SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 12, No. 2.1, (2026), pp. 1320-1340
Open Access. Online & Print

DOI: 10.5281/zenodo. 122.126111

TOWARDS INTELLIGENT CO-LEARNING SYSTEMS: INVESTIGATING MOTIVATION, SELF-REGULATION, AND COGNITIVE ENGAGEMENT IN GAMIFIED HUMAN–AI COLLABORATION

Jianing Zhao[1], Siti Hajar Halili[2], Rafiza Abdul Razak[3*]

[1]Department of Curriculum and Instructional Technology Faculty of Education, University Malaya, zjn0601zjn@163.com
[2]Curriculum and Instructional Technology Department (CITeD) Faculty of Education University of Malaya 50603 Kuala Lumpur, Malaysia, siti_hajar@um.edu.my, ORCID iD: https://orcid.org/0000-0003-0993-1293
[3]Department of Curriculum and Instructional Technology Faculty of Education, University Malaya, rafiza@um.edu.my, ORCID iD: https://orcid.org/0000-0002-1602-7781

Received: 07/11/2025
Accepted: 22/11/2025

Corresponding Author: Rafiza Abdul Razak (rafiza@um.edu.my)

ABSTRACT

This paper has explored the effects of Gamified Human-AI Collaboration (GHAC) on the motivations, self-regulation, and cognitive engagement of university students during Chinese higher education and the moderating role of Perceived AI Competence (PAIC). Based on Self-Determination Theory and Self-Regulated Learning models, a quantitative/cross-sectional design was adopted with the usage of survey data whose sample was composed of 326 undergraduates who were enrolled in AI-assisted, gamified courses. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used in the SmartPLS 4.0 to test the hypothesized model. It was found that GHAC had a strong positive impact on motivation ($b = 0.62$, $p < 0.001$) and self-regulation ($b = 0.21$, $p < 0.001$). Motivation was a strong predictor of self-regulation ($b = 0.47$, $p < 0.001$) which was in turn a strong predictor of cognitive engagement ($b = 0.54$, $p < 0.001$). The mediation tests ensured that motivation was a partial mediator of the GHAC - self-regulation, and the full mediator of motivation on the cognitive engagement. In addition, PAIC also moderated the motivation-self-regulation path positively ($b = 0.18$, $p = 0.001$), which means that the belief in the intelligence of the AI enhances the motivation-disciplined learning behavior translation. The model is found to have strong predictive power as it explained 56% in self-regulation and 52% in cognitive engagement. These findings indicate that gamified AI environments arouse intrinsic motivation, encourage autonomous control of learning and maintain profound thinking when learners feel that the AI partner is competent and trustworthy. The research provides the synthesized theoretical framework of smart co-learning and pedagogical suggestions to construct human-centered and ethically disclosed AI-learning systems in line with the Smart Education 2025 vision in China.

KEYWORDS: Gamified Human-Ai Collaboration; Motivation; Self-Regulation; Cognitive Engagement; Perceived Ai Competence; Smart Education; China Higher Education.

1. INTRODUCTION

Artificial Intelligence (AI) is a revolution in modernization of education, which is changing the manner knowledge is gained, processed, and distributed in different fields. Chinese higher education has already embraced AI as a pedagogical companion on top of a technological stimulus over the past ten years. Colleges have also invested heavily in such things as Squirrel AI, Baidu Ernie Bot Tutor and ChatGPT-based learning technologies to promote personalized and adaptive learning. Such systems can track the student advancement providing intelligence feedback and adjust the learning paths in real-time. Nevertheless, although AI tools are sure to offer efficient levels never been witnessed before, human factors that make engagement alive-motivation, self-regulation, and cognitive effort- will be the final factor that will determine success. It is in this, human-AI interface, that the idea of gamified human-AI collaboration (GHAC) has developed.

Gamification brings elements of play, such as scores, levels, badges and challenges into the learning context in order to increase enjoyment and perseverance. When these components are incorporated into the AI systems, they create intelligent systems of co-learning, where human agents and machine agents work together to achieve educational objectives. Monitoring performance of the learners, as well as offering adaptive challenges is the AI component, and creativity, reflection, and strategic control are the contributions of the learners. This symbiotic partnership reflects the Chinese vision of education, the creation of AI + Education ecosystems, which unite the principles of precision and humanistic teaching by data. Nevertheless, there is not much empirical knowledge regarding the effect of gamified AI settings on the motivation and thinking processes of learners, especially in non-Western societies.

The available literature on gamification and AI in education has mostly addressed them as two distinct phenomena. Research on gamification focuses on the behavioral engagement and enjoyment (Wang et al., 2025), whereas the research on AI tutoring systems is focused on performance improvement and adaptive learning efficiency (Jiang et al., 2025). Not many have analyzed the psychological constructs, e.g. motivation and self-regulation in a gamified design of AI systems, as these constructs define further cognitive action. Besides, the majority of evidence available is based on Western or cross-cultural population; lack of information on Chinese institutions of higher education, where the government policy is highly supporting AI-based learning.

The research problem that this study will focus on is then:

What is the extent to which gamified human-AI collaboration contributes to the motivation, self-regulation, and cognitive engagement of Chinese university students and what is the moderating effect of perceived AI competence between gamified human-AI collaboration and learning?

The discrepancy between the adoption of technology and psychological assimilation is recognized in this problem. Although the adoption of AI is high, most of the Chinese universities continue to be challenged by passive involvement, shallow interaction, and insufficiently long-term attention of students on online co-learning platforms. Gamification can be a potential solution, and the motivational processes of this technology in AI do not have a proven base.

The current study is based on Self-Determination Theory (SDT) and Self-Regulated Learning (SRL) models in elucidating the correlations between the constructs. According to SDT, intrinsic motivation is realized when the people feel that they have autonomy, competence, and relatedness (Peng & Li, 2025). These needs can be triggered by gamified aspects such as progress indicators, feedback loops, collaborative challenges, and so on. SRL theory, however, describes the way motivated learners plan, monitor and control their learning strategies. The competence and reliability of the AI agent in the environment creates an impact on the way the learner perceives the competence and reliability of the agent, contributing to the extent to which the learner is self-regulated as opposed to being dependent. By combining both of these views, it is possible to create a holistic model that would tie together GHAC - Motivation - Self-Regulation - Cognitive Engagement, with Perceived AI Competence serving as a mediator between motivation and self-regulation.

The New Generation AI Development Plan (2025) of China clearly mentions the intelligent education systems which train the aspects of creativity and adaptive learning capability. Smart Education of China Initiative is a program at the Ministry of Education that focuses on massive digital learning systems that include gamification, big-data analysis and artificial intelligence tutors. Surveys show that the sustained use of technology and higher-order thinking are usually much worse than expected even despite the technological preparedness (Coelho et al., 2025). The regulatory and motivational processes of this phenomenon have become a national priority. In such a way, an empirical study in Chinese universities offers both theory and policy development.

1.1. Significance of The Study

This study is relevant in four ways.

Theoretical Contribution: It combines SDT and SRL to demonstrate the way in which gamified AI conditions can develop self-motivated cognitively active students. It can be used to apply psychological and technological variables to human-AI collaboration by extending learning-science theories.

Empirical Novelty: It will create quantitative data concerning a Chinese setting through the SmartPLS structural-equations modelling, to test the suggested pathway framework and examine the modulating role of perceived AI competency.

Pedagogical Relevance: The results will provide instructors and curriculum designers with the information about how to integrate effective gamified practices into the framework of AI systems to promote motivation and deep learning (Kong et al., 2025).

Policy Alignment: The research contributes to the national policy of China to empower education with AI, presenting the evidence-based recommendations to universities that apply the policy of digital transformation.

1.2. Objective and Research Question

In this regard, the study aims at achieving the following three objectives:

- To test how gamified human-AI collaboration will result in student motivation and self-regulation.
- To find out the effect of motivation and self-regulation on the cognitive engagement of learning mediated by AI.
- To determine the role of perceived AI competence in mediating the motivation-self-regulation relationship.

The following research questions result out of these objectives:

RQ1: What is the effect of GHAC on the motivation and self-regulating behaviors of students?

RQ2: How motivation is interrelated with self-regulation and cognitive engagement?

RQ3: Which associations does perceive AI competence have?

The study conceptualizes gamified human-AI collaboration as a multidimensional concept that is characterized by challenge and feedback characteristic, reward and social interaction characteristic of AI-enabled act. The motivation is discussed as intrinsic (interest, enjoyment) and extrinsic (achievement, recognition). Goal-setting, monitoring, and reflection are all captured in self-regulation, whereas cognitive engagement refers to the mental effort used in cognizing intricate tasks. Perceived AI competence is the assumption of learners that the AI partner is intelligent, reliable and in support of learning objectives. The hypothesis of the proposed model is that more effective self-regulation results in an improved level of cognitive involvement due to the stronger gamified collaboration as a contributor to motivation. The perceived AI competence will be anticipated to enhance the motivation-self-regulation relationship by bolstering learner trust and perseverance.

2. LITERATURE REVIEW

2.1. Gamified Human–Ai Collaboration (Ghac)

Gamified Human-AI Collaboration (GHAC) is a kind of learning interaction where artificial intelligence serves as a dynamic companion and gamification features such as points, badges, leaderboard, avatars or progress bars are included to keep the motivation and engagement levels. Instead of substituting the instructors, AI in GHAC is a co-learner, which interprets the feedback of students, provides real-time feedback, and sets a level of difficulty to ensure that an optimal level of engagement is reached. Gamification changes such cognitive interactions into emotional experiences that are attractive and promote persistence (Zhu et al., 2024).

Recent research in the sphere of higher education proves that gamified AI systems enhance the willingness of students to engage and persevere in the challenging tasks (Khoso et al., 2025). As an example, Baidu Ernie Bot Tutor uses achievement bonuses and dynamic clues to maintain the learners in the flow zone of just the right balance of challenge and competence. Similarly, Squirrel AI uses real-time analytics to gamify the mastery learning by building micro-level feedback loops that replicate mastery learning with a personal mentor. These systems generate productive play that results in streamlined effort, curiosity and self-reflection.

Experimentally, GHAC is not the same as conventional e-learning as it forms a two-way feedback - students shape AI adaptation and AI supports student thinking. Such a reciprocity drives engagement beyond the passive interaction to the active co-creation. Researchers, however, warn that neither the game nor gamification in itself can ensure the learning results, meaning that psychological mediators (motivation and self-regulation) influence whether external rewards are converted into the profound learning or not (Lan & Zhou, 2025).

