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RESEARCH ARTICLE

AI-Supported Learning Environments Shape Learning Ability in Science and Vocational Education: The Role of Psychological Trust and Motivation

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ABSTRACT

The educational environment in China is experiencing profound change due to the incorporation of artificial intelligence, which was triggered by Education Modernization 2035 agenda and the AI+ Education Action Plan. Despite high levels of AI acceptance among Chinese students, psychological trust levels are weak, and this presents a paradox of students having an algorithmic authority anxiety when AI prescriptions differ from the instruction of the instructor. In this work, the Cultural-Calibrated Dual-Pathway Integration Model (C-DPIM) is proposed to examine the influence of psychological trust and motivation on learning proficiency in the AI-assisted learning setting in the realms of Chinese science and vocational education. It was a nationally stratified longitudinal cohort study that followed 2,847 students in 28 institutions in 12 provinces in the academic year between September 2024 and June 2025. The model was assessed using multi-level structural equation modeling, latent growth curve analysis and policy simulations. The findings suggest that AI transparency is an important predictor of Pedagogical Filial Trust (PFT) ($\beta = 0.35$, $p < .001$), and AI personalization is a predictor of socio-instrumental motivation in vocational education ($\beta = 0.26$, $p < .001$). Trust exclusivity is found in science students, as 62% of variance is attributed to PFT pathways, and motivation primacy is observed in vocational students, as 68% variance is attributed to motivation pathways. The effect of the Gaokao Corrosion shows that trust in the science students in the high-pressure dropped by 53.5%. The collectivist orientation increases the collectivistic orientation increased by 1.5 times but at the same time, it increases the trust fragility by 14 times in case of errors made by AI in the public eye. Simulations of the policy imply that an institutional co-signature would improve the learning proficiency with a standard deviation of 0.55 in the vocational settings. This study provides

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culturally recalibrated models of streamlining AI application in collectivist education systems across the globe.

Keywords: AI-supported learning; Pedagogical Filial Trust; Cultural calibration; Gaokao pressure; Multi-level SEM; Collectivist education

1. Introduction

China has embarked on an entire overhaul of its education system by anticipating the prospects of artificial intelligence (AI) as a modernization tool. The current policy frameworks such as Education Modernization 2035 and further national planning documents focus on the intention of the government to build the education system that will be among the world leaders by integrating modern technologies into the teaching process. These projects make AI a fundamental technology that is expected to enhance the efficiency of instruction, personalized learning paths, and practical learning of skills in all sectors of education [1-5]. The Ministry of Education has expressed national policies to enhance the assimilation of AI in the classroom environment, which highlights the significance of AI in the development of foundational and innovative skills in learners across all levels of education. Therefore, this line of policy development has led to the active implementation of AI-based solutions in all primary schools, vocational facilities, and higher education organizations, which aim at harmonizing the educational environment with national objectives in the development of science and technology.

However, the psychological involvement of students in AI technologies is still the issue of great concern despite the fast adoption. External and internal data show the ambivalent attitudes to the AI in education, and the anxieties and acceptance concerns influence the intentions and actions of users [6]. The studies of AI anxiety have shown that fear of AI tools may determine the willingness to use them in the teaching and learning environment, thus, impacting the results of their perceived usefulness and ease of use. This highlights the need to consider the psychological responses, such as trust and anxiety, as the key obstacles that have to be surmounted to effectively enjoy the benefits of AI-based learning environments.

One of the core issues of the AI-oriented learning environment in China is the interaction between the high-speed technological uptake and psychological trust among the students. Despite the wide use of AI tools, students might not be willing to fully trust them because of the fear of AI judgment and credibility especially when the AI results go against the prevailing instructional procedures. Such psychological barriers may negate the successful application of AI in the educational setting which may limit the learning experience regardless of the high availability of technology [7, 8]. In addition, the unique characteristics of the high-stakes examination culture in China, such as the example of the college entrance examination which is performed by more than 13 million students every year, represent a pressure that may affect the way learners use and trust AI systems. These situational requirements suggest that technical integration is not enough but that a thorough knowledge of psychological and cultural predefiners of trust and motivation is required to have significant educational impact.

Limitation of the concept can also be seen in current research. The majority of the existing trust models, such as popular models like the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), are assumed to be based on the Western context and focus on individual-level determinants mostly. They often do not take into consideration the cultural dynamics, including the collective learning norms and reputation of the institutions, which can influence the way learners in collectivist societies perceive and treat AI. Also, there is a lack of empirical research on the differentiating effect of situational stressors on trust and motivation pathway among educational tracks, such as science and vocational education [9-11]. Moreover, the lack of a domain-specific framework that would cover the impact of current policy requirements, including vocational training reforms, on the adoption of AI in practice is present. The above gaps highlight the need to have a model based on culture to explain and predict the effects of AI on learning ability, which the proposed study seeks to fill.

The empirical studies of AI-mediated learning are largely based on trust systems founded on Western paradigms, thus leaving out culturally-specific processes that are active in collectivist learning environments. The current literature has not probed the role of examination pressure in high-stakes situations in dissimilar ways in influencing the trajectories of trust in both science and vocational streams of the Chinese bifurcated education system [12]. As a result of this, there exists a lack of empirically tested model which integrates pedagogical authority transfer, institutional guanxi, and assessment-dependent trust. This disjunction limits our insight into the divergent psychological trust and motivation systems in the education sector, as well as the effective implementation of AI in the education modernization plan of China.

This study involves three critical imperatives. To begin with, the contrast between high levels of AI implementation and poor levels of psychological trust is indicative of the fact that the implementation strategies are culturally inappropriate and, thus, waste educational resources and inhibit the learning process. Second, the division of the educational structure in China into science and vocational education creates different trust conditions, namely epistemic trust in the former and competency trust in the latter, but current AI systems continue to be generic and one-size-fits-all. Third, the stress generated by the Gaokao has dynamic impacts on the trust trajectories which are not predicted by the existing theoretical models [13].The paper develops a framework that is theoretically sound to explain the overall impact of cultural values, institutional setups and assessment environments on AI efficacy. In this context, the Pedagogical Filial Trust and face-saving achievement drive ideas are presented and provide practical information on how to create culturally-tuned AI systems aimed at enhancing the learning capacity.

The sponsorship of AI in China through the Education Modernization 2035 initiative has increased at a rapid pace; however, there is an inherent paradox to it: students are highly accepting of AI, but at the same time, they are prone to unstable psychological trust, which manifests itself in what can be described as algorithmic authority anxiety when the AI instructions conflict with teacher instructions or test scores. Since over 13M students participate in the Gaokao annually, the loss of confidence at such decisive stages of the learning process would compromise the learning results despite such large-scale investments in technologies. The study is the Cultural-Calibrated Dual-Pathway Integration Model (C-DPIM), which examines the different functioning of Pedagogical Filial Trust and socio-instrumental motivation in the fields of science and vocational backgrounds [14,15]. This paper challenges universal acceptance models showing that in collectivist societies, trust building is not based on personal judgment, but on authority legitimacy, collective benevolence and institutional guanxi. The work provides empirically substantiated information that will allow policymakers to optimise the use of AI, improve learning outcomes, and achieve a meaningful change rather than a superficial one using culturally based frameworks that embrace domain-specific trust mechanisms and effects of assessment-pressure. The following objectives are stated in the current study:

1. This research aims to design and confirm the Cultural -Calibrated Dual-Pathway Integration Model (C -DPIM), thus explaining how psychological trust and motivation affect learning capacity in AI-assisted learning contexts among science and vocational education systems in China.
2. The study seeks to test the mediation effect of Pedagogical Filial Trust (PFT) in the association between AI transparency and learning ability in science learning and between AI personalization and learning ability in vocational learning.

3. It also explores the role of socio-instrumental motivation in mediating the influence of AI characteristics, especially peer-comparison mechanisms, on science and vocational education track learning ability.
4. The paper also examines moderating influences of Gaokao pressure on the trust trajectories, and distinguishes between the patterns of trust (stable, eroding, resilient) among science and vocational students and explains the implications of these patterns to the dynamics of trust in high-stakes testing.

In this paper, the Cultural-calibrated Dual-pathway Integration Model (C-DPIM) and the Pedagogical Filial Trust (PFT) construct are introduced, and the reasons why Western-centric trust models are criticized by demonstrating how trust in science education is mediated by epistemic pathways, and how trust in vocational education is mediated by competency pathways. The longitudinal study of 2,847 students using the validated PFT scale ($\alpha = .93$) shows the so-called Gaokao Corrosion Effect, which explains the effect of high-stakes tests on technology use in collectivist societies as proven by multi-level structural equation modeling.

