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Original Paper

Exploration of the Relationship between College Youth's Willingness to Use Large Models and their Behavior: Based on the Mediating Effect of Human-Computer Trust

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Abstract

As technology advances quickly, large language models are growing fast. College students, who are used to digital tools, use these models more and more, but there are still trust problems.

This study used both surveys and interviews. It built a research model based on human-computer trust theory and the SIRAM model to find out what affects college students' willingness to use these models, and how trust plays a middle role.

Using SPSS 26.0 and AMOS 26.0 to analyze survey data, we found that cognitive and emotional trust greatly influence usage intention. Factors like usefulness, enjoyment, sociability, and adaptability also affect intention through trust. Interviews looked at how students use the models, trust issues, and ways to build trust, helping improve human-computer relationships.

Keywords

large models, human-computer trust, SIRAM model, trust crisis

1. Introduction: Human-Computer Trust in the Era of Large Models

Amid rapid technological advancement, large language models (LLMs) like ChatGPT and Wenxin Yiyan have surged, with open-source models from DeepSeek driving innovation. These text-pre-trained deep learning models propel AI from perception to creation, profoundly impacting society and economy.

As digital-era pioneers, college youth widely use LLMs, altering their learning and life while facing higher digital literacy demands. China regulates such applications via policies like the Interim Measures for the Administration of Generative Artificial Intelligence Services, focusing on ideology and academic fairness in universities.

Yet LLMs bring both opportunities and challenges, with prominent human-machine trust crises: questionable information accuracy, value coordination complexities, and technical stability concerns, threatening youth's cognition and development. Studying trust mechanisms from a journalism and communication perspective holds significant theoretical and practical value, forming the research background. Against this backdrop, this study proposes the following research questions to guide in-depth exploration:

Research Question 1

Does the dimension of human-machine trust exhibit a mediating or moderating effect in the decision-making process of youth groups regarding LLM technology use?

Research Question 2

What is the current status of university youth's LLM usage? What trends are presented by the current human-machine trust crisis?

Research Question 3

What implications can the factor of trust bring to the design and development of future AI products? In what direction will future human-machine trust relationships evolve in the LLM era?

2. Literature Review and Theoretical Origin

2.1 The Intertwined Context of Large Models and Human-Computer Trust

Large models, as key AI technologies, have drawn wide attention. With growing autonomy, they've shifted from "imitating human thinking" to "human-like thinking" (Zhang & Ren, 2023), but this has also brought a trust crisis.

Scholars note AI trust is often analyzed through cognitive (perceptions of reliability, ability) and emotional (from interaction resonance) trust (Johnson & Grayson, 2005; Cai & Law, 2022). Existing studies on LLM trustworthiness mainly focus on the models themselves (Sun, Huang, Wang et al., 2024; Alghamdi, Masoud, Alnahit et al., 2024; Hong, Duan, Zhang et al., 2024; Wu & Sun, 2023), while fewer explore college youth's acceptance of large models from human-machine communication and trust perspectives, making such exploration valuable.

2.2 SIRAM Model

Traditional models like TAM and UTAUT, though widely used to study user behavioral intention, are less suitable for new AI acceptance research due to AI's human-like thinking (Lu, Cai, & Gursoy, 2019).

The Socially Interactive Robots Acceptance Model (SIRAM), built by integrating UTAUT and TAM (Shin & Choo, 2011), focuses on factors influencing the acceptance of socially interactive robots, including perceived usefulness, enjoyment, sociability, adaptivity, and social presence. It's more fitting for AI acceptance research as it incorporates traits of socially interactive robots.

Given modern large language models have human-like attributes and rich "human-oriented" value (Chen, 2024), this study adopts the SIRAM model, taking perceived usefulness, enjoyment, sociability, and adaptivity as independent variables, cognitive and emotional trust as mediators, and usage intention as the dependent variable.