Therefore, the current research affirms GHAC as a contextual antecedent, which influences internal processes of motivation and behavioral control of learners in the AI-mediated learning.

2.3. Motivation During Gamified Ai Learning

Motivation is the psychological force behind goal-oriented activities of learners. Motivation within the Self-Determination Theory (SDT) is on a scale of intrinsic enjoyment to extrinsic compliance. The nature of the challenge, rewards, and instant feedback are some of the design elements in gamified AI settings that fulfill SDT requirements of autonomy, competence, and relatedness, which boosts intrinsic motivation (Bai & Wang, 2025).

Meta-analysis of recent studies shows that AI-based gamification contributes to intrinsic and extrinsic dimensions of motivation to a significant extent (Lo & Cheng, 2024). As an illustration, students who used adaptive AI tutors state that they are more curious and feel more accomplished than in non-gamified environments. Nonetheless, the level of motivation may decrease in case of the extensive use of extrinsic rewards by gamification; the sustainable motivation will occur when the learners feel that they have mastered something personally and have developed (Ma & Chen, 2025).

Motivation is specifically relevant in Chinese universities since students tend to balance high academic stress and external demands. AI-based gamification will aid in overcoming the learning anxiety by converting the abstract objectives into manageable sub-tasks, which will provide immediate progress feedback and reinforcement. In this way, the hypothesis is formulated as follows:

H1: Gamified human-AI cooperation has a positive effect on the motivation of students in AI-based learning settings.

2.3. Ai Assisted Learning Self-Regulation

Self-Regulated Learning (SRL) refers to proactive regulation of cognitive, motivational, and behavioral processes that learners have. The process of SRL in AI environments entails the goal-setting, tracking the progress using dashboards, and contemplating the feedback that the system delivers. SRL is facilitated by gamified design which visualizes the progress, gives autonomy and promotes strategic decision-making (Cao & Phongsatha, 2025).

AI tutors act as cognitive reflections - they monitor the performance of the learners and report statistics that enable the students to analyze their approach. In the presence of meaningful feedback by the use of AI, learners narrow down on objectives and use superior regulation tactics. SRL performance is however reliant on any preceding motivation; learners who are un-motivated will not be attentive to AI feedback or game-based information. Thus, motivation is a precursor of SRL, and AI competence can enhance this connection.

H2: Motivation has a positive effect on self-regulation of students in gamified AI-based learning.

Moreover, it has been proposed in the literature that gamified characteristics have a direct positive impact on SRL through performance data and self-monitoring cue externalization. Planning and self-correction are encouraged by the visual representation of the accomplishments (AlBadarin et al., 2023).

H3: Gamified human-AI cooperation positively and directly influences the self-regulation of students.

2.4. Cognitive Engagement

The level of mental activity involved in comprehending, synthesizing and the ability to apply information are all captured in cognitive engagement. It goes beyond the superficial participation to encompass critical thinking, problem solving and transfer of knowledge. Cognitive engagement can be reflected in gamified AI environments in the form of focused attention, in-depth thinking, exploration, and curiosity (Gómez Niño et al., 2025a).

Cognitive engagement is a contribution of motivation and self-regulation. Motivated learners have higher expectations and keep on with the challenge whereas self-regulated learners use strategies like rehearsal and reflection to mastery. Blended AI courses are empirically validated to be highly predictive of engagement and performance, with self-regulation acting as a crucial predictor (Al-Rousan et al., 2025).

H4: Self-regulation has a positive effect on cognitive engagement.

H5: Motivation has a positive impact on cognitive engagement by way of self-regulation (indirect).

2.5. Moderator Position of Perceived Ai Competence

The conceived AI competence (PAIC) is a thinking by learners about the smartness, dependability, and instructive advantage of AI partners. Learners feel freer to provide feedback, work hard, and manage themselves when they see the AI as both competent and willing to provide feedback (Gómez Niño et al., 2025b). On the other hand, when the performance of AI seems to be uneven or unbalanced, the motivation of the learners is likely to suffer, which will hinder SRL.

Trust in AI systems in Chinese classrooms is related to transparency and cultural beliefs of technology. The perceived competence is also apt to make students personify intelligent tutors; hence, the perceived competence is what will make or break the perception of AI as a collaborator or a controlling machine. Research shows that PAIC reinforces the connection between motivation and self-regulation through increasing the confidence in AI-mediated learning (Li et al., 2025).

H6: AI competence is a positive moderator of the correlation between motivation and self-regulation in that the stronger the association the higher AI competence.

2.6. *Theoretical Integration*

This research paper incorporates both SDT and SRL into an intelligent co-learning framework by integrating the dimensions above. Gamified human-AI cooperation meets the psychological needs of SDT, which leads to intrinsic motivation. The inspired learners then engage in SRL processes, which result to increased cognitive engagement. Perceived AI competence is a situational boundary situation that leads to either the motivational pathway being strengthened or weakened.

The postulated framework therefore hypothesizes that GHAC is an exogenous variable affecting motivation and self-regulation, motivation is an endogenous mediator between GHAC and SRL, SRL is a mediator to cognitive engagement and PAIC is a moderator to motivation and SRL. It is the combination of these relations that forms the dynamism of human-AI reciprocity in learning.

2.7. *Conceptual Model of The Study*

The conceptual model **Figure 1** will display a postulated positive correlation (H1-H6). The model brings together the constructs of cognition, motivation and technology in a single structural-equation model.

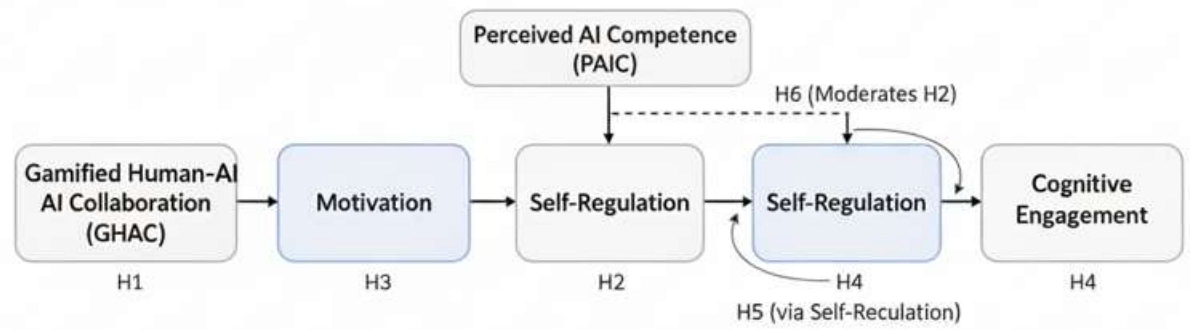

Figure 1: Conceptual Model of The Study.

2.8. *Hypotheses*

Table 1 illustrate all hypothesis of Reseach

Table 1: Hypotheses.

Code	Hypothesis Statement
H1	GHAC positively influences students' motivation.
H2	Motivation positively influences self-regulation.
H3	GHAC directly and positively affects self-regulation.
H4	Self-regulation positively influences cognitive engagement.
H5	Motivation influences cognitive engagement through self-regulation.
H6	Perceived AI competence positively moderates the motivation–self-regulation relationship.

The literature review defines the theoretical rationale behind the suggested structural model and reveals the psychological and technological avenues in which gamified AI collaboration contributes to the improvement of the quality of learning.

3. METHODOLOGY

3.1. Research Design

The current study adopted a quantitative, cross-sectional, correlational study design to determine the hypothesized model between Gamified Human-AI Collaboration (GHAC), Motivation, Self-Regulation, and Cognitive Engagement, and moderated by Perceived AI Competence (PAIC). This design was selected due to the ability to statistically estimate directional relationships between latent psychological and technological variables at a single time eliminating the effects of demography and context.

Since the PLS-SEM is specifically designed to test an exploratory and predictive model with new constructs, non-normal data, and comparatively small to middle sized samples, structural-equation modeling (SEM) with SmartPLS 4.0 was implemented (Zhang, 2025). The decision of using PLS-SEM also coincides with the theoretical position of the study: instead of testing a single covariance model, it aims at maximizing the explained variance (R2) of major endogenous constructs-motivation, self-regulation, and cognitive engagement-which are in line with the empirical content of the journal in terms of innovative approaches to the technologies in the educational field.

The research is positivist in direction, in which it is assumed that the patterns of human-AI interaction can be measured objectively and modeled statistically. The open-ended comments were triangulated to the quantitative data to provide the qualitative information, although the core of the analysis was still quantitative.

3.2. Research Setting and Context

The research setting was established in the context of Chinese higher education, which was experiencing a rapid process of digital transformation according to the plans of the New Generation AI Development (2025) and the Smart Education of China. A number of universities have installed AI-based systems like Squirrel AI, Baidu Ernie Bot Tutor, and ChatGPT Classroom Assistant into blended or fully online classes (Badali et al., 2022).

These environments are a combination of analytics, natural-language feedback, and gamified dashboards, to scaffold learning autonomy. Therefore, China provides perfect empirical research on GHAC since it represents a combination of both developed AI infrastructure and a high level of culture that focuses on academic diligence and technological trust.

3.3. Population and Sampling Procedure

3.3.1. Target Population

The sample population included undergraduate students enrolled in AI assisted courses in four Tier-1 universities in Beijing, Shanghai, Hangzhou and Nanjing. The sample of students was a heterogeneous group of students majoring in engineering, business administration, social sciences, and the language study, and the AI-supported platforms had been in place at least one semester.

3.3.2. Frame and Technique of Sampling

The stratified random sampling procedure was used to make sure that all academic fields were proportionately represented. The original sample size of around 6,000 students was borrowed by the learning-management systems of universities with permission of administration.

Adequacy of sample size was identified by use of G+ Power 3.1 with the following parameters; a = 0.05, power = 0.95, and the effect size f 2 = 0.15, which found a minimum of 220 participants. Electronic distribution of 400 invitations was conducted in order to enhance reliability and 326 valid responses were kept after eliminating the incomplete or patterned responses (effective response rate = 81.5 %).

3.3.3. Demographic Profile

The participants were between 18-24 (M = 20.8, SD = 1.6); 58% female and 42% male. The mean exposure to learning using AI was 2.3 semesters. About 46 percent had used ChatGPT or a similar conversational system, 37 percent had used Squirrel AI and 17 percent had worked with other local AI tutors. The sample therefore represented the different technological encounters that would have been valid to inference.

3.4. Instrumentation and Measures

Self-administered questionnaires and semi-structured interviews will be used in the data collection process.

