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Constructing an Adaptive Training Model for Electronic Information Postgraduates Using Causally Interpretable Artificial Intelligence

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Abstract

The cultivation of innovation capability in electronic information postgraduates faces multiple obstacles, including complex and nonlinear interactions among influencing factors and consistently delayed evaluation feedback. As a result, conventional training models cannot adapt dynamically to individual characteristics. To address this limitation, this paper proposes an adaptive training model grounded in causally interpretable artificial intelligence. First, a three-dimensional feature set encompassing individual endowments, training process support, and the external ecological environment is constructed. Subsequently, a neural acyclic directed mixed graph learning method extracts the causal network structure among these features, identifying critical pathways and potential confounders. Finally, this causal structure is incorporated as prior information into an XGBoost-SHAP framework, which produces a dual-output evaluation model that simultaneously generates personalized student innovation capability reports and supervisor effectiveness reports. The model achieves adaptive evolution through a dual closed-loop mechanism, in which causal discovery drives iterative feature set updates and evaluation feedback drives dynamic adjustments to training strategies. This research offers a new pathway that fuses causal mechanisms with interpretable artificial intelligence for cultivating innovation capability in electronic information postgraduates.

Keywords

innovation capability cultivation, electronic information postgraduates, causal discovery, interpretable artificial intelligence, adaptive training model

1. Introduction

Graduate education supplies high-level talent for an innovation-driven nation. The electronic information industry is strategic, foundational, and pioneering. Its rapid technological iteration, deep interdisciplinary integration, and short knowledge renewal cycles demand higher continuous learning and original innovation than other engineering fields. Current training confronts three interlocking constraints. First, a structural gap persists between training objectives and industrial technology evolution; some curricula adhere to traditional frameworks and fail to address emerging directions such as AI chips and intelligent sensing. Second, practical training lacks depth and breadth, with experimental projects emphasizing verification tasks and offering inadequate exposure to unstructured engineering problems. Third, the evaluation system relies heavily on singular quantitative indicators like publication counts, neglecting innovative behaviors such as technical breakthroughs and original solutions. These constraints form systemic barriers. Precisely identifying key influencing factors and implementing differentiated training has become an urgent reform question.

Scholars have explored training model reform and innovation capability evaluation. Ma et al. [1] examined cultivation paths for integrated circuit design postgraduates using a demand-capability-process-evaluation system. Luo et al. [2] constructed a four-in-one model integrating case courses, engineering practice, mentoring, and feedback. Chen et al. [3] proposed an AI-empowered multimodal innovation practice reform. Shi et al. [4] emphasized pedagogical innovation and university-industry cooperation. Bai et al. [5] introduced a “1234” model with dual-supervisor teams and a triple PDCA cycle. Wan [6] developed an IPSO-LSTM evaluation model to classify innovation capability. Hou et al. [7] analyzed entrepreneurial competence through awareness, skills, and practice. Luo et al. [8] built a talent cultivation system stressing industry-education and science-education integration. Sun et al. [9] designed an integrated through-curriculum system for local universities. Zhou et al. [10] explored a multi-level model incorporating an experimental innovation center. Zhang et al. [11] reported on university-enterprise cooperation through joint bases and industry projects. Ouyang et al. [12] revealed how disciplinary ecology constrains capability cultivation. Mo et al. [13] discussed reform paths in professional-degree programs in the AI era. In evaluation, Wang et al. [14] applied AHP and entropy weight to build an index system. Zhang et al. [15] used fsQCA to identify multiple equivalent paths, showing innovation capability emerges from condition configurations. Zhou et al. [16] analyzed digital literacy’s impact on innovation capability.

Existing reforms concentrate on structural aspects. A systematic framework that accurately identifies key factors shaping individual innovation capability and implements differentiated training remains absent. Because electronic information postgraduates face exceptionally fast knowledge renewal, innovation often manifests as rapid responses to cutting-edge directions including AI chips, 6G, and intelligent sensing. Existing evaluation methods remain at correlation-based prediction, failing to reveal causal influence. Three shortcomings stand out. First, analyses rely on linear associations and cannot capture nonlinear causal structure. Bai et al. [5] focused on process standardization without causal inference. Zhang et al. [15] identified multi-path equivalence but not causal direction. Second, training schemes and feedback are static. Wan’s [6] model offers unidirectional feedback without a closed loop. Third, evaluation outputs lack interpretability. Wang et al. [14] quantified capability but could not reveal differential impact pathways, leaving postgraduates and supervisors unable to devise targeted plans.