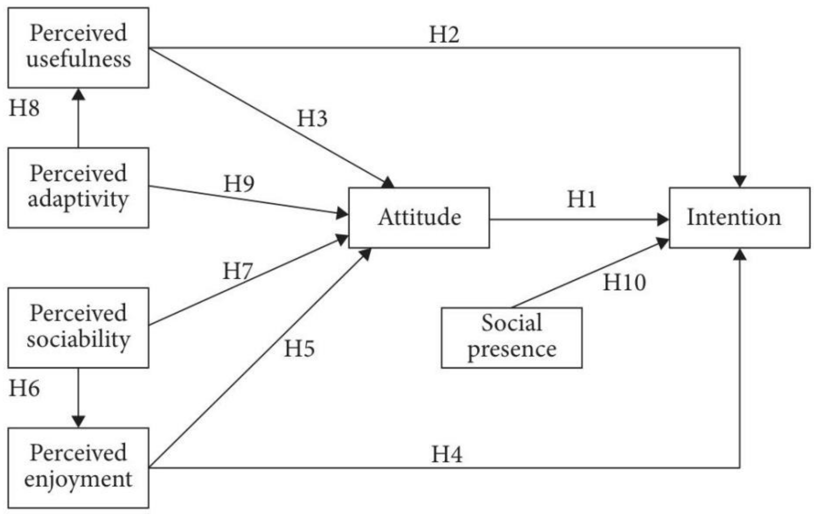


Figure 1. The SIRAM Model

3. Research Design

3.1 Research Hypotheses

Drawing on literature and theories, this study develops a model with the following hypotheses:

H1: College youth's cognitive trust in large models positively impacts usage intention.

H2: Their emotional trust in large models positively impacts usage intention.

(Shi et al. (Shi, Gong, & Gursoy, 2021) found cognitive and emotional trust significantly influence AI adoption willingness)

H3: Perceived usefulness positively affects usage intention.

H4: Perceived usefulness positively affects cognitive trust.

H5: Perceived usefulness positively affects emotional trust.

(Yoon et al. (Yoon & Rolland, 2015) confirmed perceived usefulness impacts usage intention; Zhou (Zhou, Tang, & Xiao, 2021) and Geng (2021) linked it to cognitive/emotional trust)

H6: Perceived enjoyment positively affects usage intention.

H7: Perceived enjoyment positively affects cognitive trust.

H8: Perceived enjoyment positively affects emotional trust.

(Cheng and Le (2018) and Lawson (Lawson, Mayer, Adamo-Villani et al., 2021) showed perceived enjoyment influences trust)

H9: Perceived sociability positively affects usage intention.

H10: Perceived sociability positively affects cognitive trust.

H11: Perceived sociability positively affects emotional trust.

(Junglas et al. (Junglas, Goel, Abraham et al., 2013) noted perceived sociability boosts usage intention; Chen et al. (Chen & Zhang, 2023) linked human-like interaction to trust)

H12: Perceived adaptability positively affects usage intention.

H13: Perceived adaptability positively affects cognitive trust.

H14: Perceived adaptability positively affects emotional trust.

(Young et al. (Young, Hawkins, Sharlin, & Igarashi, 2009) highlighted user expectations for adaptability; Schneider (Schneider & Kummert, 2021) found adaptability enhances trust)

H15a-d: Cognitive trust mediates the relationships between (a) perceived usefulness, (b) enjoyment, (c) sociability, (d) adaptability and usage intention.

H16a-d: Emotional trust mediates the relationships between (a) perceived usefulness, (b) enjoyment, (c) sociability, (d) adaptability and usage intention.

(Xu and Liu (2021) identified trust as a key mediator in new technology acceptance)

These hypotheses form the theoretical model of college youth's willingness to use large models.

