamic optimization and precise improvement of the curriculum.

Keywords—interdisciplinary integration, causal inference, eliminate confounding, curriculum improvement

I. INTRODUCTION

With the proposal of the “trinity of education, science and technology, and talent” strategy at the 20th National Congress of the Communist Party of China, engineering education is accelerating its transformation towards cross-disciplinary integration and addressing complex social reality issues. Against this background, interdisciplinary integrated education has become an important paradigm for cultivating future innovative talents. Interdisciplinary integrated education is driven by complex social science problems, requiring learners to creatively propose solutions through interdisciplinary integrated methods, applying diverse knowledge and skills [1]. Curriculum design should strive to approach interdisciplinary integration as much as possible.

The current curriculum design is facing three major challenges: Firstly, the interference of confounding factors makes it difficult to precisely quantify the causal chain between teaching intervention and ability achievement; Secondly, the traditional evaluation system relies on the static indicators set in the early stage of teaching and is unable to capture the changes in the intervention effect and the intervention mechanism itself in the dynamic teaching scenarios. Finally, the course lacks targeted improvements

based on the effective evaluation of teaching intervention effects and urgently needs a continuous optimization mechanism driven by “data-cause and effect” [2, 3].

Especially in interdisciplinary integrated education, limited by the disciplinary barriers of traditional education and the insufficient cross-disciplinary collaboration ability between teachers and students, teachers and students highly rely on the assistance of AI in the teaching process. However, research shows that generative AI may have negative impacts. For instance, over-reliance on AI is likely to lead to academic misconduct and reduce students' creativity levels [4, 5]. This indicates that the wide application of generative AI has further increased the complexity of educational scenarios, and the demand for eliminating confounding effects and optimizing the design and evaluation of teaching interventions has become more urgent.

In an increasingly complex educational environment, how can the causal effects of teaching intervention be accurately quantified? How can the continuous improvement of courses be achieved through a dynamic optimization mechanism? To solve the above scientific problems, based on the theory of causal science, this paper proposes the method of “introducing mediators to eliminate confounding”, and combines the counterfactual inference method to calculate the causal effect, providing scientific tools and methodological support for curriculum design. This paper takes the cognitive computing course as an example to demonstrate the specific application of the method of causal inference in the design, evaluation and improvement of interdisciplinary integrated courses.

II. INTRODUCTION TO THEORY AND METHOD

The complete expression of introducing mediators to eliminate confounding is: introducing the mediating mechanism to eliminate confounding and setting up assessment observation points to simplify the analysis.

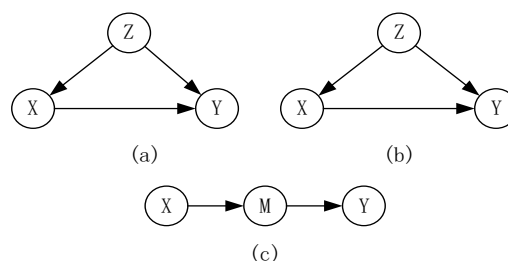


Fig. 1. Causal graph surgery and path reconstruction.

This is a method that blocks the influence of confounding factors on the intervention effect through the mediating mechanism, thereby more accurately evaluating the causal

effect of the intervention measures on the outcome variables. The main theoretical basis of this method is causal graph surgery and path reconstruction: The confounding factor Z affects both variables X and Y . When intervening in the variable X , all edges pointing to X in the causal graph are deleted to make it independent of the original parent node. After the intervention, the value of X is no longer determined by Z but is set as a fixed value x to eliminate the influence of Z on X [6, 7]. After the intervention, the causal effect is transmitted through new causal pathways (either the direct path or the indirect path through the mediating variable M), as shown in Fig. 1.