To address these gaps, this paper proposes an adaptive model based on causally interpretable AI. First, a three-dimensional feature set encompassing individual endowments, training process support, and external ecological environment is constructed. Second, the neural ADMG method [17] mines the causal network structure, handling nonlinearity and latent confounders. Third, this structure enters the XGBoost-SHAP framework [18] as prior information, generating dual-output evaluation. Finally, a dual closed-loop mechanism drives adaptive evolution: causal discovery updates the feature set, and evaluation feedback adjusts training strategies.

The remainder of the paper is organized as follows: Section 2 describes the construction of the feature set for innovation capability cultivation. Section 3 analyzes the principles and advantages of causal network structure mining based on neural ADMG. Section 4 presents the personalized evaluation and feedback model based on XGBoost-SHAP. Section 5 discusses the support mechanisms for model implementation, and Section 6 concludes the paper.

2. Construction of the Feature Set for Innovation Capability Cultivation

Following the technology-organization-environment framework [15] , this study divides the factors influencing innovation capability into three dimensions, namely individual cognition and ability endowments, training process support, and external ecological environment.

2.1 Individual Cognition and Ability Endowment Dimension

This dimension covers knowledge reserves, tool utilization, thinking quality, and psychological states.

(1) Specialized knowledge reserves form the foundation. The electronic information knowledge system spans semiconductor physics, circuit theory, signals and systems, communication principles, and computer architecture, updating far faster than traditional engineering. Shi et al. [4] noted that interdisciplinary knowledge breadth and depth shape innovative thinking. Sun et al. [9] stressed the foundational role of frontier course content. Postgraduates must integrate knowledge across levels, merging device physics with algorithm optimization in chip design or co-designing hardware and protocols in communication systems. This feature is quantified through course grades, concept mastery tests, and knowledge graph coverage.

(2) AI tool application ability has emerged as a new essential factor. R&D increasingly relies on AI-assisted toolchains for automated code generation, intelligent testing, and literature analysis. Chen et al. [3] argued that this capacity constitutes a core variable for research efficiency and innovation quality. Mo et al. [13] found that AI toolchain training significantly improved high-level problem-solving. The tool ecosystem includes hardware description languages, embedded environments, signal processing platforms, and AI tools. This feature is assessed through tool-use diversity, task completion time, and tool selection appropriateness.

(3) Innovative thinking quality reflects the cognitive capacity to identify scientific problems and construct novel solutions, often manifesting as breakthroughs challenging existing technical routes. Luo et al. [8] characterized it as involving divergent thinking, critical thinking, cross-domain associations, and the acumen to distill questions from practice. Ma et al. [1] noted that in IC design it appears as insight and courage to question established designs. Technological sensitivity to spot promising directions distinguishes innovative talent. This feature is measured through topic novelty, technical proposal originality, and innovation contributions in papers.

(4) Learning engagement and self-efficacy capture psychological energy and belief in innovative ability. Rapid iteration demands continuous tracking, making sustained engagement critical. Zhang et al. [15] demonstrated their significant positive prediction of innovation capability. Shi et al. [4] noted self-efficacy influences strategy choices and persistence. Frequent setbacks such as tape-out failures and non-convergent simulations render self-efficacy a key factor determining perseverance. This feature is quantified through research time investment, task completion rates, and self-efficacy scale scores.

2.2 Training Process Support Dimension

This dimension focuses on organizational support, divided into mentoring frequency and depth, mentoring style and strategy, and project resources and research platforms.

(1) Mentoring frequency and depth capture the temporal density and cognitive intensity of supervisor-postgraduate interactions. Electronic information training involves multiple engineering stages, each demanding specific technical decisions requiring high mentoring frequency. Bai et al. [5] observed that heavy workloads under the single-supervisor model often prevent adequate guidance. Ouyang et al. [12] found dual faculty constraints in local normal universities. Quality interactions transmit knowledge and internalize innovative methods. This feature is measured through meeting density, feedback detail and timeliness, and average session duration.