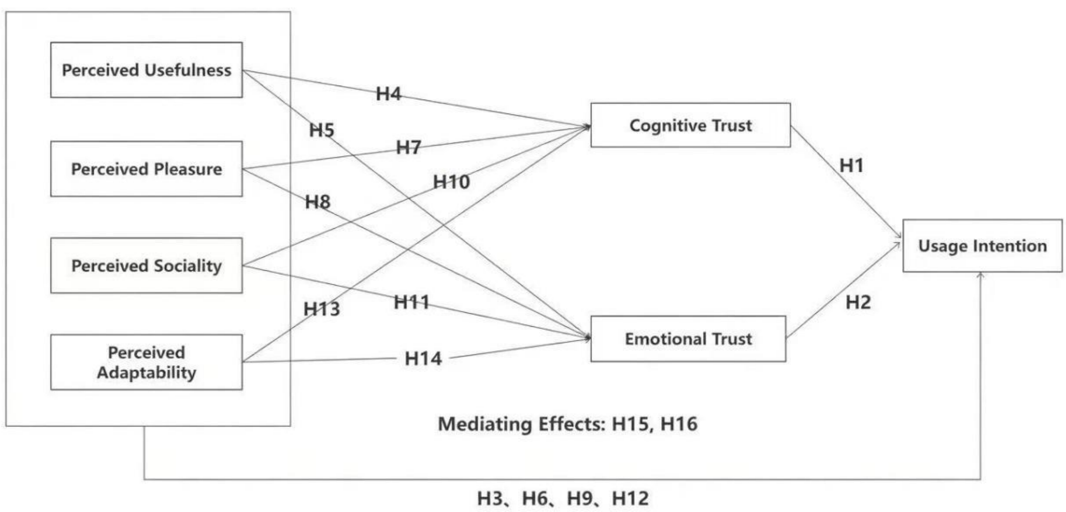


Figure 2. Theoretical Model of University Youth Groups' Intention to Use Large Language Models

3.2 Questionnaire Design and Data Collection

The scales used in this study are all derived from mature scales. Combined with the research scenario of large models, each variable is operationally defined, and a 5-point Likert scale is adopted for scoring.

There are 447 valid questionnaires in the end, with an effective rate of 86.3%.SPSS 26.0 is used to process and analyze the data to verify the model and hypotheses of this study.

After analyzing the questionnaire data, some respondents are selected for in-depth interviews to supplement and explain the questionnaire results.

4. Research Findings and Conclusions

4.1 Reliability and Validity Test of the Scale

This study first used SPSS 26.0 for reliability and validity tests. Reliability was assessed via latent variables' Cronbach's α and composite reliability. All Cronbach's α values (0.873-0.928) exceeded 0.7,indicating high questionnaire consistency and good internal structure, suitable for analysis and empirical tests.

Table 3. Results of Cronbach's α Reliability Analysis for the Overall Sample

Cronbach's Alpha	Number of Items
0.878	23

Table 4. Reliability Statistics of the Scale

Variable	Item	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	Cronbach's α
Perceived Usefulness	PU1	0.766	0.852	0.886
	PU2	0.687	0.871	
	PU3	0.69	0.87	
	PU4	0.774	0.852	
	PU5	0.727	0.864	
Perceived Enjoyment	PE1	0.757	0.793	0.863
	PE2	0.734	0.814	
	PE3	0.731	0.818	
Perceived Sociality	PS1	0.716	0.738	0.83
	PS2	0.751	0.702	
	PS3	0.605	0.844	

Perceived Adaptability	PA1	0.78	0.839	0.887
	PA2	0.762	0.854	
	PA3	0.796	0.824	
Intention to Use	IT1	0.694	0.791	0.841
	IT2	0.706	0.778	
	IT3	0.717	0.769	
Cognitive Trust	CT1	0.755	0.773	0.856
	CT2	0.717	0.81	
	CT3	0.716	0.81	
Emotional Trust	ET1	0.798	0.835	0.891
	ET2	0.759	0.869	
	ET3	0.804	0.83	

Additionally, KMO and Bartlett's sphericity tests were performed on scale items to determine suitability for factor analysis (KMO>0.7 and p<0.05). This study yielded a KMO value of 0.914 and Bartlett's test p-value of 0.001,confirming good validity and suitability for factor analysis.