The introduction of the mediating method to eliminate confounding is essentially an integration and expansion of causal graph surgery and path reconstruction: When disturbed by the unobserved confounding factor Z , for the treatment variable (intervention) X , a mediating mechanism M' can be introduced and added to the connotation of the intervention as part of the intervention mechanism. Set X as a fixed value x (such as in the intervention state, $X = 1$), the confounding effect of Z on X is eliminated, and at this time, an indirect causal path of X acting on Y through M' will emerge. While introducing the mediating mechanism, corresponding assessment observation points need to be set up. According to the data obtained from the assessment observation points, some are directly included in the students' grades, and some are used for the assessment of students' abilities, participating in the quantification of each key node in the causal analysis. At this point, if the causal path where M' is located is not analyzed, the introduced mediating variable can be directly deleted to simplify the causal diagram, and the connotation of M' is reflected through the added assessment observation points.

In the specific operation, it is first necessary to identify the potential confounding factors and analyze the mechanism of action of each variable, and construct the initial causal diagram based on experience and assumptions. Subsequently, the intermediary mechanism is incorporated through the design of the intervention process or system; Finally, the blocked confounding paths and the mediating variables that were not analyzed were deleted to simplify the causal diagram, and data were collected based on the added assessment observation points for causal effect analysis.

III. COURSE APPLICATION EXAMPLES

A. Construction of Causal Graphs

As an interdisciplinary integrated course, the Cognitive Computing course encourages students to actively use AI tools to solve practical problems across fields and in multiple ways, and to enhance their own abilities in the process. In order to explore the impact of AI usage on students' three higher-order thinking abilities of analysis, evaluation and assessment, and creativity, the teaching measures of the cognitive computing course are intervened: After each new knowledge of causal analysis, students are required to use AI tools to apply the learned content to multiple other domains to solve practical problems, and select one of the problems they are interested in for specific analysis.

Based on the existing knowledge and experience, AI-assisted research may have both positive and negative

impacts on the above three higher-order thinking abilities. For instance, AI tools can help students gain a deeper understanding of the causal relationships among variables, and their analytical thinking abilities can be significantly enhanced in this process. However, students may overly rely on the results provided by AI tools, weakening their ability to think independently and operate manually, as well as the idea of questioning the rationality of the results. The analytical thinking, critical evaluation ability and creative thinking are summarized as higher-order abilities (Y). Based on the above analysis, the causal relationship hypothesis can be proposed:

- AI-enhanced research (T) affects the cultivation of higher-order abilities.

If students can overcome the abuse and excessive reliance on AI tools, the positive impact of using AI tools may be even greater [8, 9]. Here, the behavior of students' reasonable use of AI tools to actively monitor, reflect on and adjust the learning process is summarized as the application of metacognitive strategies (M). Based on existing knowledge, experience and assumptions, the following causal paths can be proposed:

- Ai-enhanced research influences students' application of metacognitive strategies, and the application of metacognitive strategies positively affects the cultivation of higher-order abilities.

There are still some influences of factors in the implementation process of teaching intervention, such as the alternative use of AI. The use of AI substitution refers to students directly copying the content provided by AI without thinking, allowing AI to replace their own thinking, which is considered AI abuse. Obviously, this will negatively affect the implementation of intervention, the application of metacognitive strategies, and the cultivation of higher-order abilities. Based on the above analysis, the causal relationship hypothesis can be proposed:

- The alternative use of AI has an impact on AI-enhanced research, the application of metacognitive strategies, and advanced capabilities, and is a confounding factor.

In addition, there are also influences from the research environment and development expectations. The differences and limitations of the research environment (such as experimental equipment) can affect the effectiveness of AI-enhanced research and the cultivation of students' higher-order abilities. However, the course itself contains teaching contents such as simulated randomized experiments and result estimation. Therefore, this confusion of the research environment can be regarded as having been eliminated. Development expectations can affect students' enthusiasm for participating in the classroom. When students believe that the teaching content is irrelevant to their development expectations, their enthusiasm will decrease. This is more likely to lead to the improper use of AI tools, thereby affecting the application of metacognitive strategies and the cultivation of higher-order abilities. Based on the above analysis, hypotheses can be put forward:

- Learning motivation affects the application of metacognitive strategies and thereby influences the cultivation of higher-order abilities. It is a confounding factor.