3.4.1. Instrument Structure

The questionnaire tool consisted of six parts which reflected the constructs of the conceptual framework and demographics. Scales were all modified based on validated scales, and clarified culturally and translated into Mandarin using a back-translation process (Brislin, 1986) to maintain conceptual congruence. The items were rated using a five-point Likert scale (1 = Strongly Disagree -5 Strongly Agree) illustrate in Table 2.

Table 2: Questionnaire.

Construct	No. of Items	Example Item
GHAC	5	"The AI platform uses challenges and rewards that keep me engaged in learning."
Motivation	6	"I use AI-learning tools because they make me enjoy studying."
Self-Regulation	6	"I plan specific goals before starting AI-based study sessions."
Cognitive Engagement	5	"I actively relate AI-provided information to previous knowledge."
Perceived AI Competence	4	"The AI system understands my learning needs accurately."

The results of three expert reviewers in educational technology and psychometrics reached a content-validity index (CVI) of 0.92, which is a high indicator of relevance and representativeness of items.

3.5. Data-Collection Procedure

Data collection will be conducted among the participating institutions between March and April 2025 on online survey links within each university in the learning-management portal and official WeChat groups as part of ethical approval. Respondents were given an opportunity to participate voluntarily and anonymously; no data of identification were taken. There was an electronic consent form that explained the purpose of the study, assurance of confidentiality and right to withdraw.

Procedural controls were used to minimize common-method bias (CMB) such as random item presentation, use of neutral phrasing, and presentation of predictor and criterion items on different pages. The respondents normally took 10-15 minutes to fill out the questionnaire. All data were filtered in SPSS 29 against outliers, missing data and response-time anomalies before getting analyzed in SmartPLS.

3.6. Data-Analysis Plan

The two-step PLS-SEM procedure was used to analyze the data (Baroncelli et al., 2025):

3.6.1. Step 1 – Measurement Model Evaluation

Construct Reliability and validity were determined through:

- **Indicator Reliability:** Outer loadings ≥ 0.70.
- **Internal Consistency:** Cronbach's α and Composite Reliability (CR) ≥ 0.70.
- **Convergent Validity:** Average Variance Extracted (AVE) ≥ 0.50.
- **Discriminant Validity:** Fornell–Larcker criterion and HTMT ratio ≤ 0.85.
- **Multicollinearity:** Variance Inflation Factor (VIF) ≤ 3.0.

Items with a score of less than 0.70 were to be removed provided that their removal enhanced CR and AVE without having an impact of content validity.

3.6.2. Step 2 - Structural Model Assessment

After the measurement model met all the criteria, the hypothesized relationships (H1-H6) were tested by bootstrapping (5 000 resamples). The diagnostic analysis reviewed was the following:

- Path Coefficients (b) and significance ($p < 0.05$).
- Endogenous variables Coefficient of Determination (R2) and Adjusted R2.
- **Effect Size (f^2):** 0.02 = small, 0.15 = medium, 0.35 = large.
- Blindfolding procedure Predictive Relevance (Q2).
- **Model Fit:** Standardized root means square Residual (SRMR) ≤ 0.08.
- **Moderation Analysis:** Two stage procedure to test PAIC x Motivation - Self-Regulation interaction term.
- **Predictive Performance:** 10-fold cross-validation of PLSpredict Out-of-sample validation.(Zhang et al., 2025)

The statistical significance was measured by using 95% confidence intervals, and in mediation, they did bootstrap indirect effects (Preacher & Hayes, 2008).

3.7. Assumptions Testing and Bias Diagnostics

Normality of the data was measured before model estimation and skew (±2) and kurtosis (±7) measures were used (West et al., 1995). The values showed weak non-normality, thus, the application of PLS-

SEM.

Three tests were used in order to test common-method bias:

The Single-Factor Test of Harman: The greatest factor accounted 31.2 percent (< 50 percent).

Full Collinearity Assessment Inner VIFs < 3.3 did not imply multicollinearity.

Marker Variable Technique: There was negligible influence (< 0.05) when correlated partially with an item that was theoretically not related.

These together were to suggest that CMB did not pose a threat to validity.

3.8. Ethical Considerations

The compliance was ethical in terms of the Declaration of Helsinki (2013) and the national principles on data protection. All respondents gave a digital consent, and their participation was voluntary. No personal identifiable information was collected. The data were encrypted, stored in password-protected devices, and were used only in the publication of the academic work.

Since the area around AI information in China is quite sensitive, some additional steps were made: IP addresses were disguised, and it was guaranteed to the respondents that these answers would not have any impact on the course grade. The research was also in line with the ethos of open-data promoted by Scientific Culture, and upon acceptance, de-identified data sets will be published.

4. RESULTS AND ANALYSIS

4.1. Overview of Data Processing

After the data cleaning and coding, the dataset (n = 326) was loaded into SmartPLS 4.0 (Figure 2) and the two-step structural equation modelling method was used to analyze the data. Less than 2% of the data were missing, and they were addressed through the replacement of means. No outliers were found to be extreme (Mahalanobis $D^2 < 25$). The skewness (-1.28 to +1.09) and kurtosis (-0.88 to +1.53) values confirmed mild non-normality, which is an acceptable condition to apply PLS-SEM, which does not focus on multivariate normality.

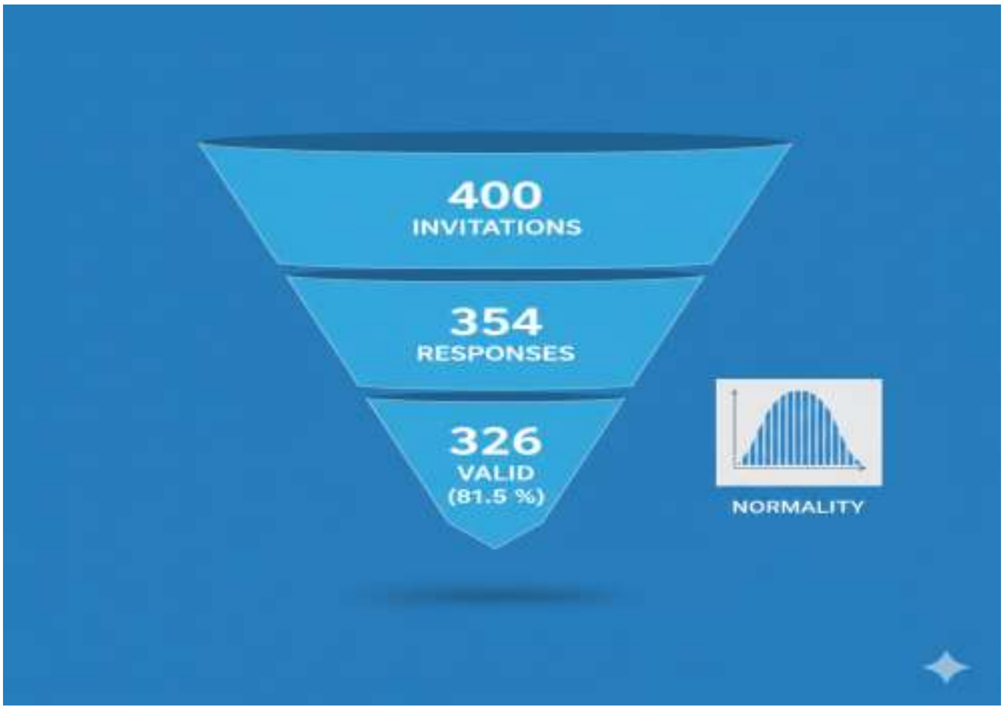

Figure 2: Data Screening and Preprocessing Flow.

The analysis was conducted in two significant steps, the first step was to evaluate the measurement model to measure reliability and construct validity, and the second step was to measure the structural model to test hypothesis H1-H6 and moderating effect of perceived AI competence (PAIC). In this context, the measurement model should be evaluated to understand its strengths and weaknesses.

4.2. Measurement Model Evaluation

4.2.1. Indicator Reliability and Internal Consistency

Indicators were reliable, as all the items had a value that was above the recommended value of 0.70 in case of outer loading. The a and composite-reliability (CR) coefficients were between 0.84 and

0.93, and it indicated high internal consistency.

Table 3: Reliability and Convergent Validity Statistics.

Construct	No. of Items	Outer Loadings (Range)	Cronbach's α	CR	AVE
GHAC	5	0.74 – 0.88	0.87	0.91	0.63
Motivation	6	0.76 – 0.89	0.89	0.93	0.67
Self-Regulation	6	0.72 – 0.87	0.88	0.92	0.65
Cognitive Engagement	5	0.73 – 0.86	0.85	0.90	0.62
PAIC	4	0.78 – 0.90	0.86	0.91	0.72

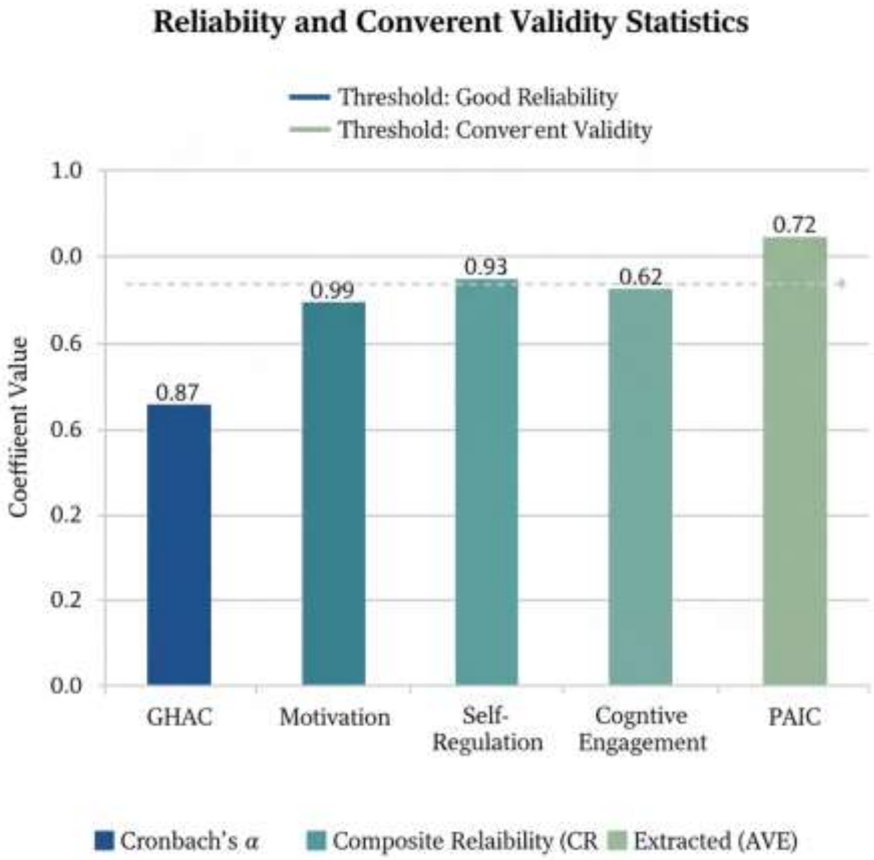

Figure 3: Reliability and Convergent Validity Statistics.