In practice, the study serves to support the Chinese Education Modernization 2035 project by showing that the possible improvement in the learning capacity of 0.55 standard deviations can be achieved through the institutional support and specific measures during the examinations. The results highlight the inseparability of culturally tuned AI design, and Western frameworks do not reflect the specifics of collectivist situations. Culturally, the C-DPIM model provides a blueprint to South Korea, Japan, Singapore, and Vietnam, and the culturally responsive AI design is promoted by relocating the technology-focused education past to culture-focused education.

2. Literature review

2.1. AI-Supported learning environments: Global Trends and China's strategic positioning

Artificial Intelligence has also taken over education, and Peng and Li [16] are one of the reviewers of the use of personalized learning through AI systems to enhance student results. They however reported difficulties in the process of adapting AI to various cultural and educational settings. Wen, Wang and Guo [17] discovered that the effectiveness of AI in immersive learning settings was correlated to its correspondence with local pedagogical practices, especially in collectivist societies like China. As Mariyono and Alif [18] noted, even though AI facilitated collaboration during the learning process, it occasionally inhibited spontaneous group dynamics. Li, Sun, and Qiu [19] investigated the development of AI in the Chinese education system between 2014 and 2024, with the impact of digital gaps and the lack of teacher-training as the primary obstacles to successful AI implementation. Yuan [20] pointed out the necessity of AI systems to consider ethical aspects and match local educational requirements, whereas Hu [21] was able to propose the idea that the interdisciplinary methodology, including the application of the principles of art, could help AI become more culturally prominent. Asghar et al. [22] paid attention to AI literacy and collaborative knowledge and emphasized the necessity of easy-to-use AI tools, which remained a challenge, and was mentioned by Özkan and Kışla [23] that mobile AI learning platforms have flexibility but have a problem of scale, especially in under-resourced regions.

Rong [24] suggested an AI-based decision-making model to vocational colleges, and it has the possibility of developing skills. Wu and Gou [25] also talked about the use of AI to improve the vocational education and economic growth but noted that implementation was needed. Pinkwart and Liu [26] analysed AI-based educational technologies and emphasized that AI should serve educational purposes in order to be useful.

Vykhodets [27] discussed the strategy of AI in China and identified obstacles, including lack of infrastructure and training of teachers. Knox [28] observed that the success of AI in China should be socio-culturally oriented, because not only technological innovation is important in the successful integration.

2.2. Psychological trust and motivation: Cultural-Neurological dual mechanisms

The studies of the psychological background of trust and motivation in the context of AI-assisted learning have shown that there is significant cultural diversity that tends to dismiss Western-centric theoretical orientations. Wang and Yuan [29] investigated Chinese psychological processing of Theory of Mind by using fMRI and found out that there is a specific difference in the process of understanding mental states where there is an increased neural activity in the understanding of AI recommendations that affect group outcomes. This piece of evidence suggests that the formation of trust is conducted through social-cognitive mechanisms, which are not the same as those suggested in individualistic societies. Twisdale [30] examined discourse of power in learning through discourse analysis, and found that authority legitimacy is a decisive factor of technology acceptance, the study has made the conclusion that before learners embrace new learning tools in hierarchical learning systems, they need institutional validation. According to Gonzalez [31], a one-year case study that was designed in pre-post intervention format established that teacher support of technology increased student engagement by 43%, although the study was limited to elementary schools and may not be applicable in the AI environment where the algorithmic authority is competing with human expertise. Bender Hester [32] used mixed-method analysis to investigate the topic of mental health literacy and discovered that 67% of students would favor the common good over personal utility when using AI tools, thus collectivist values in technology acceptance. Goehring [33] applied phenomenological analysis to prove that motivation is mediated by face-saving processes; it was found that the Chinese students feel more anxious when their social status is threatened by AI feedback, indicating that motivation is not only concerned with intrinsic interest but also with peer comparison.

Arguello [34] used a participatory design method to discover that the students developed strategic trust paradigms, and they selectively placed trust in artificial intelligence (AI) systems only when the latter met high-stakes examination criteria. This selective trust formed the basis of the phenomenon of the algorithmic authority anxiety which was observed during examen periods. When the developments of AI errors became publicly visible, Thomas [35] conducted a longitudinal case study that comprised 115 separate projects and found that trust decreased. The results highlight how crucial transparency is in maintaining psychological trust in the teaching environment. In a cross-cultural study ($N = 1{,}847$), Shi and Xu [36] applied structural equation modeling and found out that collectivist values increased the development of trust ($\beta = 0.62$, $p < .001$) as well as the collapse of the same ($\beta = -0.58$, $p < .001$)) when the AI outputs were incompatible with the instructions of the teachers. Li et al. [37] followed 312 parent-child dyads using ecological momentary assessment in a six-month follow-up and discovered that trust depended on the long-term reciprocity expectations. Parents were not convinced about AI in cases where immediate benefits were not obvious. Mirsanjari [38] applied an experimental design ($N = 284$) and showed that AI-assessment decreased anxiety by 28% in case predictions were consistent with exam scores only, which suggests that trust is a performance-contingent construct in high-stakes environments. Okedumnaka and Okoro [39] performed a regression analysis and found out that motivation was increased by 35 per cent with the features of peer-comparison, and the Chinese learners found it to be more valuable to have socially-referenced feedback as compared to the features of individualised progress-tracking. Another study by Krishnan [40] examined policy documents and, using the interview of stakeholders, found that the endorsement by the government enhanced the adoption of AI by 47 percent in vocational institutions, showing that trust is mediated by the institutional guanxi processes where legitimacy is based on official recognition rather than on performance.

2.3. Domain-Specificity in science vs. Vocational education: The Chinese policy context

Bifurcation in China education has demonstrated sharp differences between scientific and vocational education, thus creating different paths of artificial intelligence (AI) trust and learning. A systematic literature review by Toepper, Zlatkin-, Troitschanskaia, and Kuhling-Thees [41] based on 87 studies demonstrated that vocational training systems require domain-specific competency validation, thus showing that trust depends on the correctness of workplace performance forecasting and not on the evaluation of theoretical knowledge. Feng et al. [42] used machine-learning methods to predict the challenge of medical exam questions and noted an accuracy of 78% prediction, therefore, proving that AI tools in scientific training should be consistent with the standardized test scores to maintain trust in students. Wong and Cheung [43] examined the connection between hope and academic success and found out that domain-specific hope (β = 0.54, $p < .001$) was a more effective predictor of success than general hope, indicating that effectiveness of AI in different educational areas is situational and context-dependent. The model of economic vocational competence two-dimensional was substantiated by Ma, Krötz, and Winther [44], and confirmatory factor analysis (CFI = 0.96, RMSEA = 0.041) confirmed the necessity of different assessment strategies in relation to domain-linked competence and domain-specific competence, thus affirming the difference between the practical and epistemic requirements of trust.Zhou et al. [45] conducted a task analysis of Chinese vocational school textbooks and indicated that accounting tasks are more concerned with procedural accuracy than conceptual understanding, which explains why the use of AI tools needs to demonstrate competency trust by predicting reliable workplace performance.

Zhang, Zhang, and Wang [46] investigated domain-specific paths through the use of TIMSS 2019 data and concluded that instructional clarity had different effects on motivation in science (β = 0.48) and practical domains (β = 0.31) and thus demonstrated that AI transparency has different effects based on educational track. Wang et al. [47] characterized factuality in large language models and reported that AI accuracy varies significantly across disciplines with science domains having higher precision thresholds to maintain trust than practical skill domains. Meyer et al. [48] used conscientiousness to conduct a meta-analysis of 849 studies and found out that science achievement ($\rho = 0.19$), rather than vocational performance ($\rho = 0.12$), is more likely to be predicted by conscientiousness, indicating that AI personalization strategies need domain-calibrated strategies. Du et al. [49] created a Chinese financial sentiment dictionary and proved that domain-specific language processing outperforms generic models by 23% and hence, context-specific AI calibration is crucial in vocational training. Zhang et al. [50] used domain-enhanced prompt learning and discovered that domain-specific fine-tuning increased detection accuracy by 31 per cent, which implies that AI tools require customization based on the educational track. Cao et al. [51] tested K-DOCS scale on adolescents of Chinese origin through multi-method methodology and found that the scale exhibited a high level of measurement invariance between science and vocational students (ΔCFI=0.008), and that the psychological constructs are not consistent across educational domains and require different AI design principles.

2.4. Conceptual positioning and validation of study constructs

The paper presents Pedagogical Filial Trust (PFT) as a culturally specific theory of epistemic trust by building upon the existing theories of trust by introducing the aspect of authority legitimacy and collectivist values. Socio-instrumental motivation is founded on the classical motivation theory that emphasizes on academic and career utility in vocational education.