Table 5. KMO and Bartlett's Test Table

KMO		0.914
Bartlett's Test of Sphericity	Approximate Chi-Square	4679.589
	df	247
	P-value	0.000

4.2 Correlation Analysis of Research Variables

This study first used SPSS 26.0 for reliability and validity tests. Reliability was assessed via latent variables' Cronbach's α and composite reliability. All Cronbach's α values (0.873-0.928) exceeded 0.7,indicating high questionnaire consistency and good internal structure, suitable for analysis and empirical tests.

Table 6. Pearson Correlation Analysis Results among Various Dimensions

Dimension	PU	PE	PS	PA	ET	CT	IT
PU	1						
PE	.465**	1					
PS	.245**	.439**	1				
PA	.486**	.441**	.368**	1			

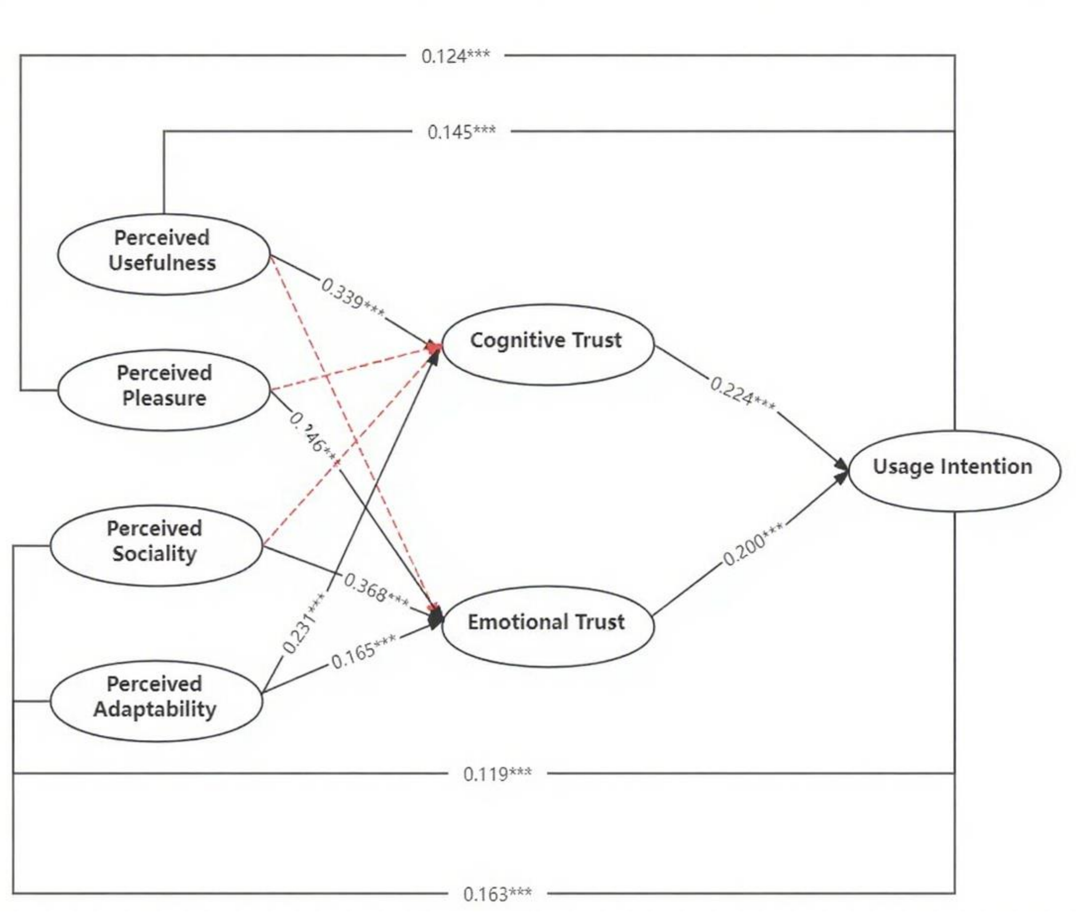
ET	.319**	.456**	.436**	.413**	1		
CT	.487**	.367**	.315**	.465**	.427**	1	
IT	.473**	.478**	.416**	.519**	.574**	.526**	1

**Significant correlation at the 0.01 level(two-tailed).

Data in Table 6 shows all seven variables had significance levels below 0.01, indicating significant positive correlations, preliminarily validating the hypotheses.