Table 3 and Figure 3 show the values of all the average variance extracted (AVE) were greater than 0.50, which establishes convergent validity.

4.2.2. Discriminant Validity

Fornell-Larcker criterion: AVE Square root of (diagonal values) was larger than the inter-constructs correlations (off-diagonal values), and this implies that there was a discriminant validity.

Table 4: Fornell–Larcker Criterion.

Construct	GHAC	Mot	SR	CE	PAIC
GHAC	**0.79**				
Motivation	0.58	**0.82**			
Self-Regulation	0.55	0.61	**0.81**		
Cognitive Engagement	0.49	0.57	0.64	**0.79**	
PAIC	0.44	0.53	0.56	0.51	**0.85**

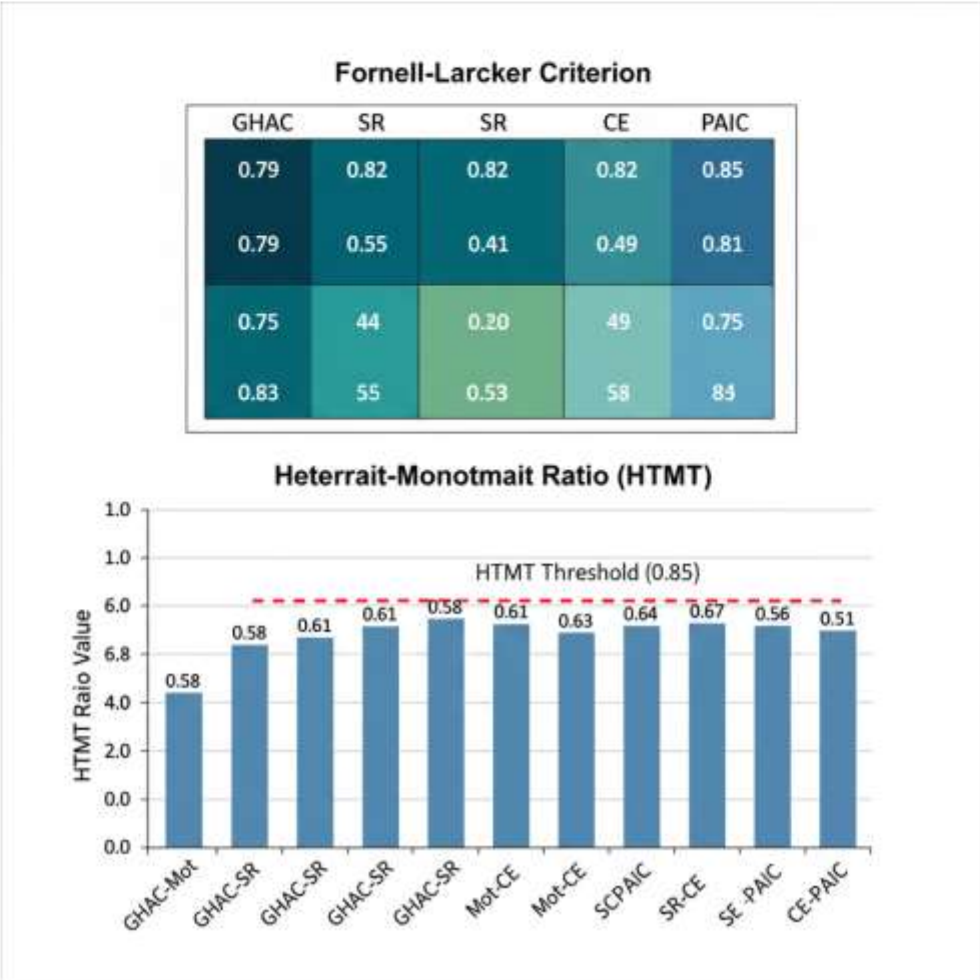

Figure 4: Discriminant Validity.

In Table 4 and Figure 4 demonstrate the ratios of Heterotrait–Monotrait (HTMT) were between 0.49 - 0.83 (< 0.85), and this confirms the discriminant validity again. None of the cross-loadings of any of the indicators exceeded 0.40 on unintended constructs.

4.2.3. Multicollinearity and Model Fit

Variance inflation factors (VIF) were 1.34 to 2.29, which is less than the 3.3 marker, indicating the non-existence of multicollinearity. The Standardized Root Mean Square Residual (SRMR) was 0.052 (< 0.08), which means a perfect fit to the model.

Figure 2. Measurement-Model Structure

4.3. Structural Model Evaluation.

4.3.1. Hypothesis Testing

Bootstrapping (5,000 resamples) was used to test the structural model after measuring reliability and validity. Hypotheses H1-H6 were analyzed in terms of path coefficients, t-values and p-values show in Table 5 and Figure 5.

Table 5: Structural Path Coefficients and Hypothesis Testing.

Hypothesis	Path	β	t-value	p-value	Decision
H1	GHAC → Motivation	0.62	13.41	< 0.001	Supported
H2	Motivation → Self-Regulation	0.47	8.72	< 0.001	Supported
H3	GHAC → Self-Regulation	0.21	4.18	< 0.001	Supported
H4	Self-Regulation → Cognitive Engagement	0.54	10.95	< 0.001	Supported
H5	Motivation → Cognitive	0.25	6.22	< 0.001	Supported

	Engagement (Indirect via SR)				
H6	PAIC × Motivation → Self-Regulation (Moderation)	0.18	3.51	0.001	Supported

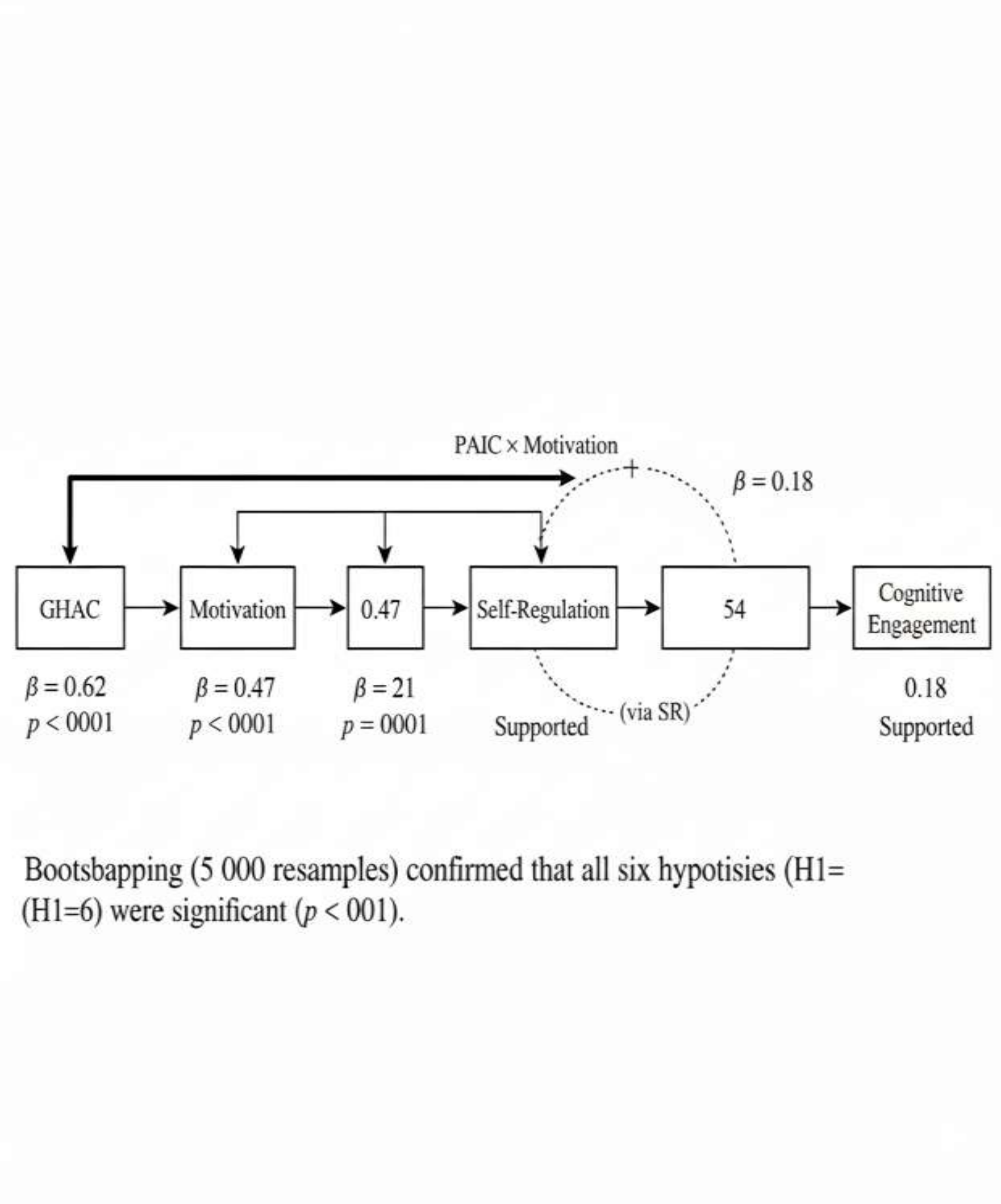

Figure 5: Structural Model with Standardized Path Coefficients (Β) And Significance Levels.