Based on the above analysis, the causal diagram shown in Fig. 2 can be obtained:

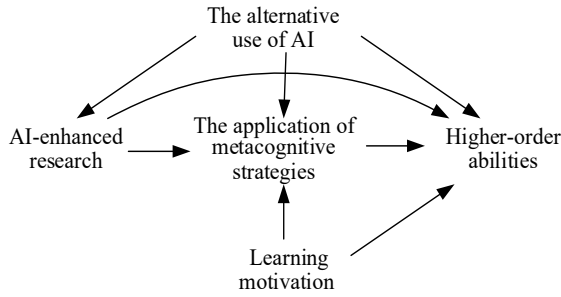


Fig. 2. A causal graph containing confounding factors and mediating variables.

B. Eliminate Confounding and Simplify Causal Diagrams

Take eliminating the confounding impact of AI substitution on AI-enhanced research as an example: Introduce the “Iterative interaction with AI” intermediary between AI-enhanced research and higher-order capabilities, that is, require students to conduct multiple iterative interactions with AI for each problem, thereby regulating students’ rational use of AI tools. The confounding impact of AI substitution on AI-enhanced research has been eliminated.

Set up the “Iterative interaction” assessment observation point and score the implementation of this assessment observation point in the assignments submitted by students.

Referring to the above-mentioned actions for eliminating confounding and simplifying causal graphs, as well as the setting of corresponding assessment observation points, other confounding factors can be eliminated. Five assessment observation points were obtained in the process of introducing intermediaries to eliminate confounding. In addition, according to the actual situation, assessment observation points were also set for some teaching contents. The specific Settings of the assessment observation points are shown in Table 1.

Table 1. Assess the setting of observation points

Confounding factor	The introduced intermediary	Assessment observation points
The alternative use of AI (Affect T and Y)	Interact iteratively with AI	Iterative interaction
The alternative use of AI (Affect M)	Human judgment	Rationality judgment of data sources
		Real operation of code
		Feasibility Analysis of solutions
Development expectation (Affect T and Y)	Solve practical problems across fields	Divergent application and specific analysis
--	--	Causal analysis
--	--	Dynamic optimization

It should be noted that whether the introduced intermediary mechanism is truly effective will directly affect the effect of eliminating confounding influences. How to ensure that the intermediary mechanism is truly effective mostly involves human factors. In the practice of course teaching, schools, teachers and students all need to pay attention to this point.

This study conducts mediation analysis based on the application of metacognitive strategies. Therefore, the mixed and introduced mediation nodes, as well as the related arrows, can be directly deleted, but their connotations are all reflected in the students’ grades and ability assessment data through

the set assessment observation points. The main causal diagram obtained after simplification is shown in Fig. 3.

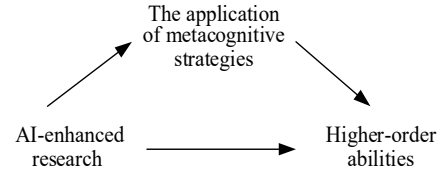


Fig. 3. Main causality diagram.

C. The Design of Evidence Structure for Student Performance and Ability Evaluation Based on Assessment Observation Points

Record the data of the assessment observation point of “iterative interaction” as A; The data for “rationality judgment of data sources”, “Real operation of code”, and “feasibility analysis of solutions” are respectively recorded as B₁, B₂, and B₃; The data of “Divergent Application and Specific Analysis” is denoted as C; The data of the two assessment observation points, “Causal Analysis” and “Dynamic Optimization”, which are set according to the teaching content, are respectively recorded as D and E. The score intervals of the above assessment observation points are all [0, 5].

Combining the generation process and significance of the assessment observation points, as well as the specific content of the job Settings, and comprehensively considering the influence of the usage mode of AI on higher-order abilities, the weights of some items were adjusted to obtain the final composition of the variable data [10]. The following is the specific data composition of some variables:

Metacognitive strategy application (M):

$$M = A + B_1 + B_2 + B_3 \quad (1)$$

Analytical Thinking (Y₁):

$$Y_1 = \frac{A}{5} (D + B_1 + B_2 + B_3) \quad (2)$$

Critical evaluation ability (Y₂):

$$Y_2 = B_1 + B_2 + B_3 \quad (3)$$

Creative thinking (Y₃):

$$Y_3 = \frac{A}{5} (C + E) \quad (4)$$

The higher-order ability (Y) is the sum of Y₁, Y₂, and Y₃.