4.3 Structural Equation Model Test

Aiming at the research hypotheses put forward above, this study uses AMOS 26.0 software for hypothesis testing. The structural equation model diagram is shown in the figure:



Most of the fit indices of the structural equation of this study are ideally fitted, and the model hypothesis test can be further carried out.

Table 7. Parameter Estimation Table of the Confirmatory Factor Analysis Model for the Research Model

Statistical Test Index Evaluation Indicators		Adapted Standards or Critical Values	Test Result Data
Absolute Fit Index	CMIN/DF Value	Between 1-3	1.82
	square(X^2)Value	P>0.05(Not reaching a significant level)	0
	RMR Value	<0.08	0.05
	RMSEA Value	<0.08	0.05
Incremental Fit Index	IFI	>0.90	0.95
	TLI	>0.90	0.94
	NFI	>0.90	0.9
Parsimonious Fit Index	PGFI	>0.50	0.71
	PNFI	>0.50	0.77

4.4 Model Analysis and Hypothesis Testing

Hypothesis verification results:

Table 8. Summary Table of Model Path Hypothesis Test Results

Path Relationship	Standardized Estimate	S.E.	C.R.	P	Hypothesis	Supported or Not
Cognitive Trust→Usage Intention	0.224	0.061	3.647	***	H1	Supported
Affective Trust→Usage Intention	0.2	0.059	3.392	***	H2	Supported
Perceived Usefulness→Usage Intention	0.145	0.057	2.55	0.011	H3	Supported
Perceived Usefulness→Cognitive Trust	0.339	0.064	5.009	***	H4	Supported
Perceived Usefulness→Affective Trust	0.078	0.061	1.284	0.199	H5	Not Supported
Perceived Enjoyment→Usage Intention	0.124	0.06	2.061	0.039	H6	Supported
Perceived Enjoyment→Cognitive Trust	0.114	0.069	1.652	0.099	H7	Not Supported
Perceived Enjoyment→Affective Trust	0.246	0.068	3.635	***	H8	Supported

Perceived Sociality→Usage Intention	0.163	0.081	2.028	0.043	H9	Supported
Perceived Sociality→Cognitive Trust	0.175	0.091	1.918	0.055	H10	Not Supported
Perceived Sociality→Affective Trust	0.368	0.091	4.031	***	H11	Supported
Perceived Adaptability→Usage Intention	0.119	0.057	2.105	0.035	H12	Supported
Perceived Adaptability→Cognitive Trust	0.231	0.065	3.535	***	H13	Supported
Perceived Adaptability→Affective Trust	0.165	0.063	2.63	0.009	H14	Supported

4.5 Mediating Effect Analysis

This study used AMOS 26.0's Bootstrap method to test cognitive and emotional trust as mediators between perceived factors (usefulness, enjoyment, sociability, adaptability) and behavioral intention: cognitive trust mediated perceived usefulness (95%CI [0.022,0.134], $p<0.05$) and adaptability (95%CI [0.010,0.109], $p<0.05$)→H15a, H15d supported; it did not mediate enjoyment (CI[-0.014,0.083]) or sociability (CI[-0.008,0.105])→H15b, H15c not supported; emotional trust mediated enjoyment (CI[0.010,0.106]), sociability (CI[0.018,0.152]), and adaptability (CI[0.001,0.081], all $p<0.05$)→H16b, H16c, H16d supported; it did not mediate usefulness (CI[-0.013,0.050])→H16a not supported.