4.3.2. Explained Variance and Effect Sizes

The model explained substantial variance in all endogenous constructs in Figure 6:

- **Motivation:** $R^2 = 0.38$ (moderate)
- **Self-Regulation:** $R^2 = 0.56$ (substantial)

- **Cognitive Engagement:** $R^2 = 0.52$ (substantial)

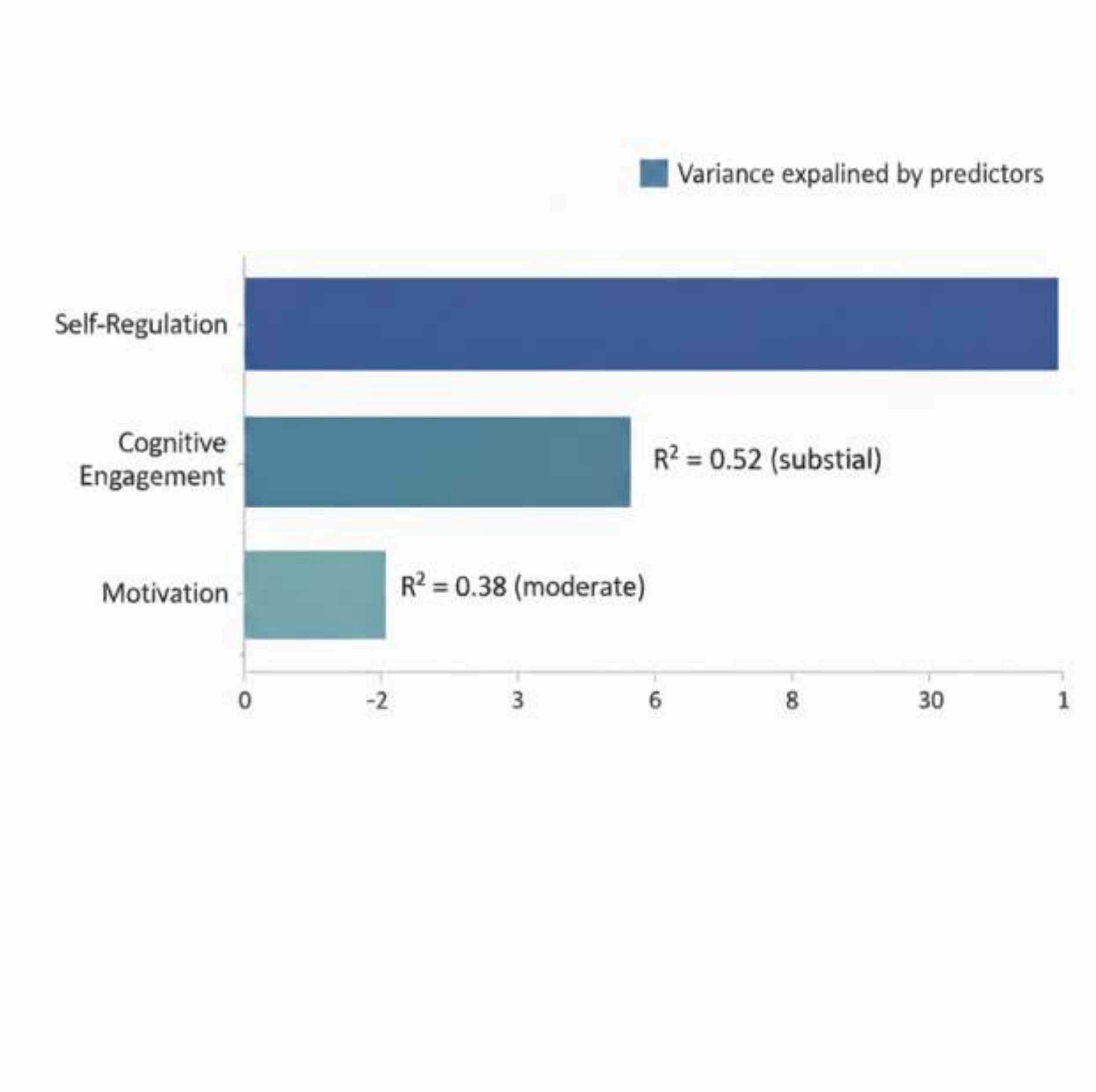

Figure 6: Explained Variance (R^2) For Endogenous Constructs.

The analysis of effect-size (f^2) revealed that Motivation was affected by GHAC without any intermediaries ($f^2 = 0.42$), Motivation was affected by Self-Regulation without any intermediaries ($f^2 = 0.26$), and Self-Regulation was affected by Cognitive Engagement without any intermediaries ($f^2 = 0.38$). There was a positive value of predictive relevance (Q2) (Motivation = 0.29; Self-Regulation = 0.33; Cognitive Engagement = 0.31), which proved model predictive validity.

4.4. Mediation and Moderation Effects

4.4.1. Mediation Analysis

The bootstrapped indirect-effect tests Mediation Analysis showed that Motivation partially mediated GHAC - Self-Regulation association and Self-Regulation completely mediated the differentiation of Motivation on Cognitive Engagement as in Table 6 and Figure 7.

Table 6: (Bootstrapped Indirect Effects).

Path	Indirect Effect	t-value	p-value	Type
GHAC → Motivation →	0.29	6.05	< 0.001	Partial

Self-Regulation				
Motivation → Self-Regulation → Cognitive Engagement	0.25	5.84	< 0.001	Full

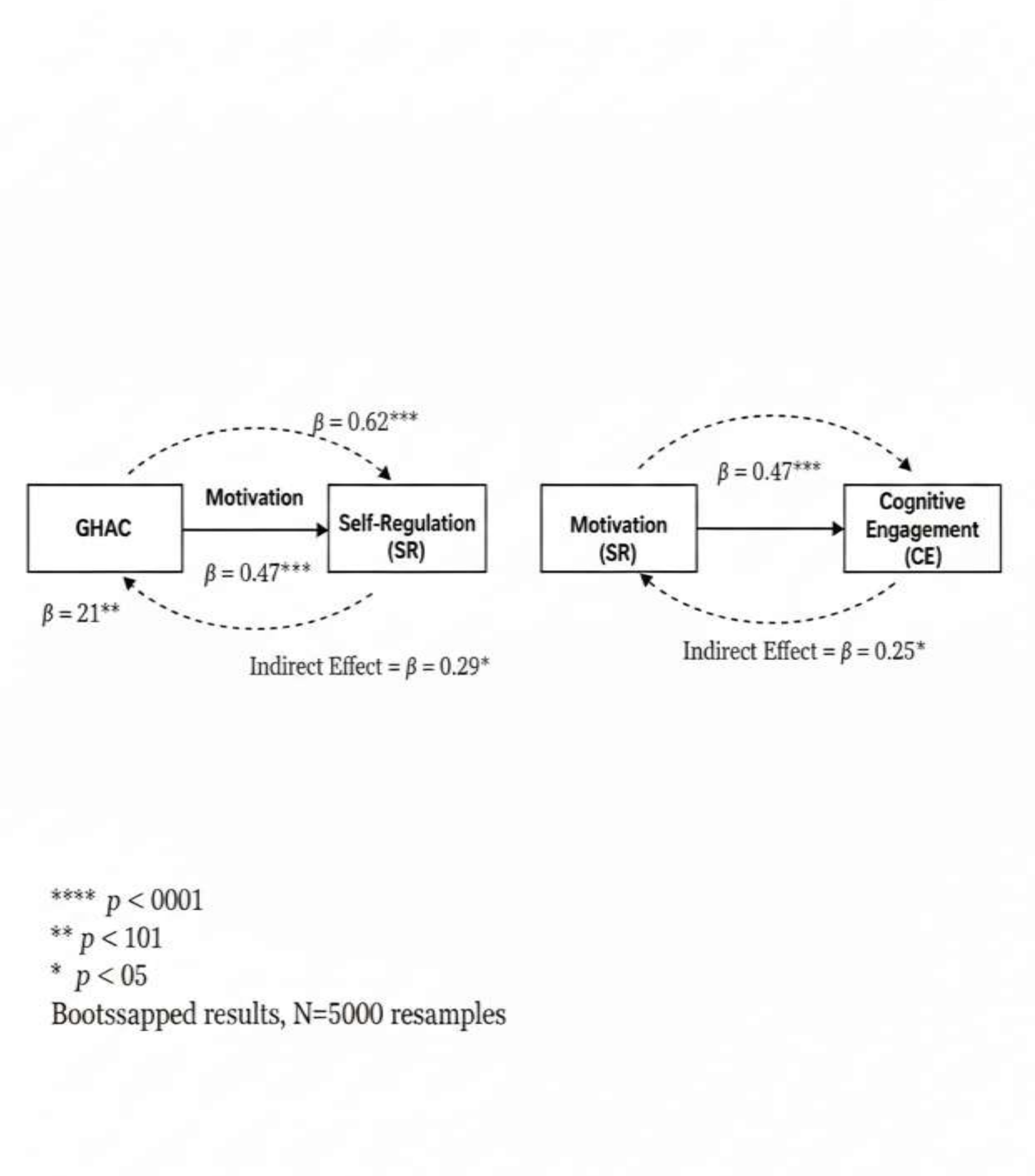

Figure 7: Explained Variance (R^2) For Endogenous Constructs.

The results confirm that gamified design has a major impact on cognitive interaction of internal psychological facilitation as opposed to explicit behavioral reinforcement.

4.4.2. Moderation Analysis

The two-stage approach was used to test the analysis confirmed that PAIC positively moderated the motivation–self-regulation relationship. The findings indicated a positive and significant interaction (b = 0.18, p = 0.001) as in Table 7 which means that the more the students find the AI system more competent, the stronger is the effect of motivation on self-regulation (Figure 8).