D. Data Analysis and Continuous Improvement

Homework was set based on the content of the previous part to obtain the grading data of 104 students who participated in this course. After deleting the invalid data, the valid data of 89 students were finally obtained. Iterative interaction with AI is the most important indicator reflecting whether teaching intervention is reasonably received. It is stipulated that A value of A less than or equal to 2 is considered as no intervention received. Thus, 89 students are divided into the “intervention receiving group” and the “non-intervention receiving group”.

Table 2. Table of valid data grouping situation (PAET)

Student serial number	T	M _(T=0)	Y _(T=0)	M _(T=1)	Y _(T=1)
1	1	--	--	13.00	23.80
2	1	--	--	15.00	29.40-
3	1	--	--	14.00	23.00
4	1	--	--	13.00	23.20
6	1	--	--	17.00	33.80-
16	0	9.00	13.80	--	--
17	0	8.00	12.00	--	--
23	0	4.00	5.20	--	--
24	0	12.00	19.20	--	--
34	0	6.00	7.80	--	--

Table 3. The distribution of mediating and outcome variables in the two groups of data

Distributed parameter	T = 0		T = 1	
	M	Y	M	Y
μ	7.48	11.07	14.63	28.15
σ	3.41	5.50	3.19	7.79

Tables 2 and 3 respectively present the real data of some students in the two groups and the overall variable distribution of the two groups of data. Several students were randomly selected from these two groups. A causal model was constructed based on their grade data and causal graphs. The data of the remaining students were used to correct the distribution parameters [11, 12]. Among which:

$$M = 7.48 + 7.16T + \eta \quad (5)$$

$$Y = -5.18 + 1.52T + 2.17M + \zeta \quad (6)$$

Adjust the value of the intervention variable T in the regression equation to obtain the counterfactual data of the students in the intervention group in the non-intervention state, as well as the counterfactual data of the students in the non-intervention group in the intervention state, the results are shown in Table 4. Subsequently, the counterfactual simulation method of structural equation (SEM) was used to simulate the situation where the mediating variable remained in the unintervened state under the intervention conditions, that is, Y (1, M(0)) [13]. For each student, artificially set M = M(T=0), then set T = 1, substitute M(T=0) and T = 1 into the regression equation of Y, and calculate Y (1, M(0)).

The data visualization results of Y (0, M(0)), Y (1, M(1)) and Y (1, M(0)) are shown in Fig. 4, and the expected values are shown in Table 5.

Calculate the direct causal effect (DE) and the indirect causal effect (IE) according to formulas (7) and (8):

$$DE = E[Y(1, M(0))] - E[Y(0, M(0))] \quad (7)$$

$$IE = E[Y(1, M(1))] - E[Y(1, M(0))] \quad (8)$$

Table 4. The counterfactual results of the two sets of data (part)

Student serial number	T	M _(T=0)	Y _(T=0)	M _(T=1)	Y _(T=1)
1	1	5.84	6.72	13.00	23.80
2	1	7.84	12.32	15.00	29.40-
3	1	6.84	5.92	14.00	23.00
4	1	5.84	6.12	13.00	23.20
6	1	9.84	16.72	17.00	33.80-
16	0	9.00	13.80	16.16	30.88
17	0	8.00	12.00	15.16	30.88
23	0	4.00	5.20	11.16	22.28
24	0	12.00	19.20	19.16	36.28
34	0	6.00	7.80	13.16	24.88