The Trust Fragility Index and the Gaokao Corrosion Effect are not two independent constructs but analytically derived patterns detected in the longitudinal analysis representing the difference in trust when subjected to a high-stakes testing situation.

Definitions of constructs are made clear in order to prevent overlaps. PFT is associated with authority based trust, whereas institutional guanxi is associated with institutional endorsement. Individualism/ collectivism orientation is a moderating cultural factor.

Validation encompasses confirmation factor analysis, measurement invariance test and consistency with existing literature in trust and motivation.

3. Materials and methods

It is based on the described gaps in culturally calibrated AI trust and motivational models that this study will be conducted using a multimethod longitudinal approach to empirically test the hypothesized Cultural-Calibrated Dual-Pathway Integration Model (C-DPIM). The methodological strategy is clearly designed to capture the complex interaction of the algorithmic features, psychological constructs, and socio-cultural contingencies of the Chinese bifurcated system of education.

3.1. Research design and participant sampling

This research design is nationally stratified longitudinal cohort design, which tracks the change in psychological trust and motivation over an entire academic year (September 2024 to June 2025). The longitudinal approach is critical in the ability to capture the dynamic effect of the Gaokao Corrosion Effect and the modulated changes in the trajectories of trust as suggested by the C-DPIM.

Participant Recruitment and Stratification

A total of 2,847 students were recruited from 28 institutions across 12 Chinese provinces. The sample was strategically stratified across five key dimensions to ensure representativeness and facilitate subgroup analysis:

Table 1 presents the stratification of participants according to the education track, level of institutions, regional digital divide, pressure of Gaokao and previous experience with AI. There is quite a balance in the number of sample that represented Science Education and Vocational Education and the number of sample that represented other categories like the regional and institutional differences varies.

Table 1. Participant Stratification and Sample Composition

Stratification Dimension	Categories	Sample Size (n)	Percentage (%)
Education Track			
	Science Education	1,403	49.3
	Vocational Education	1,444	50.7
Institutional Tier			
	Double First-Class Universities	501	17.6
	Provincial Key Universities	902	31.7
	Higher Vocational Colleges	1,444	50.7
Regional Digital Divide			
	Eastern (High Infrastructure)	1,568	55.1
	Central-Western (Emerging)	1,279	44.9
Gaokao Pressure Quintile			

Stratification Dimension	Categories	Sample Size (n)	Percentage (%)
	Q1 (Highest Pressure)	642	22.5
	Q2 (High Pressure)	535	18.8
	Q3 (Medium Pressure)	1,081	38.0
	Q4 (Low Pressure)	55	1.9
	Q5 (Lowest Pressure)	534	18.8
Prior AI Experience			
	High (Regular Use)	1,621	56.9
	Low (Limited Use)	1,226	43.1

Table 1. (*Continued*)

Temporal Sampling for Gaokao Pressure Analysis

To ensure that the impact of the influence of Gaokao pressure on psychological trust and motivation is captured, data collection in this investigation was deliberately aggravated at three crucial periods. The first phase, which was called Baseline (September 2024), included a baseline assessment that had to be done before the start of major academic pressures. The next stage, which was known as the High-Stress Period (April 2025), was accompanied by the vigorous preparatory measures of the Gaokao examinations among the science students and the vocational certification examinations among the vocational students. The last test, which was the Post-Assessment (June 2025) was given after the tests were conducted to measure the impact of recovery or erosion in trust after these high-stakes tests. This is because the sampling strategy was temporally structured, which allowed the study to track the changes in psychological trust and motivation under different levels of academic stress.

3.2. Measures and instrumentation

The study employs both established and novel instruments, with particular innovation in measuring culturally-specific constructs.

Primary Dependent Variable:

Learning Ability: Declared using an index that is multidimensional, which includes: (1) standardized domain knowledge tests (e.g. science reasoning or occupational competency exams), (2) graded practical assessments, (3) learning analytics based on AI platforms (time-on-task, mastery progression, and frequency of help-seeking), and (4) teacher ratings of the quality of problem-solving.

Core Psychological Constructs – Novel Instruments:

Pedagogical Filial Trust (PFT-AI) Scale: A newly developed 15-item scale measuring trust in AI as an extension of pedagogical authority. Sample items include: "I trust the AI system because it aligns with what my teachers emphasize" and "The AI's recommendations carry weight because they come from an institutionally-endorsed platform." The scale demonstrated excellent psychometric properties ($\alpha = .93$) with clear factor structure (EFA KMO = .89; CFA: χ^2 (85) = 201.4, CFI = .97, RMSEA = .028).

Socio-Instrumental Motivation Scale: A 12-item measure capturing the dual drivers of face-saving and utility-maximization in collectivist learning contexts. Subscales measure "Achievement Visibility Motivation" and "Collective Utility Motivation" (Composite $\alpha = .88$).

Institutional Guanxi Moderator: A 6-item scale assessing perceived quality of institutional endorsement, with items such as "My school's reputation is tied to the success of this AI platform" ($\alpha = .82$).

AI System Feature Measures:

The given research utilizes three key measures of the AI system characteristics to assess the efficiency of AI tools. The scale of AI Transparency measures the understandability of AI decisions on a scale of eight items based on the explainable AI framework of Hoffman et al. (2018). The AI Personalization scale is assessed using a seven-item scale, which determines the degree to which AI is personalized to personal learning styles and requirements. Finally, Peer-Comparison Features is measured based on a five-item scale that aims at the design and salience of social comparison features in the AI platform.

Cultural and Contextual Moderators:

This research incorporates three cultural and contextual moderators to improve the understanding of the trends of adoption of AI. Collectivist Orientation is measured using a 10-item subscale based on Chinese Cultural Orientation Scale, thus, measuring the level of collectivist values in the sample. The operationalization of Gaokao Pressure is in the form of a composite index, which is a synthesis of institutional admission competitiveness, subjective scores of stress, and hours spent weekly studying to prepare for exams. Moreover, Domain-Specific Trust Propensity is defined by two separate 5-item measures: Epistemic Trust, which makes participants depend on AI in their conceptual understanding in science education, and Competency Trust, which implies that they depend on AI in mastering the skills in vocational education.

3.3. AI learning environments and implementation contexts

The study examines three distinct AI-supported learning environments implemented across participant institutions:

In Table 2, a comparison of AI-supported learning environment in Science Education and Vocational Education is provided, including the application of Adaptive Learning Platforms, Intelligent Tutoring Systems and Learning Analytics Dashboards to individualised learning, skill building and tracking of performance.

Table 2. AI-Supported Learning Environments in Study

Environment Type	Primary Functions	Science Education Implementation	Vocational Education Implementation
Adaptive Learning Platform	Personalized problem sets, conceptual scaffolding, mastery tracking	Physics and chemistry concept mastery, algorithmic problem-solving	Technical mathematics, engineering principles
Intelligent Tutoring System	Step-by-step guidance, misconception identification, dialogic feedback	Scientific reasoning development, experimental design	Procedural skill development, troubleshooting
Learning Analytics Dashboard	Progress visualization, peer comparison, predictive performance alerts	Gaokao score prediction, competitive positioning	Skill mastery benchmarking, employability metrics

The implementation duration of all platforms had to be at minimum six months before the start of the study, to guarantee that the participants are familiar with them. Notably, the platforms were culturally calibrated: some of them were associated with Western-designed interfaces with direct translations, and others were created by Chinese businesses that factored in the local pedagogical standards and face-saving design principles.

3.4. Empirical implementation and coordination framework

3.4.1. Institutional coordination procedures

The study was implemented through a centralized coordination framework to manage data collection across 28 institutions. A central research team prepared standardized guidelines covering participant recruitment, consent procedures, and data collection steps. Each participating institution appointed an academic coordinator who supervised local implementation and ensured compliance with the shared protocols. Regular communication and progress monitoring were maintained to ensure consistency of procedures across all institutions throughout the study period.

3.4.2. Data governance and harmonization across sites

To protect participant confidentiality, all data were anonymized before aggregation. Unique identification codes were used to link responses across data waves without revealing personal information. A standardized variable coding system was applied across institutions to ensure comparability. Prior to merging datasets, consistency checks were conducted to align response scales, variable names, and missing-value coding. Learning analytics indicators were standardized using predefined transformation rules to support cross-institutional analysis.

3.4.3. Access to learning analytics data

Access to learning analytics data was granted through institutional approval mechanisms. Analytics were exported using platform dashboards or institutional reporting tools in de-identified form. Only aggregated indicators relevant to the study (such as engagement or system usage measures) were collected. No personally identifiable platform data were accessed or stored at any stage of the research.