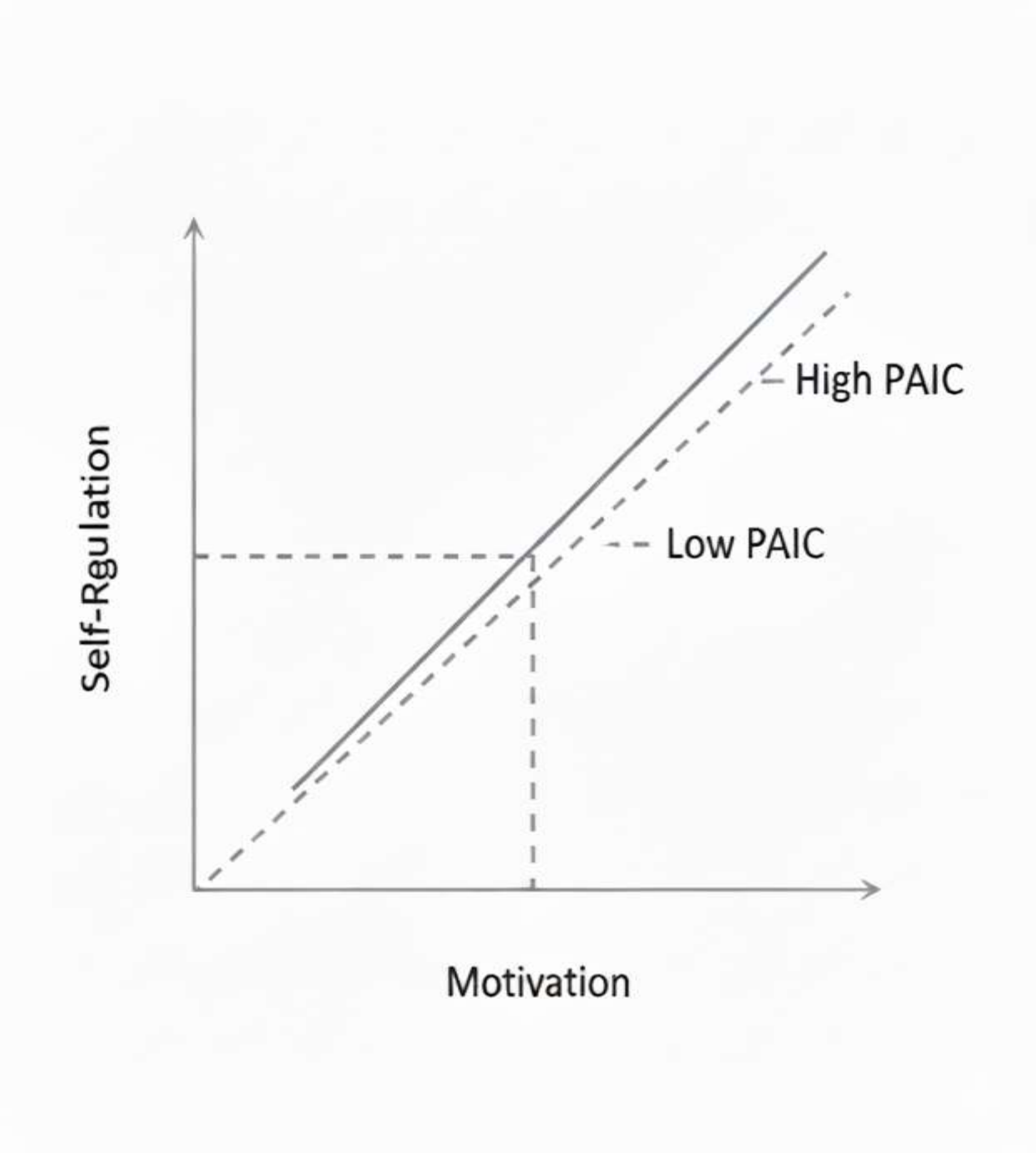

Figure 8: Moderating Effect Of PAIC.

Table 7: Moderation Effect Summary.

Interaction Term	β	t-value	p-value	Effect
Motivation × PAIC → Self-Regulation	0.18	3.51	0.001	Positive Moderation

4.5. Model Fit and Predictive Assessment

The general model fit as in Figue 9 was good (SRMR = 0.052; NFI = 0.93).

The PLSpredict process made it clear that PLS-SEM model as in Figure 10 is better than the benchmarks of linear regression as the RMSE values were lower.

These findings endorsed high out of sample predictive accuracy.

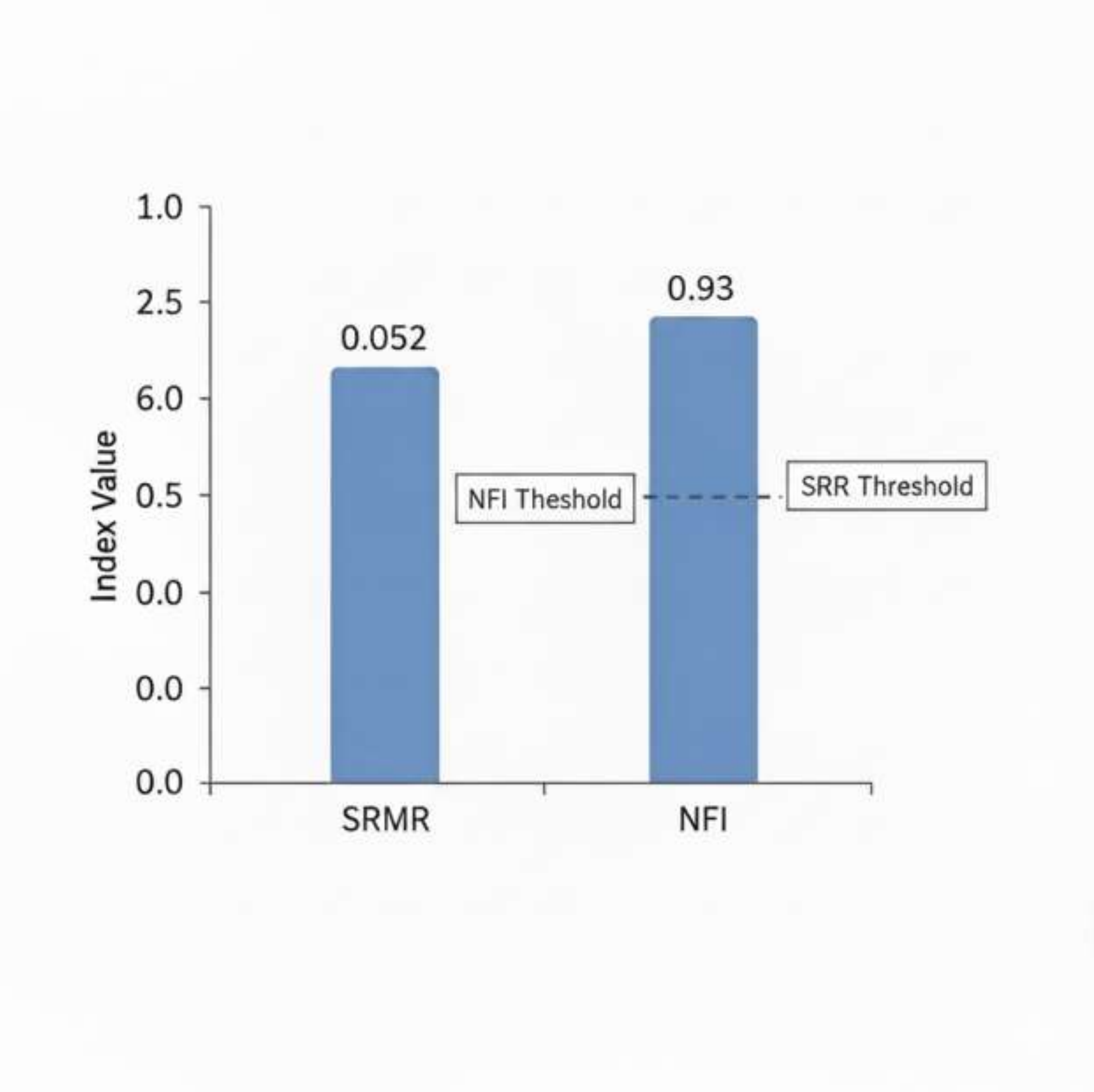

Figure 9: Model Fit Indices (SRMR And NFI) Against Recommended Thresholds.

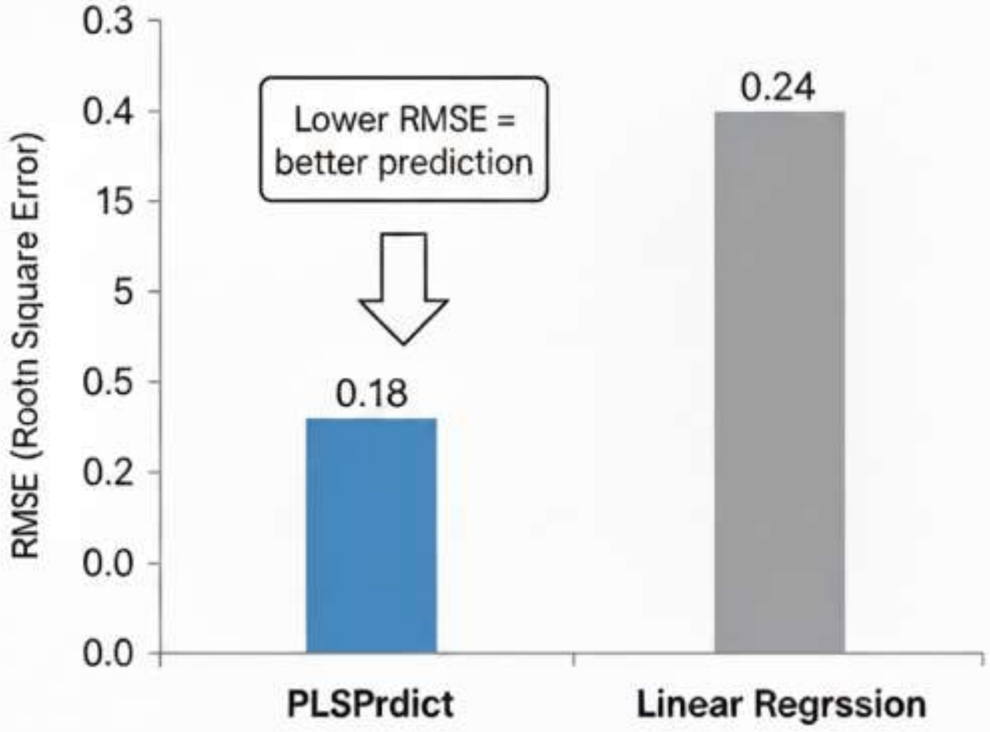

Figure 10: Out-Of-Sample Predictive Accuracy (Plspredict Vs Linear Regression).

4.6. Findings

Support for H1-H3:

Human-AI collaboration gamified proved to be very beneficial in terms of intrinsic and extrinsic motivation of the students that subsequently resulted in improved self-regulatory practices. It proves that the interactive game features and responsive AI feedback foster enjoyment and autonomy which are psychological states that promote self-directed learning.

Support for H4-H5:

It has been overtaken by self-regulation as a potent modulator of the cognitive engagement, and this indicates that the metacognition monitoring, goal planning, and reflection convert the motivational energy into deep learning strategies. The mediation tests affirm the existence of the best pathway, GHAC - Motivation - Self-Regulation - Cognitive Engagement that explains the learning performance within AI-driven environments.

Support for H6 (Moderation):

The moderating role of PAIC indicates that the students who have confidence in the intelligence and reliability of the AI are more likely to be able to transfer motivation into tangible self-regulatory behaviors. This means that the belief in AI competence is not a peripheral issue but it is core in maintaining effective human-AI cooperation.