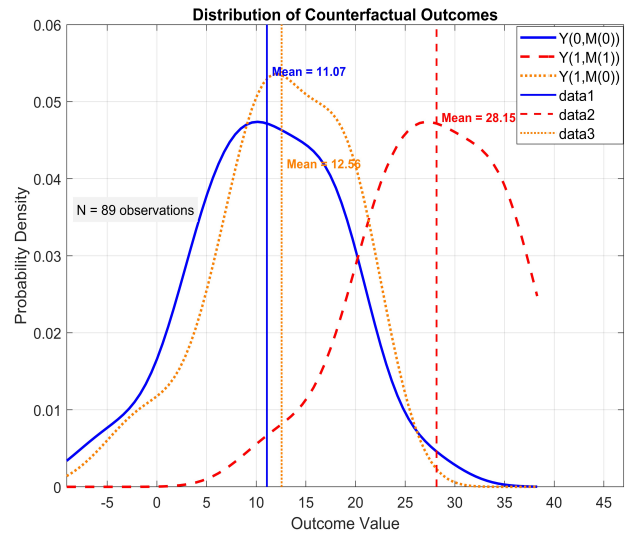


Fig. 4. Distribution maps of the three groups of data.

Table 5. The expected values of Y(0, M(0)), Y(1, M(1)), and Y(1, M(0))

M(m)	T	T = 0	T = 1
m = 0		E = 11.07	E = 12.56
m = 1		--	E = 28.15

The results show that the direct causal effect is 1.49, the indirect causal effect is 15.59, and the total effect is the sum of the two, that is, 17.08. The direct causal effect is positive, but the value is relatively small, indicating that the intervention has a subtle direct promoting effect on the cultivation of higher-order abilities. The indirect causal effect is positive and accounts for a relatively large proportion, indicating that the intervention has a significant positive impact on higher-order abilities through mediating variables. The total effect is positive, indicating that the overall impact of the intervention on higher-order abilities is positive. However, we still need to pay attention to the existing problems and optimize the intervention design to maximize the positive effect.

In response to the above causal effect analysis, an improved scheme of strengthening metacognitive strategy training is proposed, aiming to further enhance the mediating effect. The specific improvement contents include:

- Set up guided AI usage training tasks. The design task requires students to explain the purpose and process of using AI. Set up an AI usage step recording area in the after-class exercises to force students to reflect on the thinking path of each step.
- Embed the “metacognitive Questioning” module, and add a self-questioning session at each task stage, such as: “Why do I use AI in this way?” and “How would I solve this problem if I didn’t use AI?”.
- Based on the traces of AI usage in students’ homework, teachers provide feedback on the rationality of their strategies and suggestions for improvement.

IV. CONCLUSION

Based on the urgent demand for interdisciplinary integrated education in the information age, and aiming at the core problems existing in the current curriculum design, such as the interference of confounding factors, the limitations of

static evaluation, and the lack of dynamic optimization mechanisms, this paper proposes the method of “introducing mediators to eliminate confounding” based on the theory of causal science. This method blocks the confounding path by introducing the mediating mechanism and combines multi-dimensional assessment observation points to achieve the scientific quantification and precise evaluation of teaching effects.

Taking the cognitive computing course as a practical case, this paper analyzes the complex influence mechanism of the use of AI tools on students’ higher-order abilities. Meanwhile, it specifically demonstrates how to eliminate the interference of confounding factors by introducing mediating variables and quantify the effect of teaching intervention by setting assessment observation points, providing feasible methods for the design, effective evaluation and improvement of interdisciplinary integrated courses. The research results show that although AI-enhanced research has a promoting effect on ability cultivation, it is mainly an indirect positive effect generated through the mediating path of metacognitive strategies, highlighting the importance of cultivating students’ application of metacognitive strategies and critical use of AI tools. Based on this, the research proposes a three-in-one improvement scheme of “guided AI usage training – metacognitive questioning – teacher feedback”, providing an operational optimization path for maximizing the positive effect of teaching intervention.

This paper provides an operational and verifiable causal inference tool for educational science. Future research will further optimize the human-machine collaboration mechanism and explore a long-term optimization path driven by cross-cycle data, providing methodological support for the digital transformation of education.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Jing Zhou conducted the research, analyzed the data, and wrote the paper; Bin Duan provided guidance; both authors had approved the final version.

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