

Unpacking AI Adoption in Health Management: A PLS-SEM Analysis

Qianyu Luo

*College of Health Management, Shanghai Jian Qiao University, Shanghai, China
lqy_1313@126.com*

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Abstract: This research examines how three key aspects of ChatGPT – explainability, perceived ease of use, and technical trust – shape user health management practices, focusing on the role of perceived ease of use. We analyze the survey data from 106 health and social work professionals in China using PLS-SEM. The findings reveal that ChatGPT’s clarity enhances both technical trust and perceived ease of use, while technical trust further strengthens perceived ease of use, directly improving health management practices. Moreover, perceived ease of use mediates the effects of explainability and technical trust on health behaviors, with confidence and ease of use forming a chain mediation between explainability and health management. Our research extends the theoretical framework for ChatGPT’s application in health management and provides practical implementation insights.

1. Introduction

Generative Pre-trained Transformers (GPTs) represent a class of advanced AI systems capable of understanding and generating complex, long-form content. ChatGPT, developed by OpenAI, is a large language model built on the GPT architecture that enables human-like conversational interactions in real-time. ChatGPT has been proved to enhance various applications. In healthcare, ChatGPT can generate explanatory text to improve patient communication and support clinical decision-making, and supplement conventional care by aiding treatment adherence and offering scalable support, thereby contributing to well-being and reducing the burden on traditional care systems^[1]. Against this backdrop, we examine the mechanisms – specifically, explainability, technical trust, and perceived ease of use – that underpin the effective integration of ChatGPT into health management behaviors.

AI systems with complex algorithms often lack transparency, creating a “black-box” problem that makes their decisions difficult to explain and can lead to erroneous outputs in critical settings like healthcare, where explainability is essential^[2]. Specially, we use “explainability” rather than “interpretability” because it emphasizes users’ subjective comprehension over objective model transparency. Therefore, their use in medicine requires cautious, ethical, and validated application to ensure safety^[3]. Improving explainability is thus key to the responsible integration of AI. Concurrently, technical trust, defined as a user’s willingness to rely on a technology based on its

perceived reliability and value, is especially nuanced in healthcare^[4]. In our model, technical trust is therefore positioned as the critical mediator that channels ChatGPT's explainability into a stronger perception of ease of use, thereby encouraging positive health management behaviors.

This study develops and validates a conceptual model that explains the psychological mechanisms behind adopting ChatGPT for health management. The model proposes a sequential pathway wherein ChatGPT's explainability builds technical trust, which then increases perceived ease of use, ultimately driving health management behaviors. These relationships were tested using a questionnaire survey analyzed via PLS-SEM. The research contributes a novel sequential mediation model, offering a refined understanding of how AI explainability translates into behavioral intention. It also provides actionable insights, demonstrating that enhancing explainability is a fundamental prerequisite for building trust and usability, which are critical for the successful integration of AI tools like ChatGPT into personal healthcare.

2. Assumptions

2.1. Explainability and Technical Trust

Trust in advanced technologies like ChatGPT is not established solely through performance accuracy but also requires an understanding of their internal reasoning. This is especially critical in high-stakes fields like medicine, where clinicians must evaluate multiple factors before making final decisions. Consequently, reliance on a system that provides accurate but unexplained outputs is inadequate. Recent studies have linked explainability with trust^[2,5]. Therefore, interpretability serves as a fundamental antecedent to trust. We test the following hypothesis:

H1: ChatGPT's explainability has positive effect on its technical trust.

2.2. Explainability and Perceived Ease of Use

Rooted in the established Technology Acceptance Model, which posits perceived usefulness and ease of use as fundamental determinants of user adoption, recent researches extend these principles to human-AI interactions^[6]. In critical decision-making contexts, fostering user engagement depends significantly on the system's clarity and comprehensibility. Explainable AI addresses this by making an algorithm's processes transparent, thereby helping users understand its functionality and build appropriate trust. This enhanced understanding directly improves the user experience, making the technology more intuitive and manageable. Consequently, we hypothesize that:

H2: ChatGPT's explainability positively affects its perceived ease of use.

2.3. Technical Trust and Perceived Ease of Use

Perceived ease of use (PEOU) is a core determinant of technology adoption. In the context of AI systems, this perception is shaped not only by interface design but also by users' underlying trust in the technology itself. The Elaboration Likelihood Model indicates that the trust in technology itself is a central-route belief, formed through deliberate evaluation of its capabilities, or through the route where behavioral beliefs and attitudes are fostered by strong cognitive effects^[7]. Once established, this technical trust reduces the cognitive load required for subsequent interactions and thereby enhancing the perception that the system is easy to use. Thus, we propose that trust in IT (a central, high-cognition belief) will partially mediate the effect of trust in IT support (a peripheral, low-cognition belief) on PEOU. These lead to the following hypotheses:

H3: ChatGPT's technical trust positively affects perceived ease of use.