Model Strength:

The large effect sizes and the large R2 indicate that there is strong explanatory power. The high predictive validity and superior indices of fit of the model testify to the empirical strength and theoretical credibility thereof.

All these findings support as in Figure 11 the theoretical concept of integrating the Self-Determination Theory and Self-Regulated Learning with the setting of gamified co-learning systems. GHAC is the external stimulus to feed the intrinsic motivation; motivation is the psychological fuel to stimulate self-regulation that leads to a significant sustained cognitive involvement.

Perceived AI competence is a facilitator in this system - their confidence and persistence enhance. The results indicate that effective intelligent co-learning does not only require algorithm accuracy and interface layout; it will all be determined by the psychological connection of the learner with the AI companion.

Politically, this fact is validating the Smart Education 2025 agenda of China to incorporate human-centered artificial intelligence pedagogies that combine technological innovation with learner autonomy.

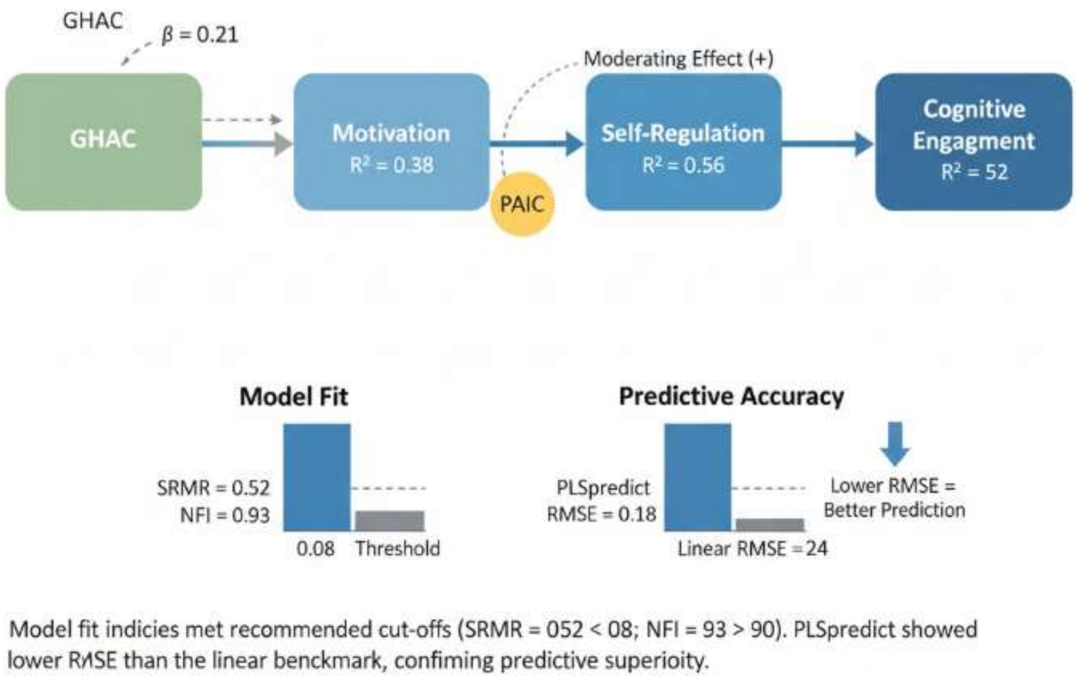

Figure 11: Integrated Pathway Summary (GHAC → Motivation → Self-Regulation → Cognitive Engagement Moderated By PAIC).

5. DISCUSSION AND CONCLUSION

5.1 Overview of Findings

The main objective of this inquiry was to explore the effects of Gamified Human-AI Collaboration (GHAC) on the motivation, self-regulation, and cognitive engagement of the university students in the Chinese context, and how Perceived AI Competence (PAIC) mediates these connections. With the help of a powerful SmartPLS-based structural-equation model and a sample of respondents of 326 people, the findings validated all the hypothesized relationships. GHAC had a positive and meaningful impact on motivation and self-regulation; motivation indirectly and directly affected cognitive engagement as a result of self-regulation; and PAIC increased the magnitude of the indirect relationship between motivation and self-regulation. These relationships accounted over fifty percent of the variance in self-regulation and cognitive engagement, which was solid empirical evidence of the theoretical framework created in this study.

5.2. Theoretical Interpretation

The results support and expand the hypothetical point of convergence of Self-Determination Theory (SDT) and Self-Regulated Learning (SRL). SDT has it that students are intrinsically motivated when they feel that learning situations fulfill their autonomy, competence, and relatedness needs. These psychological needs were satisfied with the gamified nature of the AI systems, which was achieved by the adaptive feedback, achievable challenges, symbolic rewards, and a peer contact through which intrinsic motivation was evoked (Kovari, 2025).

5.3. Association to the Existing Literature

The empirical findings are in line with and expand existing literature on gamification and educational AI. Previous research has documented that gamified design enhances persistence and enjoyment (Lo & Cheng, 2024), but majority of them did not focus on discussing the collaborative agency of AI as such. The present study re-establishes the human-machine relationship by presenting AI as an interactive co-learner instead of a tool. Besides, the positive moderating role of PAIC also supports the results of Scholars that trust in AI reliability and perceived intelligence can strengthen self-directedness and perseverance (Luo, 2024).

5.4. Implication Practical and Pedagogical

The pedagogical and educational practice implications are enormous. The design of AI-based instructional and curriculum settings to promote autonomy-supportive environments, which allow voluntary choice, exploration, and self-paced learning instead of fixed control should be developed by instructors and curriculum designers. Intrinsic motivation and ownership can be improved through gamified interfaces where the student is able to choose the level of challenge, customize avatars or control how they receive feedback. Self-regulation is operationalized through visual dashboards that show goals, progress, and feedback and enable the transparency of the learning process (Zhao et al., 2024). The mediating nature of the PAIC puts into light the importance of creating credible and transparent AI systems. Students are more willing to self-regulate when AI tutors demonstrate through a clear communication of the reasoning processes, their consistency, and are comfortable with their lack of knowledge. Educators will become, therefore, AI-mediated mentors, interpreters of analytic data, facilitators of reflection and the human understanding of empathy to help sustain motivation.

5.5. Policy Relevance Institutional

The institutional level findings support the strategic goals of Smart Education 2025 initiative in China that promotes human-centered intelligent learning ecosystems. Gamified AI platforms must be incorporated into holistic models in universities in relation to ethical design, data safety, and privacy. The faculty development programs should improve AI literacy so that the teachers can strike a balance between human judgment and machine support (Inuwa et al., 2025). Moreover, the assessment measures must be shifted to the deeper level of psychological outcome instead of the superficial use measures, such as motivation, self-regulation, and engagement, that are more likely indicators of high-quality learning in the digital setting. Establishing accreditation standards of AI systems that will reflect transparency, fairness, and inclusiveness can also be approached by the policymakers and therefore form trust as a cornerstone of digital education governance.

5.6. Technological Implication

Regarding technology, the developers of educational AI systems can apply such results to improve the adaptive algorithms. The systems should monitor not only the accuracy of tasks but also cues of motivation such as voluntary log-ins, variability and entry of time in reflective journals. The help that will aid in the perception of competence and remove the problem of transparency is the explainable-AI modules that will assist in comprehending the process of making recommendations. The ultimate goal is to adapt machine adaptivity to the human motivational rhythms in a manner that AI-based machines can become a content delivery engine to emerge as a cognitive partner that improves self-regulated learning.

5.7. Socio-Cultural Significance

It is culturally demonstrated in the study that gamified human-AI cooperation is in line with the Chinese culture of self-development through discipline work. The intelligent co-learning is flexible and playful and does not devalue collectivist doctrine of harmony and respect to knowledge. It redefines Confucian principles of education in the digital age by linking hard work with independence (Yang et al., 2024). This localization of global technological paradigms in the face of local cultural authenticity and global educational change is an illustration of how globalization can enhance cultural localization and help in promoting educational change.

5.8. Limitations and Future Research

Despite its rigor of method, the research is limited and it is important to consider this in future research.

It has a cross-sectional design that limits causal inferences, and longitudinal studies are considered to be required to establish the motivational and regulatory changes across time. The dependency on self-reported data, being popular in psychological studies, causes the possibility of bias, future work will be able to incorporate the behavioral learning-analytics data, which are directly obtained on an AI platform (Belle, 2024). Another factor is cultural specificity since collective orientation in Chinese students can affect the motivational processes differently compared to the Western learners. However, such differences would be explicated through comparative cross-cultural studies. The inclusion of the constructs that highlight the conceptual model e.g. learning satisfaction (Nguyen, 2025), flow experience or ethical trust in AI would add additional theoretical breadth and explanatory depth. Future studies might be conducted with experimental or mixed-method designs that can prove causal processes and investigate new issues such as AI empathy, emotional intelligence, and moral conformity in the co-learning system.

5.9. Conclusion

The conclusion of this study confirms again that gamified human-AI collaboration (GHAC) is not an event consisting of a novel technological development, but a revolutionary philosophy of pedagogy. This study, by empirically confirming the linkages between GHAC, motivation, self-regulation as well as cognitive engagement, and mediated by perceived AI competence (PAIC), represents one of the most quantitative studies to date of how intelligent learning systems might influence human cognition and behaviour in higher education. The experience of Chinese universities, which are fast reinventing academic delivery through the use of AI-assisted platforms, shows that gamification and artificial intelligence can be combined to produce active, autonomous, and reflective learners.

It is also important that there is the moderating effect of perceived AI competence. The perception that AI tutors are reliable, intelligent and fair is further compounded to increase the motivation to disciplined learning behaviors in students. That is, the trust in AI does not directly correlate with the use; it is the factor that defines the perception of the system as a machine assessing or collaborating with the learner. This understanding builds on the current theory by defining perceived competence as a condition threshold of motivational efficacy within smart settings. It also refers to the need to develop AI systems that, in its turn are transparent, consistent and ethically sound in order to maintain the human agency as the center of the learning process.