(2) Mentoring style and strategy concern educational philosophy. Innovation requires heuristic guidance rather than standard answers. Luo et al. [2] advocated a dual-supervisor system combining academic planning and industry practice. Ouyang et al. [12] recommended small supervisor teams from complementary areas. Team-based mentoring offsets individual limitations in engineering experience. This feature is captured through student evaluations, supervisors' self-reported philosophies, and peer reviews.

(3) Project resources and research platforms reflect the projects, equipment, and exchange opportunities supervisors can allocate. Research depends on advanced equipment and tools; tape-out costs are high, and testing requires specialized instruments. Zhang et al. [15] established innovation resources as a core organizational precondition. Luo et al. [8] proposed that high-level platforms and major projects create authentic research contexts. Access to tape-out opportunities, testing equipment, and EDA tools determines whether postgraduates complete the full innovation chain. This feature is assessed through project level and number, per capita equipment usage, and exchange opportunity frequency.

2.3 External Ecological Environment Dimension

This dimension addresses macro-conditions beyond the university, covering academic exchange, industry-education integration, and institutional culture.

(1) The academic exchange and competition environment includes campus forums, conference participation, and competition traditions. Short technology cycles demand continuous frontier tracking. Zhang et al. [15] confirmed innovation culture as a core environmental factor. Wang et al. [14] assigned academic exchange an 18% weight. Top conferences serve as initial platforms for frontier achievements, enabling timely learning of new directions. This feature is quantified through annual presentations, conference attendance per capita, competition participation rates, and award levels.

(2) Industry-education integration depth measures university-enterprise synergy in talent cultivation and technology development. Industrial demand steers innovation direction. Bai et al. [5] identified integration as a key pathway for enhancing practice capability. Luo et al. [8] noted it enables engagement with authentic application scenarios. Zhang et al. [11] demonstrated that collaborative projects significantly improve practice levels. This feature is measured through joint laboratory numbers, enterprise supervisor proportions, and average enterprise project hours.

(3) Innovation culture and institutional support involve value climates, IP protection, and achievement recognition. Electronic information outputs are diverse, including chips, protocol stacks, patents, and papers. Compared with other disciplines, the pathway to application is shorter and demands flexible institutional support. Ma et al. [1] argued for a demand-oriented, competence-centered system. Zhang et al. [15] showed innovation culture as a core condition across multiple paths. A failure-tolerant atmosphere and reasonable ownership rules affect willingness to engage in high-risk research; the chip design cycle often exceeds one year, requiring long-cycle outcome safeguards. This feature is assessed through innovation activity participation, project approval rates, and supportive policy completeness.

Together, these three dimensions encompass ten core features, constructing a framework from individual cognition through organizational support to ecological conditions. Figure 1 presents the feature set.

Figure 1: Construction of the feature set for innovation capability cultivation of electronic information postgraduates

3. Causal Network Structure Mining Based on Neural ADMG

After feature set construction, the causal structure must be uncovered. Conventional correlation analysis cannot distinguish causality from spurious correlations. This study adopts the neural ADMG method [17] for causal discovery, which identifies nonlinear relationships and handles latent confounders.

3.1 The Necessity of Causal Discovery

Relationships among variables exhibit nonlinearity and strong coupling. Zhang et al. [15] showed innovation capability emerges from condition combinations. A bidirectional causal relationship may exist between AI tool ability and innovative thinking [13] A latent confounder, such as intrinsic motivation, may jointly influence mentoring frequency and learning engagement, and ignoring it would overestimate mentoring effects [12] . Traditional models cannot differentiate these from confounding effects. Chen et al. [3] noted that deep learning models remain opaque regarding causal direction. Causal discovery aims to infer causal direction and structure from observational data, providing a causally interpretable foundation for personalized evaluation.

3.2 Basic Principles of the Neural ADMG Method

Ashman et al. [17] proposed modeling ancestral relationships with directed acyclic mixed graphs, where directed edges represent direct causal effects and bidirected edges indicate latent confounders. The method proves latent confounding is identifiable under bow-free ADMG and nonlinear additive noise assumptions and uses autoregressive flows for learning. It offers three advantages over traditional methods: it handles nonlinearity without presupposing linearity, explicitly models latent confounders to avoid omitted variable bias, and adopts gradient-based optimization with good scalability.