H4: ChatGPT's technical trust mediates the relationship between explainability and perceived

ease of use.

2.4. Perceived Ease of Use and Health Management Behavior

ChatGPT's inclusion in medical self-service tools has greatly encouraged users' good health practices. Grounded in established technology acceptance literature, PEOU is a well-recognized antecedent to the adoption of self-service technologies, and it significantly influences usage intention and behavior^[8]. Based on the conceptual model illustrated in Figure 1, we propose that the PEOU of ChatGPT is the key mechanism linking its technological attributes to health management outcomes, and users' perception of ChatGPT as effortless to interact with is hypothesized to directly promote engagement in health management behaviors. Furthermore, PEOU is also posited to mediate the effects of explainability and trust in its technology on health management behavior. Finally, a sequential mediation pathway is also proposed, wherein explainability fosters technical trust, which in turn enhances perceived ease of use, ultimately leading to improved health management. On these bases, we suggest:

H5: ChatGPT's perceived ease of use positively affects health management behavior.

H6: ChatGPT's perceived ease of use mediates the effect of explainability on health management behavior.

H7: ChatGPT's perceived ease of use mediates the effect of technical trust on health management behavior.

H8: ChatGPT's explainability affects health management behavior sequentially through technical trust and perceived ease of use.

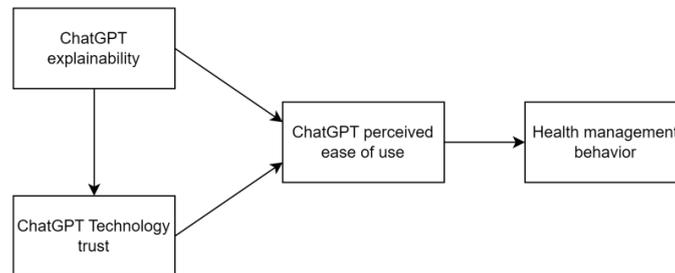


Figure 1: Conceptual framework.

3. Study Design and Data

Based on the assumptions, we investigate how ChatGPT's perceived ease of use directly and indirectly affects health management practices. Specifically, we conducted an online survey targeted at Chinese health and social work professionals via Credamo platform. The poll was restricted to those who have utilized ChatGPT for medical services to ensure the sample's representativeness. Questions about participants' knowledge of ChatGPT and experience of health services were included in the questionnaire, and respondents who cannot fit these requirements were excluded. Specific IP address limits were put in place to reduce sample bias, which set up a predetermined interval for survey dissemination within a specific duration and banned multiple replies from the same IP address. Concepts including explainability and technical trust, perceived ease of use, and health management are all incorporated into the questionnaire items (see Appendix). Experts in the domains of artificial intelligence and health examined the questionnaire to improve its validity. The last survey was conducted in August 2024. A 36% response rate was obtained from the 360 completed and returned surveys out of the 1,000 sent. After removing invalid replies, 106 valid questionnaires were kept, producing an effective response rate of 10.6%. Table 1 lists the

main sample demographic features. We use the method of partial least squares for structural equation modelling. Data analysis is conducted via SPSS Statistics 24.0 and SmartPLS 4.0.

Table 1: Key demographic features of the sample.

Demographic Features	N = 106	Percentage (%)
Gender		
Female	83	78.3
Male	23	21.7
Education		
Master degree or above	15	14.2
Bachelor degree	72	67.9
College degree	15	14.2
High school or below	4	3.8
Age		
18-25	41	38.7
26-35	42	39.6
36-45	12	11.3
Above 45	11	10.4
Annual income		
Above 20k	7	6.6
120k-200k	24	22.6
60k-120k	51	48.1
Below 60k	24	22.6
Married or not		
Yes	55	51.9
No	51	48.1

4. Main Results

4.1. Measurement Model Assessment

We first assess the internal consistency and dependability using Cronbach's alpha (α) and composite reliability (CR). From Table 2, all α and CR values range from 0.723 to 0.898, exceeding the recommended threshold of 0.7, thus demonstrating adequate reliability^[9]. For testing convergent validity, we evaluate based on outer loadings and the average variance extracted (AVE). From Table 2, all outer loadings are above 0.65 and all AVE values are above 0.5, both surpassing the benchmarks, thus confirming satisfactory convergent validity^[10].