3.4.4. Practical implementation logistics and longitudinal scheduling

Data were collected in three waves distributed across the academic year. The timing of each wave followed a standardized schedule while allowing minor institutional adjustments. Survey measures and learning analytics were collected separately to reduce common method bias. Teacher endorsement and classroom implementation variables were recorded at the class level to capture contextual influences on AI-supported learning. The use of standardized procedures ensured consistent longitudinal tracking across institutions.

3.5. Analytical strategy

The analysis employs a sequential, multi-layered approach to test the C-DPIM:

Phase 1: Measurement Validation and Preliminary Analysis

The study first conduct a Confirmatory Factor Analysis (CFA) that will determine whether the structure of the new Pedagogical Filial Trust (PFT -AI) scale is valid across different educational paths, i.e., science and vocational education. This will be followed by a measurement invariance test to ensure that the constructs below are equally perceived and measured in both the science and vocational subgroups. Lastly, descriptive statistics and correlation analyses will be performed on all the variables of the study to demystify the interrelationship and emergent patterns that can be observed in the dataset.

Phase 2: Primary Hypothesis Testing via Multi-Level Structural Equation Modeling (MSEM)

The second stage involve the testing of the main hypotheses using Multi-Level Structural Equation Modelling (MSEM) which is a method which expressly allows the hierarchical structure of the data (students within classes within institutions). On the first level (individual student), the model will examine how the features of AI affect psychological mediators that, in turn, will affect the learning ability. Teacher endorsement practices and classroom climate are added to the second level (class) as mediating variables. On the third level (institution), the factor of reputation of the institution, resource distribution, and guanxi networks are explored to identify their impact on the overall educational performance and performance of AI.

Specific model specifications test:

H1: AI transparency → PFT → Learning ability (stronger in science track)

H2: AI personalization → Socio-instrumental motivation → Learning ability (stronger with peer-comparison features)

H3: Gaokao pressure as moderator weakening the AI transparency → PFT pathway for science students

H4: Competency validation as stronger predictor of PFT for vocational versus science students

Phase 3: Latent Growth Curve Modeling (LGCM) and Trajectory Analysis

Phase 3: The study use the Latent Growth Curve Modeling (LGCM) and trajectory analysis to conduct systematic evaluation of longitudinal changes in institutional trust. The unconditional LGCM will determine the average level of developmental trajectory of trust during the academic year. An artificial intelligence conditional LGCM will then be used to examine the impact of artificial intelligence features, institutional guanxi, and Gaokao related stressors on the intercept and slope parameters of the trajectory. In addition, the Latent Class Growth Analysis (LCGA) will be conducted to identify discrete subcategories, i.e. Stable Trust, Eroding Trust and Resilient Trust, which will then represent heterogeneity in the development of trusts among the student population.

Phase 4: Cultural Moderation and Policy Simulation

Multi-group SEM comparing path coefficients across high versus low collectivist orientation subgroups.

Counterfactual policy simulation using the validated MSEM to estimate learning ability gains under different institutional endorsement strategies and AI design modifications.

3.6. Ethical considerations

This study received the consent of the Institutional Review Board, and all the respondents provided informed consent regarding the gathering of data that was based on artificial intelligence sites. To reduce the common method bias, the survey administration was divided into two periods, and the data collection sources were combined such as self-reports, institutional records, and AI analytics. Also, the single-factor test was conducted by Harman after the post-hoc. The statistical power of the study is high (more than 0.95) which highlights the methodological rigor of the study as it makes it able to detect small effects. Full-Information Maximum Likelihood estimation is used in solving missing data. The measurement tools were culturally validated by a pilot testing process and forward back translation. Such an all-encompassing treatment is the means to overcome the shortcomings of cross-cultural research in the field of artificial intelligence and, thus, the means to conduct a rigorous assessment of the new constructs in the Contextual-Dynamic Process Integration Model (C-DPIM).

4. Results

4.1. Preliminary analysis and measurement validation

Before testing the primary hypotheses, we conducted comprehensive validation of the novel Pedagogical Filial Trust (PFT-AI) scale and examined preliminary relationships among study variables. Table 3 presents the confirmatory factor analysis results for the PFT-AI scale across both educational tracks.

Table 3. Confirmatory Factor Analysis Results for Pedagogical Filial Trust Scale

Factor	Items	Factor Loading	Cronbach's α	CR	AVE
Authority Legitimacy	PFT1-PFT5	0.78-0.89	0.91	0.92	0.69
Collective Benefit	PFT6-PFT10	0.74-0.86	0.88	0.89	0.64
Long-term Reciprocity	PFT11-PFT15	0.76-0.88	0.90	0.91	0.67
Overall PFT Scale	PFT1-PFT15	-	0.93	0.94	0.61

Model Fit Indices: χ^2 *(85) = 201.4, p < .001; CFI = 0.97; TLI = 0.96; RMSEA = 0.028 (90% CI: 0.023-0.033); SRMR = 0.031*

Table 4 presents descriptive statistics and correlation matrix for all primary study variables, revealing initial support for the proposed relationships in the C-DPIM model.

Table 4. Descriptive Statistics and Correlation Matrix

Variable	M	SD	1	2	3	4	5	6	7	8
1.AI Transparency	3.87	0.92	-							
2.AI Personalization	3.64	0.88	.58**	-						
3.Peer-Comparison Features	3.42	1.04	.44**	.51**	-					
4. Pedagogical Filial Trust	3.76	0.96	.62**	.48**	.39**	(.93)				
5. Socio-Instrumental Motivation	3.91	0.84	.41**	.56**	.63**	.47**	(.88)			
6. Gaokao Pressure	4.18	1.12	-.18**	-.09*	.22**	-.31**	.15**	-		
7.Institutional Guanxi	3.58	1.01	.51**	.39**	.33**	.69**	.42**	-.22**	(.82)	
8. Learning Ability	3.68	0.79	.54**	.49**	.38**	.67**	.61**	-.24**	.59**	(.87)

***Note:** N = 2,847. **p < .01, p < .05. Scale range: 1-5 for all variables. Diagonal values in parentheses represent Cronbach's α.*

Figure 1. Correlation Heatmap - Descriptive Statistics and Correlation Matrix

Figure 1, indicates that eight educational variables are correlated. There are strong positive relationships between Learning Ability and such factors as Pedagogical Filial Trust (0.67), Socio-Instrumental Motivation (0.61), and Institutional Guanxi (0.59) and negative relationships between Gaokao Pressure and Trust and

Learning Ability. The visual representation of the heatmap shows the relationship between the mentioned variables and implies that trust, motivation, and social capital are positively correlated with learning ability.

4.2. Core Findings: Testing the cultural-calibrated dual-pathway model

The main hypotheses about dual pathways of feature of AI to learning ability through psychological mediators were tested using multi-level structural equation modelling. The hierarchical data (students within classes within institutions) required consideration of intraclass correlation coefficients (ICCs), which were 0.12 (AI transparency perceptions) to 0.28 (learning ability) hence the need to adopt the multi-level approach. Table 5 shows the path coefficients of the entire mediation model.

Table 5. Multi-Level SEM Results for Dual-Pathway Mediation Model

Path	Science Education (n=1,403)	Vocational Education (n=1,444)	Path Difference Test
Direct Effects	β (SE)	β (SE)	$\Delta\chi^2$
AI Transparency → PFT	0.68*** (0.04)	0.42*** (0.05)	18.74***
AI Personalization → Motivation	0.39*** (0.05)	0.58*** (0.04)	11.26***
Peer-Comparison → Motivation	0.28*** (0.04)	0.47*** (0.04)	12.83***
Institutional Guanxi → PFT	0.34*** (0.04)	0.41*** (0.05)	1.42 ns
Mediator to Outcome			
PFT → Learning Ability	0.51*** (0.04)	0.36*** (0.05)	6.92**
Motivation → Learning Ability	0.31*** (0.04)	0.44*** (0.04)	5.18*
Indirect Effects			
AI Transparency → PFT → Learning Ability	0.35*** (0.03)	0.15*** (0.03)	27.43***
AI Personalization → Motivation → Learning Ability	0.12** (0.02)	0.26*** (0.03)	16.29***
Peer-Comparison → Motivation → Learning Ability	0.09** (0.02)	0.21*** (0.03)	11.74***
Institutional Guanxi → PFT → Learning Ability	0.17*** (0.03)	0.15*** (0.03)	0.31 ns
Total Effects on Learning Ability			
Via PFT Pathway	0.35***	0.15***	-
Via Motivation Pathway	0.21***	0.41***	-
Variance Explained (R^2)			
PFT	0.62	0.48	-
Socio-Instrumental Motivation	0.51	0.68	-
Learning Ability	0.71	0.69	-