3.3 Application of Causal Networks in Postgraduate Innovation Capability Cultivation

Applying neural ADMG to electronic information postgraduate data achieves three objectives. First, it identifies critical causal pathways from individual endowments, training support, and external environment to innovation capability. For instance, AI tool ability may shorten simulation cycles and enable more tape-out attempts, or industry-education integration may enhance technological sensitivity. Second, it detects latent confounders; if intrinsic motivation jointly affects learning engagement and mentoring frequency, increasing frequency alone would not suffice. Third, it drives iterative feature set updates by revealing missing features, such as frontier tracking habits.

3.4 Transferring the Causal Network to the Evaluation Model

The mined causal directions and pathways are transferred via three mechanisms. Parent node features pointing to innovation capability receive higher prior attention weights in XGBoost. Mediating mechanisms supply causal chain contexts for SHAP explanations, elevating interpretation from statistical association to causal action. Latent confounders indicated by bidirected edges are flagged as variables to be controlled, enhancing evaluation robustness. Figure 2 illustrates this transfer logic, embedding causal discovery outcomes as prior structural information within the XGBoost-SHAP framework.

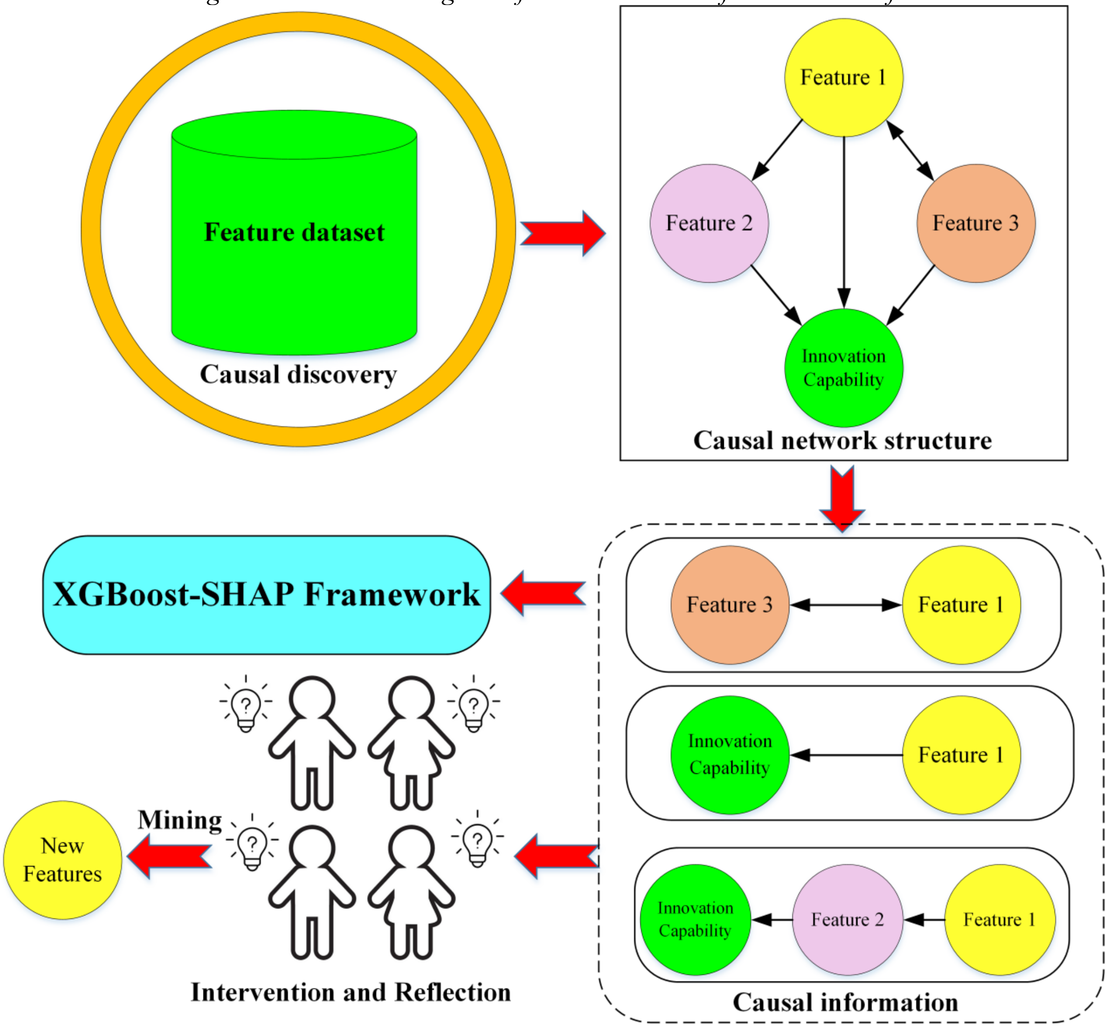
4. Personalized Evaluation and Feedback Model Based on XGBoost-SHAP