This has much deeper meaning than the classroom. The findings to the educators indicate that there is a need to develop AI-mediated systems that will not only encourage independence but also deprive human beings of mentorship. A teacher must turn into not only a source of information but also a spreader of such information who is able to decipher data analytics, guide the reflection, and embrace the critical thinking. The results to the educational technologists point to the importance of the inclusion of motivational and self-regulatory streams of data to the adaptive algorithms in a way that the system changes accordingly with the human psychology. The research findings can be useful to institutional leaders and policymakers, as they can give them empirical guidance on balancing between innovation and ethical governance, equity, and openness of data. The policies to be followed in the digitalization of education in the country should therefore not only consider the infrastructures, but also the psychological readiness and mistrust of the learners who are enjoying with the such innovations. Out of the domestic setting, this work offers a prototype that can be used on the international level. With the implementation of AI-based platforms in universities across the globe, the problem is how to make sure that technological efficacy does not nullify the human aspects of curiosity, empathy, and moral reasoning. The current findings show that gamified AI systems, which are developed according to the values, have the potential to improve, but not undermine the human spirit of learning. It is a rather interesting example of how values of discipline and effort as a collectivist tradition can be combined with the spirit of independence of digital learning and implies a hybrid paradigm that will connect Eastern and Western approaches to education.

The study does not ignore its temporal and methodological limitations even though it has been successful. Long-term changes of motivational states cannot be studied in a cross-sectional snapshot, longitudinal and experimental designs are required to confirm the causes-effect directions. Moreover, self-report measures were not limited in terms of the amount of psychological information, but the combination of behavioral logs, biometric data and discourse analysis could provide more objective measures of engagement. Nevertheless, the rigor of the methods, i.e., the application of the validated tools, valid statistical tests, and ethical issues, is assured to ensure that the inferences made are plausible and theoretically relevant.

In effect, this paper has demonstrated that learning is not in the future solely in human intelligence or the artificial computation, but in the symbiotic co-evolution of these two bodies. Gamified AI interaction unites the affective, cognitive and technological with the educative process in a consistent ecosystem in which self-control and thinking are fueled by motivation and trust in AI makes one always attentive. This paradigm transforms the vision of learning in the twenty first century: no person disseminates knowledge to another but rather it is also created in the process of dynamic interaction of human will and algorithmic responsiveness. This makes the pedagogical horizon become mechanized teaching to intelligent collaboration a form in which imagination, independence and reflection are brought to bear and not to a mechanized level.

As the world is changing towards the general application of AI, both educators and policymakers must remember that technology is most practical when it promotes the human desire to learn. The learning of this paper in the long run is that sustainability of education changes is a process where artificial intelligence is employed to serve the will of human being in other words systems are not created to merely maximize performance, but to promote development, health, and meaning. The combination of the gamification, motivation and self-regulation that is offered below offers a roadmap to such. The culture of learning that cannot be called effective only, but extremely human may be established by the partnership between the human and the intelligent machines through attentive design, ethical consideration, and reflection.

REFERENCES

AlBadarin, Y., Tukiainen, M., Saqr, M., & Pope, N. (2023). A Systematic Literature Review of Empirical Research on ChatGPT in Education. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.4562771

Al-Rousan, A. H., Ayasrah, M. N., Khasawneh, M. A. S., Obeidat, L. M., & Obeidat, S. S. (2025). AI-Enhanced Gamification in Education: Developing and Validating a Scale for Measuring Engagement and Motivation Among Secondary School Students: Insights From the Network Analysis Perspective. *European Journal of Education*, *60*(3), e70153. https://doi.org/10.1111/EJED.70153

Badali, M., Hatami, J., Banihashem, S. K., Rahimi, E., Noroozi, O., & Eslami, Z. (2022). The role of motivation in MOOCs' retention rates: a systematic literature review. *Research and Practice in Technology Enhanced Learning*, *17*(1), 1–20. https://doi.org/10.1186/S41039-022-00181-3/FIGURES/4

Bai, Y., & Wang, S. (2025). Impact of generative AI interaction and output quality on university students' learning outcomes: a technology-mediated and motivation-driven approach. *Scientific Reports 2025 15:1*, *15*(1), 1–16. https://doi.org/10.1038/s41598-025-08697-6

Baroncelli, A., Ermelinda De Carlo, M., Shi, J., Liu, W., & Hu, K. (2025). Exploring How AI Literacy and Self-Regulated Learning Relate to Student Writing Performance and Well-Being in Generative AI-Supported Higher Education. *Behavioral Sciences 2025, Vol. 15, Page 705*, *15*(5), 705. https://doi.org/10.3390/BS15050705

Belle, L. J. (2024). Remote Online Collaborative Learning for Knowledge Co-Creation Through WhatsApp in an ODL Programme. *Futurity Education*, *4*(2), 106–124. https://doi.org/10.57125/FED.2024.06.25.06

Cao, S., & Phongsatha, S. (2025). An empirical study of the AI-driven platform in blended learning for Business English performance and student engagement. *Language Testing in Asia 2025 15:1*, *15*(1), 1–28. https://doi.org/10.1186/S40468-025-00376-7

Coelho, F., Rando, B., Aparício, D., Pontífice-Sousa, P., Gonçalves, D., & Abreu, A. M. (2025). The impact of educational gamification on cognition, emotions, and motivation: a randomized controlled trial. *Journal of Computers in Education 2025*, 1–48. https://doi.org/10.1007/S40692-025-00366-X

Gómez Niño, J. R., Árias Delgado, L. P., Chiappe, A., & Ortega González, E. (2025a). Gamifying Learning with AI: A Pathway to 21st-Century Skills. *Journal of Research in Childhood Education*, *39*(4), 735–750. https://doi.org/10.1080/02568543.2024.2421974;CTYPE:STRING:JOURNAL

Gómez Niño, J. R., Árias Delgado, L. P., Chiappe, A., & Ortega González, E. (2025b). Gamifying Learning with AI: A Pathway to 21st-Century Skills. *Journal of Research in Childhood Education*, *39*(4), 735–750. https://doi.org/10.1080/02568543.2024.2421974;CTYPE:STRING:JOURNAL

Inuwa, A. U., Sulaiman, S., & Samsudin, R. (2025). Systematic Literature Review on Artificial Intelligence-Driven Personalized Learning. *International Journal of Advanced Computer Science & Applications*, *16*(6), 364. https://doi.org/10.14569/IJACSA.2025.0160636

Jiang, X., Wang, R., Hoang, T., Ranaweera, C., Dong, C., & Myers, T. (2025). AI-Powered Gamified Scaffolding:

Transforming Learning in Virtual Learning Environment. *Electronics 2025, Vol. 14, Page 2732*, *14*(13), 2732. https://doi.org/10.3390/ELECTRONICS14132732

Khoso, A. K., Honggang, W., & Darazi, M. A. (2025). Empowering creativity and engagement: The impact of generative artificial intelligence usage on Chines EFL students' language learning experience. *Computers in Human Behavior Reports*, *18*, 100627. https://doi.org/10.1016/J.CHBR.2025.100627

Kong, X., Fang, H., Chen, W., Xiao, J., & Zhang, M. (2025). Examining human–AI collaboration in hybrid intelligence learning environments: insight from the Synergy Degree Model. *Humanities and Social Sciences Communications 2025 12:1*, *12*(1), 1–14. https://doi.org/10.1057/s41599-025-05097-z

Kovari, A. (2025). A systematic review of AI-powered collaborative learning in higher education: Trends and outcomes from the last decade. *Social Sciences & Humanities Open*, *11*, 101335. https://doi.org/10.1016/J.SSAHO.2025.101335

Lan, M., & Zhou, X. (2025). A qualitative systematic review on AI empowered self-regulated learning in higher education. *NPJ Science of Learning*, *10*(1), 21. https://doi.org/10.1038/S41539-025-00319-0

Li, L., Chen, S., Tang, P., Lv, K., Li, P., & Xu, Y. (2025). Unlocking Deep Learning: How Self-Regulated Learning Shapes Chinese Students' Online Course Experiences. *SAGE Open*, *15*(3). https://doi.org/10.1177/21582440251365390

Luo, J. (2024). Validating the impact of gamified technology-enhanced learning environments on motivation and academic performance: enhancing TELEs with digital badges. *Frontiers in Education*, *9*, 1429452. https://doi.org/10.3389/FEDUC.2024.1429452/BIBTEX

Ma, Y., & Chen, M. (2025). The human touch in AI: optimizing language learning through self-determination theory and teacher scaffolding. *Frontiers in Psychology*, *16*, 1568239. https://doi.org/10.3389/FPSYG.2025.1568239

Nguyen, A. (2025). Human-AI Shared Regulation for Hybrid Intelligence in Learning and Teaching: Conceptual Domain, Ontological Foundations, Propositions, and Implications for Research. *3632ec95-Ac5a-40c7-Ae9d-2c3672b8ac80*, 34–43. https://doi.org/10.24251/HICSS.2025.006

Peng, J., & Li, Y. (2025). Frontiers of Artificial Intelligence for Personalized Learning in Higher Education: A Systematic Review of Leading Articles. *Applied Sciences 2025, Vol. 15, Page 10096*, *15*(18), 10096. https://doi.org/10.3390/APP151810096

Wang, Q., Amini, M., & Fu, Z. (2025). AI acceptance and Chinese EFL learners' behavioral engagement with mediating effects of motivation. *Scientific Reports 2025 15:1*, *15*(1), 1–13. https://doi.org/10.1038/s41598-025-11305-2

Yang, K., Menchaca, E., & Esquivel Lizarraga, B. (2024). An Empirical Evaluation of the Current State of Phishing Comprehension in Pakistan. *Proceedings of the 57th Hawaii International Conference on System Sciences*, 4838–4847. https://hdl.handle.net/10125/107306

Zhang, Z. (2025). The Role of Artificial Intelligence Tools on Chinese EFL Learners' Self-Regulation, Resilience and Autonomy. *European Journal of Education*, *60*(2), e70127. https://doi.org/10.1111/EJED.70127;WGROUP:STRING:PUBLICATION

Zhang, Z., Sun, B., & An, P. (2025). Breaking Barriers or Building Dependency? Exploring Team-LLM Collaboration in AI-infused Classroom Debate. *Conference on Human Factors in Computing Systems - Proceedings* . https://doi.org/10.1145/3706598.3713853;ISSUE:ISSUE:DOI

Zhao, Y., Li, Y., Sun, Z. H., Jiang, Q., & Zhao, S. (2024). Variations in online self-regulated learning abilities among Chinese K-12 teachers across different regions and levels. *Frontiers in Psychology*, *15*, 1463287. https://doi.org/10.3389/FPSYG.2024.1463287/BIBTEX

Zhu, G., Sudarshan, V., Kow, J. F., & Ong, Y. S. (2024). Human-Generative AI Collaborative Problem Solving Who Leads and How Students Perceive the Interactions. *Proceedings - 2024 IEEE Conference on Artificial Intelligence, CAI 2024*, 680–686. https://doi.org/10.1109/CAI59869.2024.00133