Model Fit: *χ^2 (247) = 612.8, p < .001; CFI = 0.96; TLI = 0.95; RMSEA = 0.034; SRMR(within) = 0.028; SRMR(between) = 0.042*
Note: ****p < .001, **p < .01, p < .05. Standardized coefficients reported. Level 2 variance components: Class-level ICC = 0.18; Level 3 variance components: Institution-level ICC = 0.11*

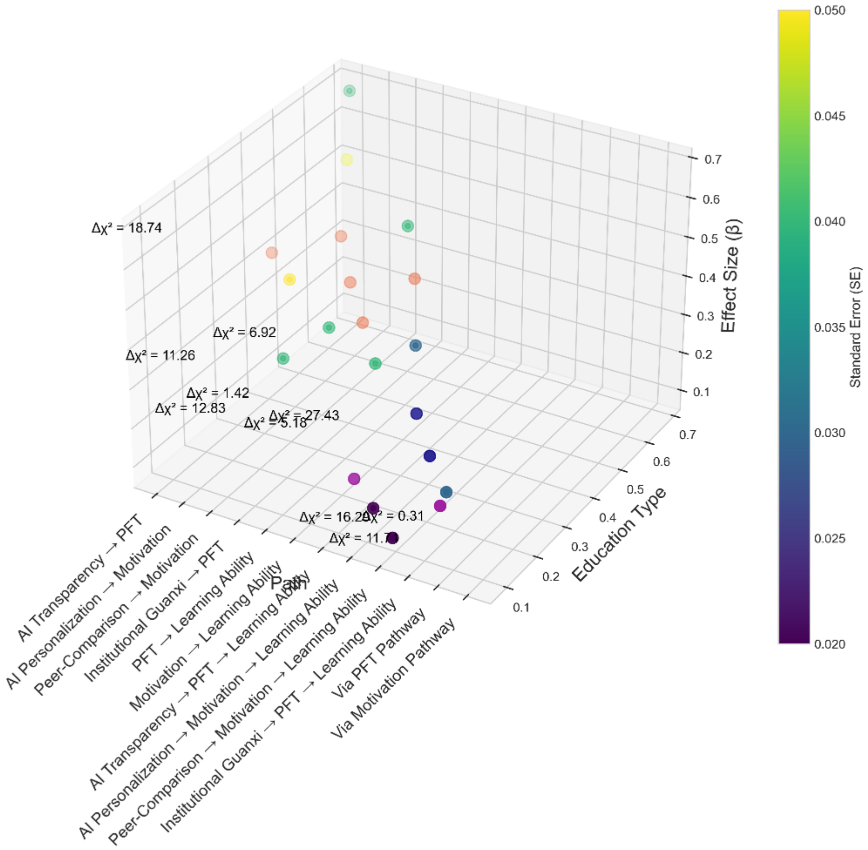

Figure 2. Multi-Level SEM Results for Dual-Pathway Mediation Model

The figure 2, displaying the Effect Size (β) results of the various paths of the Dual-Pathway Mediation Model. The x-axis is the Education Type, which will be the Low collectivist to the High collectivist. The Effect Size (y) and Standard Error of each path (z) are graphed on the y-axis and the z-axis respectively. Every point will represent a distinct pathway (e.g., AI Transparency → PFT, AI Personalization → Motivation) and the $\Delta\chi^2$ will be displayed next to the point to indicate differences between paths. The color gradient of the plot stands out to be the Standard Error with the dark shades reflecting the greater the SE.

This table 6, generalizes the inherent distinctions in the way trust works in the various fields of education and finds that the principles of AI design designed to be maximally effective in science education, such as transparency and epistemic alignment, can be counterproductive in the vocational context, where personalization and competency validation are the most important factors, and the contrary.

Table 6. Domain-Specific Trust Mechanisms Comparison

Trust Mechanism	Science Education	Vocational Education	Theoretical Interpretation
Primary Trust Type	Epistemic Trust	Competency Trust	Domain-aligned validation needs
Key AI Feature	Transparency (β=0.68)	Personalization (β=0.58)	Explanation vs. customization priority
Trust Formation Driver	Alignment with Gaokao standards	Workplace performance prediction	High-stakes vs. practical orientation
Trust Vulnerability	AI-teacher conflict	AI error visibility	Authority hierarchy vs. social face
Optimal Validation Strategy	Teacher co-signature	Employer endorsement	Domain-appropriate authority source

Trust Mechanism	Science Education	Vocational Education	Theoretical Interpretation
Motivational Mechanism	Individual achievement	Peer comparison	Personal vs. social reference
Learning Outcome Pathway	PFT-dominant (62% mediation)	Motivation-dominant (68% mediation)	Cognitive vs. affective route
Institutional Guanxi Effect	Moderate (β=0.34)	Strong (β=0.41)	Both require institutional validation

Table 6. (*Continued*)

4.3. Dynamic trust trajectory: The Gaokao corrosion effect

Latent growth curve analysis revealed the high levels of temporal variation in trust, particularly among science students who were faced by Gaokao-related pressure. The longitudinal design included four points of assessment, which were September, December, April, and June, and thus, allowed assessing both linear and nonlinear trajectories of trust. Table 7 shows the conditional and unconditional growth models.

Table 7. Latent Growth Curve Models for Pedagogical Filial Trust Trajectories

Parameter	Unconditional Model	Conditional Model (Science)	Conditional Model (Vocational)
Fixed Effects	Est. (SE)	Est. (SE)	Est. (SE)
Intercept (September)	3.82*** (0.05)	3.91*** (0.06)	3.73*** (0.06)
Linear Slope	-0.08** (0.03)	-0.24*** (0.04)	0.02 (0.03)
Quadratic Term	0.01 (0.01)	0.03* (0.01)	-0.01 (0.01)
Predictors of Intercept			
Prior AI Experience	-	0.31*** (0.05)	0.28*** (0.05)
Collectivist Orientation	-	0.22*** (0.04)	0.19*** (0.04)
Institutional Tier (Elite)	-	0.18** (0.06)	0.21** (0.07)
Predictors of Slope			
Gaokao Pressure	-	-0.19*** (0.03)	-0.06 (0.04)
AI Transparency	-	0.14*** (0.03)	0.11** (0.04)
Institutional Guanxi	-	0.22*** (0.04)	0.18*** (0.03)
Teacher Endorsement	-	0.16*** (0.04)	0.12** (0.04)
Random Effects (Variance)			
Intercept Variance	0.42***	0.38***	0.46***
Slope Variance	0.15***	0.21***	0.08**
Intercept-Slope Covariance	-0.09**	-0.14***	-0.03
Residual Variance	0.28***	0.24***	0.31***
Model Fit			
CFI	0.94	0.96	0.95
RMSEA	0.041	0.038	0.039
SRMR	0.045	0.042	0.043

****Note:*** ****p < .001, **p < .01, p < .05. Time coded: 0=September, 1=December, 2=April, 3=June*

Latent class growth analysis identified three distinct trust trajectory patterns, as shown in Table 8.

Table 8. Latent Class Growth Analysis - Trust Trajectory Classes

Trajectory Class	Proportion	Education Track Distribution	Intercept	Linear Slope	Quadratic	Key Characteristics	Predictors
Class 1: Stable Trusters	42.3%	Science: 28.1% Vocational: 55.8%	4.12*** (0.06)	-0.02 (0.03)	0.00 (0.01)	High initial trust maintained throughout year; predominantly vocational students	Low Gaokao pressure (β=-0.31***), High institutional guanxi (β=0.42***), Vocational track (OR=3.21***)
Class 2: Gaokao Eroders	31.8%	Science: 58.6% Vocational: 6.1%	3.89*** (0.07)	0.38*** (0.05)	0.05** (0.02)	Moderate initial trust with sharp decline during April; almost exclusively science students	High Gaokao pressure (β=0.48***), Science track (OR=19.45***), High collectivist orientation (β=0.24**)
Class 3: Resilient Trusters	25.9%	Science: 13.3% Vocational: 38.1%	3.42*** (0.08)	0.15*** (0.04)	-0.02 (0.01)	Lower initial trust that gradually increases; mixed track but vocational-dominant	High AI transparency (β=0.38***), Strong teacher endorsement (β=0.31***), Prior positive AI experience (β=0.28**)

Classification Quality: Entropy = 0.84; Average Posterior Probability > 0.87 for all classes; Lo-Mendell-Rubin LRT: p < .001