The causal structure enters the evaluation model as prior information. This study employs the joint XGBoost-SHAP approach [18] with the feature set and causal network as combined inputs to achieve high-precision dual-output prediction and individualized interpretation.

4.1 The XGBoost Dual-Output Evaluation Model

XGBoost sequentially builds decision trees fitting residuals, modeling complex nonlinear relationships with high accuracy. Xian et al. [18] verified its superior performance in educational prediction. Its advantages include automatic handling of nonlinear interactions, regularization to prevent overfitting in small samples, and high training efficiency. The model combines the three-dimensional feature set and the causal network as inputs. The feature set supplies raw variables, and the causal network supplies prior constraints to distinguish causal from spurious associations. Two outputs are specified, namely a personalized innovation capability profile and a supervisor effectiveness report. Training data from historical records including grades, outputs, awards, and evaluations enable multi-task supervised learning of both mappings.

Figure 2: Schematic diagram of causal network information transfer



4.2 SHAP-Based Causal Interpretability Analysis

The black-box nature of XGBoost is addressed by SHAP, which computes marginal contributions via Shapley values [18] . This study further introduces the causal network as a prior constraint. Causal SHAP analysis fulfills three functions. First, it ranks causal feature contributions, distinguishing direct contributions from parent nodes and indirect contributions through mediating paths. AI tool ability may contribute directly by improving coding efficiency and indirectly by enabling broader simulation exploration. Second, it generates individualized causal explanations, showing which features exerted direct or indirect driving effects and which acted as constraints, upgrading diagnosis from correlation to mechanism. Third, it reveals directional effects, identifying positive promoters and negative constraints, with causal direction corroborating the directionality.

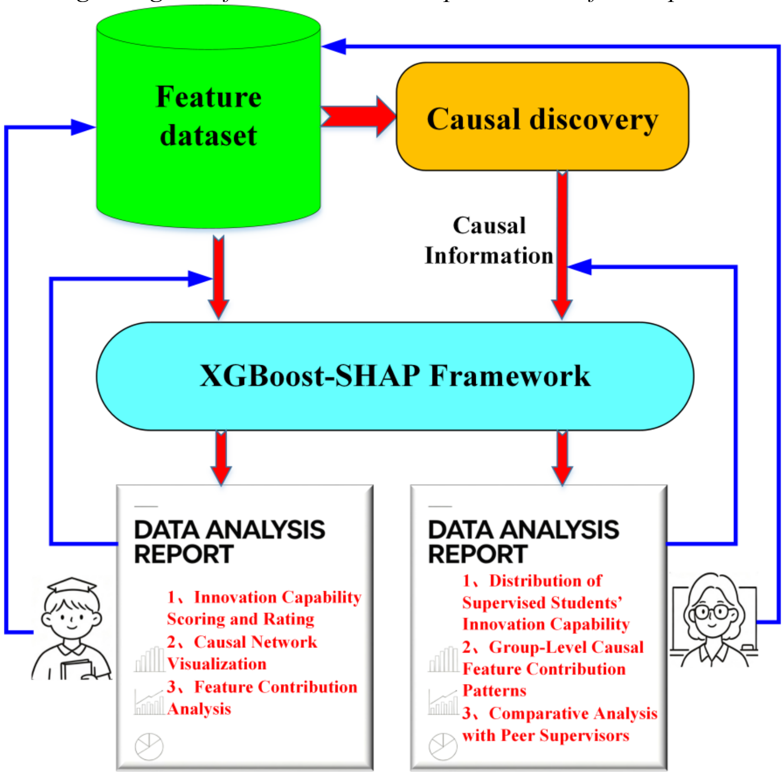
4.3 Personalized Feedback Reports and Supervisor Effectiveness Reports