Table 9. Results of Standardized Bootstrapping Mediation Effect Tests

Hypothesis	Hypothesized Path	Estimate	SE	Lower	Upper	P	Test Result
H15a	Perceived Usefulness→Cognitive Trust→Usage Intention	0.072	0.028	0.022	0.134	0.003	Supported
H15b	Perceived Enjoyment→Cognitive Trust→Usage Intention	0.026	0.024	-0.014	0.083	0.216	Not Supported
H15c	Perceived Sociality→Cognitive Trust→Usage Intention	0.039	0.029	-0.008	0.105	0.096	Not Supported
H15d	Perceived Adaptability→Cognitive Trust→Usage Intention	0.052	0.025	0.01	0.109	0.006	Supported
H16a	Perceived	0.016	0.016	-0.013	0.05	0.272	Not

	Usefulness→Affective Trust→Usage Intention						Supported
H16b	Perceived Enjoyment→Affective Trust→Usage Intention	0.049	0.025	0.01	0.106	0.009	Supported
H16c	Perceived Sociality→Affective Trust→Usage Intention	0.074	0.035	0.018	0.152	0.006	Supported
H16d	Perceived Adaptability→Affective Trust→Usage Intention	0.033	0.021	0.001	0.081	0.039	Supported

Empirical results: Cognitive and emotional trust directly impact college youth's usage intention. Perceived usefulness affects usage intention and cognitive trust (not emotional trust); enjoyment and sociability affect usage intention and emotional trust (not cognitive trust); adaptability impacts all three. Cognitive trust mediates usefulness, adaptability and usage intention (not enjoyment, sociability); emotional trust mediates enjoyment, sociability, adaptability and usage intention (not usefulness). Interviews supplemented quantitative findings.

4.6 Analysis of the Current Situation of College Youth Using Large Models

Trained on massive text, large models aid college students across fields. Most use them to boost learning efficiency, with trust in capabilities correlating to usage willingness.F2 cited their comprehensive functions; F4 noted faster material organization for economics assignments; M8 called them a "knowledge treasure trove" for interdisciplinary insights. F1 found combined use of models like DeepSeek and Wenxin Yiyan enhances reliability and trust.

Human-like interaction fosters emotional trust, boosting usage intent.M9 tried ChatGPT out of curiosity, impressed by its speed and accuracy. F3 felt its warmth: "It comforted me when I was down". F5 said, "It feels like chatting with a real person—I get emotionally invested".

Yet trust crises exist: M9 encountered historical timeline errors (hallucinations); M10 criticized utilitarian ethical views (value bias); F3 faced crashes (technical instability). Privacy concerns also erode trust.

To build long-term trust, students need better digital literacy; developers must reduce errors, calibrate values, and ensure security. Large models are tools—harmonious human-machine coexistence requires collaboration.

5. Conclusion

This study adopts a combined qualitative and quantitative research method, constructing an empirical model based on the human-computer trust theory and the SIRAM model to explore the driving factors influencing college youth's willingness and behavior to use large models, as well as the mediating effect of trust dimensions. Data were collected through questionnaires and analyzed using SPSS 26.0 and AMOS 26.0.It was found that cognitive trust and emotional trust significantly affect college youth's intention to use large models, while factors such as perceived usefulness, enjoyment, sociability, and adaptability indirectly influence usage intention by acting on trust. Additionally, through in-depth interviews, this study analyzed the current situation of college youth's use of large models, providing theoretical and practical references for optimizing the application of large models and building harmonious human-computer trust relationships.

Large models, as tools to assist humans in exploring the world and creating value, cannot replace human thinking and creativity. As the backbone of future social development, college youth should maintain a rational attitude when using large models, give full play to their subjective initiative, carefully identify and reasonably use the content generated by the models. Only by achieving collaborative cooperation with large models—utilizing their powerful computing and generation capabilities to expand cognitive boundaries while relying on one's own wisdom to ensure the accuracy of information and the correctness of value orientation—can a good human-computer relationship be gradually established, moving towards a harmonious future of human-machine coexistence.

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