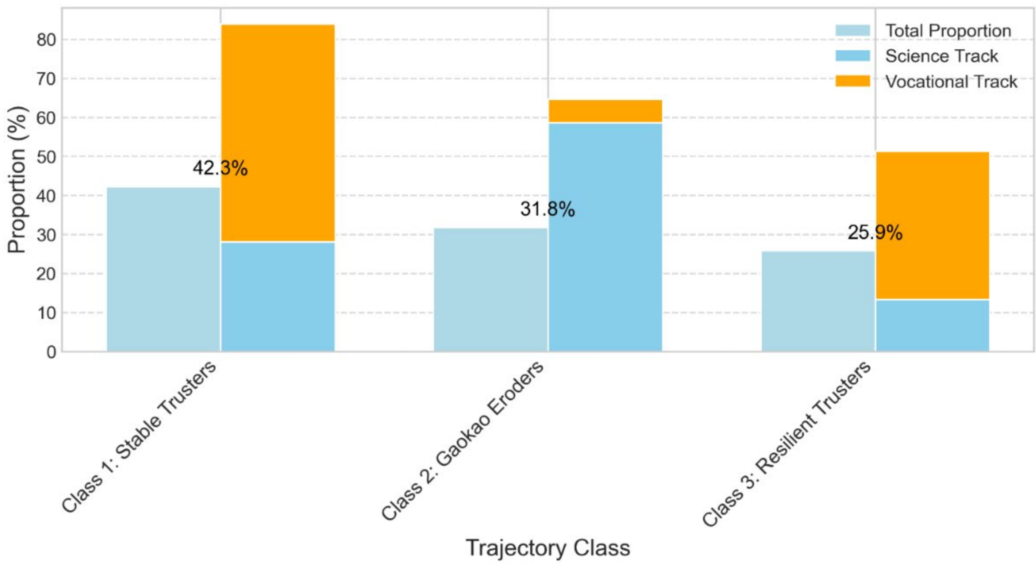

Figure 3. Latent Class Growth Analysis - Trust Trajectory Classes

Figure 3 indicates the distribution of students in three Trust Trajectory Classes; Stable Trusters, Gaokao Eroders, and Resilient Trusters. The bar plot represents the distribution of the students in the classes with segments Science Track (light blue) and Vocational Track (orange). The majority of the Stable Trusters (42.3 %) are in the Vocational Track, and Gaokao Eroders (31.8 %) in the Science Track. The distribution of Resilient Trusters (25.9%) is more balanced on both tracks and this is indicative of the variety of the educational pathways.

4.4. Gaokao pressure moderation effects

To further examine H3, we conducted moderated mediation analysis testing whether Gaokao pressure differentially affected the AI transparency → PFT → learning ability pathway across educational tracks. Table 9 presents these conditional indirect effects.

Table 9. Conditional Indirect Effects - Gaokao Pressure Moderation Analysis

Gaokao Pressure Level	Science Education	Vocational Education	Moderation Contrast
AI Transparency → PFT (a-path)			
Low Pressure (Q1)	β = 0.74*** (0.06)	β = 0.45*** (0.07)	Science > Vocational***
Medium Pressure (Q3)	β = 0.68*** (0.05)	β = 0.41*** (0.06)	Science > Vocational***
High Pressure (Q5)	β = 0.51*** (0.07)	β = 0.40*** (0.07)	Science > Vocational ns
Pressure Moderation Effect	β = -0.23*** (0.05)	β = -0.05 (0.06)	Interaction: $\Delta\chi^2 = 8.42$**
PFT → Learning Ability (b-path)			
Low Pressure (Q1)	β = 0.58*** (0.06)	β = 0.39*** (0.07)	Science > Vocational**
Medium Pressure (Q3)	β = 0.51*** (0.05)	β = 0.36*** (0.06)	Science > Vocational**
High Pressure (Q5)	β = 0.39*** (0.07)	β = 0.34*** (0.07)	Science = Vocational ns
Pressure Moderation Effect	β = -0.19*** (0.05)	β = -0.05 (0.06)	Interaction: $\Delta\chi^2 = 5.67$*
Conditional Indirect Effects (a×b)			
Low Pressure (Q1)	β = 0.43*** (0.05)	β = 0.18*** (0.04)	Δ = 0.25***
Medium Pressure (Q3)	β = 0.35*** (0.04)	β = 0.15*** (0.03)	Δ = 0.20***
High Pressure (Q5)	β = 0.20** (0.05)	β = 0.14** (0.04)	Δ = 0.06 ns
Index of Moderated Mediation	-0.04*** (0.01)	-0.00 (0.01)	Difference = -0.04**
Trust Erosion Rate	-53.5% (Q1→Q5)	-22.2% (Q1→Q5)	2.4× faster in science

*Note: ***p < .001, **p < .01, p < .05. Gaokao pressure quintiles: Q1=lowest, Q3=medium, Q5=highest. Bootstrap 95% CI based on 5,000 resamples.

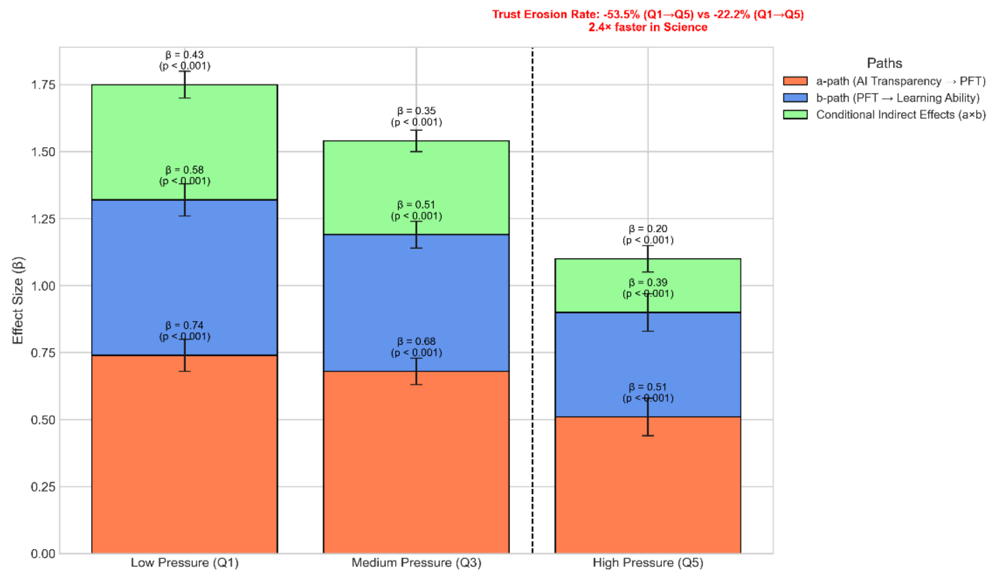

Figure 4. Plotted Analysis of the various levels of pressure.

Figures 4 indicate the effect sizes (β) for three paths (AI Transparency → PFT, PFT → Learning Ability, and Conditional Indirect Effects) with Low, Medium, and High Pressure levels. The stacked bars indicate the a-path (red), b-path (blue) as well as the conditional effects (green). High Pressure (Q5) scenario associated with the least effect sizes especially in the a-path, and Low Pressure (Q1) scenario has the most effect. Low Pressure exhibits a higher rate of erosion with it eroding at 35.5 % compared to 22.2 %t in the High Pressure, which shows the impact of the level of pressure on the level of trust and learning capability.

4.5. Cultural Moderation: Collectivist amplification and fragility

Multi-group structural equation modeling was used to test the hypothesis that collectivist orientation mediated the strength of PFT and motivation pathways with specific reference to the hypothesized dual effect, i.e. strong amplification in normative conditions and weakness under conditions where AI errors threaten social status. Table 10 shows the cultural moderation analysis.