The postgraduate innovation capability profile includes a composite score and grade, a causal network visualization displaying key pathways, and a SHAP causal contribution analysis identifying strengths and weaknesses. This forms a feedback loop of diagnosis, attribution, and targeted improvement. The supervisor effectiveness report aggregates postgraduate capability distribution, group-level causal patterns, and peer comparisons. Luo et al. [2] noted strong supervisor influence yet uneven knowledge updating. These reports enable supervisors to identify high-impact mentoring components and deficiencies for targeted adjustment.

4.4 The Dual Closed-Loop Mechanism for Adaptive Cultivation

Figure 3 illustrates the two interlocking loops. In the inner loop, evaluation feedback drives individual strategy adjustments. Postgraduates address weaknesses and supervisors optimize mentoring, and after intervention new data produce updated evaluations, forming an iterative cycle. In the outer loop, causal discovery reruns on accumulated data, potentially revealing new pathways or confounders from emerging directions such as large language model-assisted chip design, driving feature set updates and model retraining. This transforms the training model from a static design into a dynamically evolving adaptive system with cognitive-level evolutionary capacity.

Figure 3: Logic diagram of the dual closed-loop mechanism for adaptive cultivation



5. Support Mechanisms for Model Implementation

The implementation of the adaptive training model described above requires corresponding support mechanisms.

(1) Data infrastructure requires a specialized multivariate collection system for electronic information postgraduates, incorporating tape-out experiences, EDA tool usage logs, simulation cycle lengths, and co-design completion status alongside conventional metrics. Bai et al. [5] emphasized using AI and big data to capture practical teaching resources. Experiment reports, design documents, and simulation logs contain rich process-oriented data and should be systematically collected.

(2) Faculty capacity building demands that supervisors accurately interpret discipline-specific features in evaluation reports and translate diagnostics into concrete strategies. Luo et al. [8] proposed career-long development through thematic training. Differentiated modules for IC design, communication systems, and signal processing should be designed. A dual-supervisor system with academic and enterprise supervisors is essential [2] , and enterprise supervisor feedback from internship observations is vital for iterative model optimization.

(3) Institutional safeguards must accommodate the discipline's research cycles. Simulation verification can be short-term, while chip design from tape-out to testing often exceeds one year. Sun et al. [9] recommended an evaluation system benchmarked on objectives, centered on process, and evidenced by outcomes. Mid-term checkpoints for long-cycle projects should be set, and evaluation results should inform training adjustments, supervisor appraisals, and resource allocation.

(4) Ethics and privacy protection require strict standards because cultivation data involve specific technical solutions and IP. Data use must follow informed consent, minimum necessity, and purpose limitation.

Processing transparency must be maintained, and for sensitive data such as core algorithms and chip layouts, graded usage and de-identification mechanisms should protect postgraduates' IP rights and academic priority.

6. Conclusion

Cultivating innovation capability in electronic information postgraduates is a complex systems problem with numerous interacting factors and large individual differences. The proposed model integrates three-dimensional feature set construction, neural ADMG causal discovery, and XGBoost-SHAP personalized evaluation into a closed loop where causal understanding drives precise evaluation, precise evaluation drives personalized intervention, and intervention feedback drives model evolution. The core contribution lies in advancing from correlation analysis to causal mechanisms, upgrading from standardized scoring to personalized diagnosis, and transforming static schemes into a data-driven adaptive system. Future research may conduct longitudinal tracking across sub-disciplines to verify the dual closed-loop mechanism, combine causal discovery with large-scale cultivation data to improve generalization, and extend the model to related disciplines such as electronic science and technology, information and communication engineering, and integrated circuit science and engineering, adjusting the feature set according to research paradigm characteristics.

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Conflicts of Interest

The authors declare no conflict of interest.

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