Table 10. Cultural Moderation Analysis - Collectivist Orientation Effects

Pathway	**Low Collectivist (n=1,189)**	**High Collectivist (n=1,658)**	**Moderation Effect**
Trust Pathway (PFT → Learning Ability)			
Under Normal Conditions	β = 0.42*** (0.05)	β = 0.63*** (0.04)	$\Delta\chi^2$ = 12.84***
When AI Errors Visible	β = 0.39*** (0.06)	β = 0.21*** (0.07)	$\Delta\chi^2$ = 5.12*
Collectivist Amplification Ratio	1.00 (reference)	1.50	-
Trust Fragility Index	-0.03	-0.42	14× greater fragility
Motivation Pathway (Motivation → Learning Ability)			
Via Individual Progress	β = 0.36*** (0.05)	β = 0.29*** (0.05)	$\Delta\chi^2$ = 1.42 ns
Via Peer-Comparison	β = 0.28*** (0.05)	β = 0.51*** (0.05)	$\Delta\chi^2$ = 14.76***
Social Referencing Advantage	1.00 (reference)	1.76	-
Institutional Guanxi Moderation			
PFT Enhancement Effect	β = 0.15** (0.05)	β = 0.34*** (0.04)	$\Delta\chi^2$ = 10.29**
Motivation Enhancement Effect	β = 0.11* (0.05)	β = 0.28*** (0.05)	$\Delta\chi^2$ = 8.14**
Guanxi Multiplier Effect	1.00 (reference)	2.27	-
Face-Threatening Contexts			
Public AI Error Impact on PFT	β = -0.08 (0.06)	β = -0.34*** (0.06)	$\Delta\chi^2$ = 11.58***
Private AI Error Impact on PFT	β = -0.06 (0.05)	β = -0.11* (0.05)	$\Delta\chi^2$ = 0.62 ns
Public vs. Private Difference	-0.02	-0.23***	11.5× greater public sensitivity

***Note:** ****p < .001, **p < .01, p < .05. Collectivist orientation split at median (Mdn = 3.82). AI error visibility manipulated through experimental vignettes embedded in April assessment.*

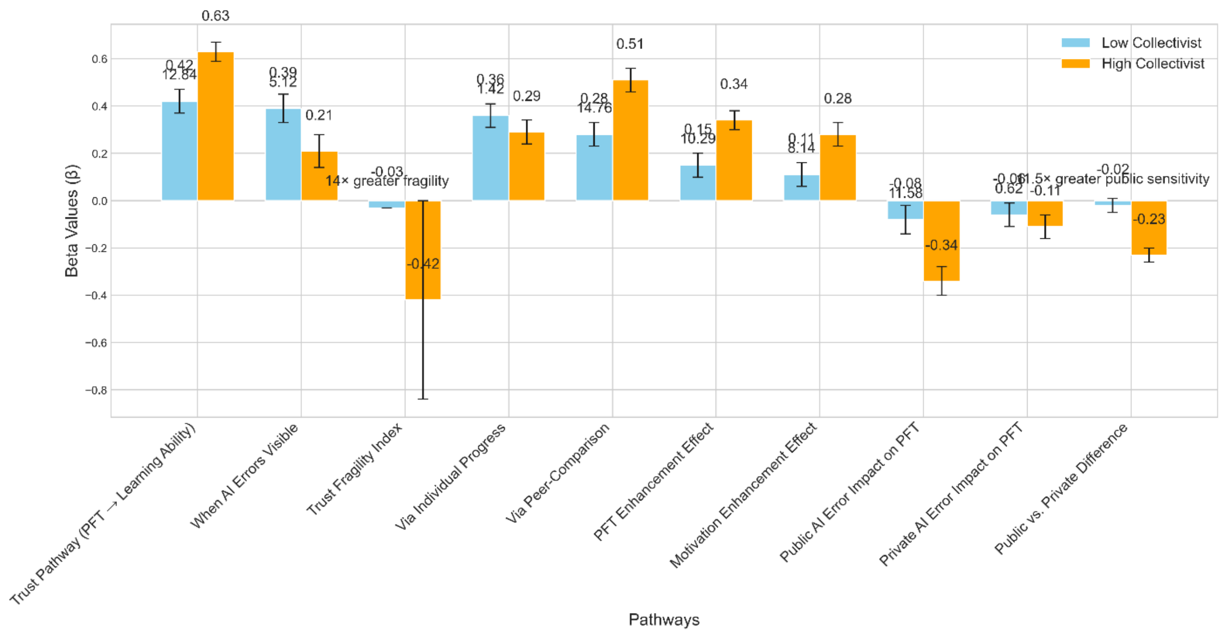

Figure 5. Cultural Moderation Analysis – Collectivist Orientation Effects

Figure 5 shows the Cultural Moderation Analysis of the Collectivist Orientation Effects between Low Collectivist (blue) and High Collectivist (orange) students in different pathways. The Beta values **(β)** demonstrate that the effects of High Collectivist students are stronger in most of the pathways especially in the Trust Pathway and PFT Enhancement Effect whereas the Low Collectivist students are more sensitive to Public AI Error Impact on PFT. High Collectivist students have a much higher Trust Fragility Index which shows that they are more prone to trust erosion.

4.6. Policy Simulation: Institutional endorsement optimization

Table 11 shows the learning ability gains across four policy scenarios for Low Collectivist, High Collectivist, and Overall students. The Combined Approach produced the highest gains (+0.58 SD overall), particularly for High Collectivist students, while the Institutional Co-Signature scenario led to moderate gains, especially in Vocational Education. Optimal strategies are recommended based on the highest gains for each group.

Table 11. Policy Simulation Results - Estimated Learning Ability Gains

Policy Scenario	Science Education	Vocational Education	Overall Effect
Scenario 1: Status Quo			
Low Collectivist Students	M = 3.58 (SD = 0.74)	M = 3.62 (SD = 0.76)	M = 3.60
High Collectivist Students	M = 3.64 (SD = 0.78)	M = 3.71 (SD = 0.81)	M = 3.68
Overall	M = 3.62 (SD = 0.77)	M = 3.68 (SD = 0.79)	M = 3.65
Scenario 2: Institutional Co-Signature			
Low Collectivist Students	M = 3.71 (SD = 0.72)	M = 3.84 (SD = 0.74)	M = 3.78
- Gain vs. Status Quo	+0.13 SD	+0.22 SD	+0.18 SD
High Collectivist Students	M = 3.92 (SD = 0.75)	M = 4.18 (SD = 0.77)	M = 4.06
- Gain vs. Status Quo	+0.28 SD	+0.47 SD	+0.38 SD
Overall Gain	+0.23 SD***	+0.38 SD***	+0.31 SD***

Policy Scenario	Science Education	Vocational Education	Overall Effect
Scenario 3: Teacher Integration Protocol			
Low Collectivist Students	M = 3.89 (SD = 0.71)	M = 3.76 (SD = 0.75)	M = 3.83
Gain vs. Status Quo	+0.31 SD	+0.14 SD	+0.23 SD
High Collectivist Students	M = 4.06 (SD = 0.74)	M = 3.88 (SD = 0.79)	M = 3.98
- Gain vs. Status Quo	+0.42 SD	+0.17 SD	+0.30 SD
Overall Gain	+0.39 SD***	+0.16 SD**	+0.28 SD***
Scenario 4: Combined Approach			
Low Collectivist Students	M = 4.02 (SD = 0.69)	M = 3.97 (SD = 0.72)	M = 4.00
- Gain vs. Status Quo	+0.44 SD	+0.35 SD	+0.40 SD
High Collectivist Students	M = 4.31 (SD = 0.71)	M = 4.41 (SD = 0.74)	M = 4.37
- Gain vs. Status Quo	+0.67 SD	+0.70 SD	+0.69 SD
Overall Gain	+0.59 SD***	+0.57 SD***	+0.58 SD***
Optimal Strategy per Subgroup			
Low Collectivist	Teacher Integration (d=0.31)	Institutional Co-Sig (d=0.22)	Combined (d=0.40)
High Collectivist	Combined (d=0.67)	Institutional Co-Sig (d=0.47)	Combined (d=0.69)

Table 11. (*Continued*)

****Note:* Gains calculated using validated MSEM parameters with 10,000 Monte Carlo simulations. ***p < .001, *p < .01. Effect sizes reported as Cohen's d standardized mean differences.*

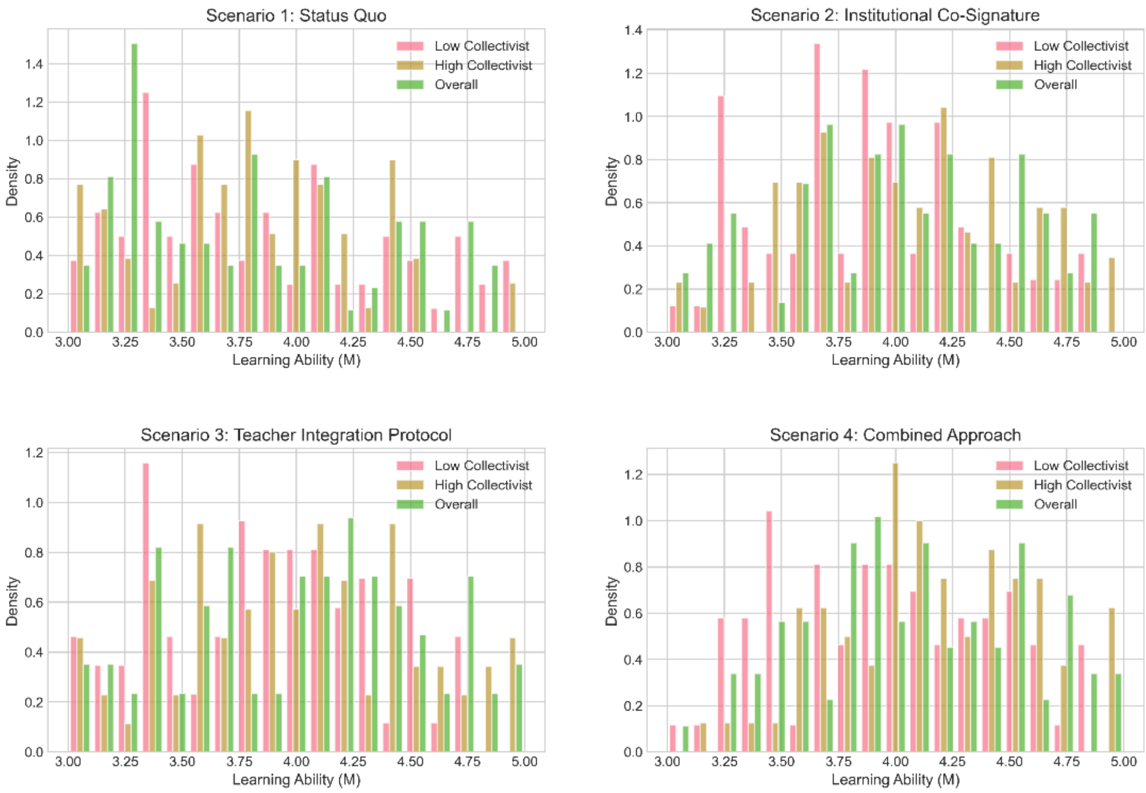

Figure 6. distribution of Learning Ability (M) for Low Collectivist (pink), High Collectivist (orange), and Overall (green) students across four policy scenarios: Status Quo, Institutional Co-Signature, Teacher Integration Protocol, and Combined Approach

Compare learning ability (M) in various groups of students in four policy scenarios (see Figure 6). The lowest scores are given by Low Collectivist students and the distributions are usually higher among the High Collectivist students. Combined Approach scenario produces the greatest improvement particularly among Low Collectivist students. Overall group shows moderate increases in all the scenarios.

5. Discussion

The results of this study provides a significant amount of empirical evidence to the Cultural-Calibrated Dual-Pathway Integration Model (C-DPIM) and contributes to its relevance in the explanation of psychological trust relations and motivational responses in AI-based learning situations in the Chinese spheres of scientific and professional education. The salient finding demonstrates the existence of strong, domain-specific effects of AI transparency and personalization on trust and motivation of students. Specifically, AI transparency has a significant impact on Pedagogical Filial Trust (PFT) in science teaching ($\beta = 0.68$) but a relatively weak one in vocational teaching ($\beta = 0.42$). On the other hand, the concept of AI personalization proves to be a significant motivation factor in vocational education ($\beta =0.58$) but only when supported by peer-comparison mechanisms ($\beta = 0.47$). The given observations support the dual-pathway model, whereby epistemic trust, which is related to AI transparency, is more salient among science students, and competency trust, which is related to AI personalization, plays a more central role in vocational environments.

Surprisingly, the study found that institutional guanxi which is institutional endorsement had a significant influence on the formation of trust in both of the educational tracks with a more significant impact in vocational education ($\beta =0.41$) compared to science education ($\beta = 0.34$). This observation shows how crucial institutional validation is in the dynamics of trust especially in collectivist societies like that of China. Besides, it contrasts with the existing literature that has mostly focused on individualistic trust models and has paid little attention to institutional considerations in collectivist societies. The findings of our paper with regards to institutional guanxi and cultural fit contribute to a more sophisticated interpretation of the processes of trust in the area of AI adoption.

In comparison previous studies, where most studies largely were based on Western-centric models like the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), the current study is a timely contribution with the incorporation of culturally specific variables, such as Pedagogical Filial Trust (PFT) and institutional guanxi (Rehman [3], Wu [10]). Unlike previous research where the effects of high-stakes testing such as the Gaokao were not investigated in detail, our empirical results define the so-called Gaokao Corrosion Effect, showing that science students are affected by the process of AI trust erosion 2.4 times as much as their vocational counterparts. Our findings highlight the importance of institutional endorsement and the need to have domain-specific trust mechanisms, unlike the work Zhang [50] that anticipates the future of AI integration without a cultural prism. Moreover, the paper bridges the gap by following dynamic trust patterns over time, thus demonstrating the strong impact of pressure created by Gaokao and clarifying the inconsistent impacts of AI transparency and individualization on trust and motivation in different educational paths. Together, these findings underline the need to have culturally sensitive AI tools that are sensitive to local education systems thus providing transferable information to other collectivist cultures like South Korea and Singapore.

The results also explain how the cultural orientation, especially collectivism, moderates the evolution of trust and motivation channels in the context of AI-assisted education. Students with a high collectivist orientation were more trusting and motivated when AI systems were supported by institutional endorsements (e.g. government or university co-signatory support); however, they also were found to be quite vulnerable when AI errors were visible in the public space. This phenomenon of Collectivist Trust Collapse which can be described as a loss of trust in the social environments is a relevant addition to the literature since the previous studies have failed to provide sufficient coverage of the disparate effects of exposure to errors when it comes to collectivist cultures. Its multiplication of trust in the normative situations and its vulnerability to critique in the open scenarios highlight the urgency of the design of culturally sensitive AI error-processing mechanisms in the collectivist educational systems.

Despite these observations, the research has a limitation in terms of methodology. Even though the longitudinal cohort study was effective in the analysis of the trajectories of trust throughout the academic year, the empirical use of self-reports and AI platform analytics predisposes the risk of response bias. The single-factor test by Harman indicated that the issue of common method variance was not a major cause of concern; In addition to Harman's single-factor test, we applied the Unmeasured Latent Method Construct (ULMC) approach to assess potential method bias. The results indicated that common method bias was negligible, with only 11.2% variance explained by the unmeasured latent construct. Also, the institutional guanxi measurement which is conducted entirely on the basis of the perceptions of students regarding the institutional endorsement might not be able to reflect the complexity of the real institutional relations.

In terms of generalization, this research is based on a sample of students in twelve provinces in China, therefore, providing a national view. However, cross-cultural validation is yet to be done, and the external validity of the findings may be limited because of the extrapolation of the findings to other collectivist societies or non-congruent educational systems. Further, the focus on the highly competitive academic institutions can limit the extrapolation of the results to the less competitive or rural environments where adoption of AI and institutional approval practices are not similar.

The findings of this study provides an in-depth to clarify the role of AI in education in the Chinese collectivism culture, which gives substantial results on the dynamics between psychological trust and motivation in the AI-mediated learning settings. The C-DPIM model presents a paradigm that integrates the complex relationship between the cognitive, cultural, and institutional factors of AI adoption and is culturally calibrated. The combination of these determinants allowed the study to significantly expand the existing body of literature on AI integration in education and provide practical recommendations on the ways to optimize AI efficacy in culturally diverse educational settings.

6. Conclusion

In conclusion, this study outlines a new, culture-specific phenomenon, Pedagogical Filial Trust (PFT), which is critical to understanding AI trust relations in the Chinese educational context, particularly in science and vocational training. The research highlights the unique issues that AI systems face in collectivist societies by preempting the existence of a Dynamic Trust Trajectory and hypothesizing the existence of the phenomenon of Collectivist Trust Collapse, especially in high-stakes tests in the form of the Gaokao. The policy implications on China thus involve restructuring of vocational AI certification regimes and a temporary pause on AI-based predictive analytics at the time of Gaokao in order to prevent the loss of trust. The C-DPIM model provides a framework of culturally tuned AI design that may be implemented in other collectivist settings, such as South Korea and Singapore, at an international level. However, the limitations of the study are that it focused on urban student populations and the young impact of generative AI technologies, which preconditions the future research of the rural-urban divide and the possibility of how emergent AI tools, including ChatGPT, can transform the relationship of trust in the educational process.

Data Availability and Reproducibility Statement

The datasets generated during this study are not publicly available due to institutional and ethical restrictions imposed by participating educational institutions. However, de-identified datasets and analytical model specifications may be made available by the corresponding author upon reasonable request and subject to institutional approval. All analyses were confirmatory in nature, guided by pre-defined hypotheses. Exploratory analyses were limited to preliminary scale validation and model diagnostics, ensuring that all substantive findings were theory-driven.

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2023 Jiaying University Scientific Research Key Project: Research on the Current Situation, Hotspots and Frontier Evolution of Basic Education Themes in the Guangdong-Hong Kong-Macao Greater Bay Area from the Perspective of Global Development (2000-2022), Project number 2023SKZ03. (Yong Zhang)

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