Table 2: Measurement model assessment.

Constructs	Items	External Loadings	VIF	Cronbach's Alpha	CR	AVE
ChatGPT's explainability (CE)	CE1	0.84	1.73	0.72	0.85	0.65
	CE2	0.73	1.24	-	-	-
	CE3	0.84	1.65	-	-	-
ChatGPT's technical trust (CTT)	CTT1	0.89	2.14	0.83	0.90	0.75
	CTT2	0.82	1.76	-	-	-

	CTT3	0.88	1.96	-	-	-
ChatGPT's perceived ease of use (CPEOU)	CPEOU1	0.76	1.56	0.80	0.87	0.63
	CPEOU2	0.80	1.58	-	-	-
	CPEOU3	0.80	1.64	-	-	-
	CPEOU4	0.81	1.73	-	-	-
Health management behavior (HMB)	HMB1	0.78	1.68	0.78	0.85	0.53
	HMB2	0.82	1.92	-	-	-
	HMB3	0.67	1.41	-	-	-
	HMB4	0.69	1.37	-	-	-
	HMB5	0.66	1.35	-	-	-

4.2. Common Method Bias

The use of surveys as a primary data source raises serious concerns about common method bias (CMB), a phenomenon identified when a single source explains over half of the variance^[11]. In our research, each component's contribution to the total variance stayed below 50%. Furthermore, we exploit the Inflation Factor (VIF) test to evaluate collinearity. Table 2 shows the VIF values for every factor, which are much below the 3.3 criterion. This suggests that common method bias is absent in our framework.

4.3. Discriminant Validity

We then evaluate discriminant validity using the Heterotrait-Monotrait ratio (HTMT) and the Fornell-Larcker criterion. The criteria are satisfied when each diagonal item representing the square root of the average variance extracted (AVE) is greater than the corresponding inter-construct correlation values^[12]. This condition is satisfied as shown in Table 3. Similarly, all HTMT values are below the 0.90 cut-off in Table 4, confirming compliance with HTMT recommendations^[13]. The results from both approaches collectively confirm that all constructs in the framework demonstrate discriminant validity.

Table 3: The Fornell-Larcker test.

	CPEOU	CTT	CE	HMB
CPEOU	0.79	-	-	-
CTT	0.56	0.86	-	-
CE	0.66	0.52	0.80	-
HMB	0.48	0.40	0.54	0.73

Table 4: The HTMT test.

	CPEOU	CTT	CE	HMB
CPEOU	-	-	-	-
CTT	0.68	-	-	-
CE	0.85	0.66	-	-
HMB	0.60	0.50	0.72	-

4.4. Model Fit

The goodness-of-fit indices for the structural model are presented in Table 5. All indices satisfy

their respective ideal thresholds, indicating that the model fits the observed data well. It is noted that when the research objective is hypothesis testing, evaluating a model’s explanatory power takes precedence over fit metrics. Nevertheless, the established model fit provides confidence in the reliability of the estimated relationships between variables.

Table 5: Model fitting index.

Index	Estimated model	Ideal Threshold Value
ChiSqr/df	1.21	< 3
RMSEA	0.04	< 0.08
PGFI	0.64	> 0.50
SRMR	0.06	< 0.08
TLI	0.96	> 0.90
CFI	0.97	> 0.90

4.5. Evaluation of Structural Models

Table 6 summarizes the structural model assessment findings. All eight proposed hypotheses are statistically supported, confirming the overall validity of the research framework. The model delineates a clear mediating pathway: ChatGPT explainability (CE) not only exerts a direct influence on perceived ease of use (CPEOU), but also fosters technical trust (CTT), which in turn enhances perceived ease of use. Ultimately, perceived ease of use serves as the key proximal driver of health management behavior (HMB). The significant path coefficients across all relationships validate the hypotheses, which confirm that users’ perception of ChatGPT as an understandable, trustworthy, and easy-to-use tool collectively encourages the adoption of health management behaviors. This path model is illustrated in Figure 2.

Table 6: Hypothesis testing.

Hypothesis	Path	β	P-values	Results
H1	CE->CTT	0.52	0.000	Yes
H2	CTT->CPEOU	0.30	0.000	Yes
H3	CE->CTT->CPEOU	0.16	0.002	Yes
H4	CE->CPEOU	0.50	0.000	Yes
H5	CPEOU->HMB	0.48	0.000	Yes
H6	CE->CPEOU->HMB	0.24	0.000	Yes
H7	CTT->CPEOU->HMB	0.14	0.002	Yes
H8	CE->CTT->CPEOU->HMB	0.08	0.008	Yes

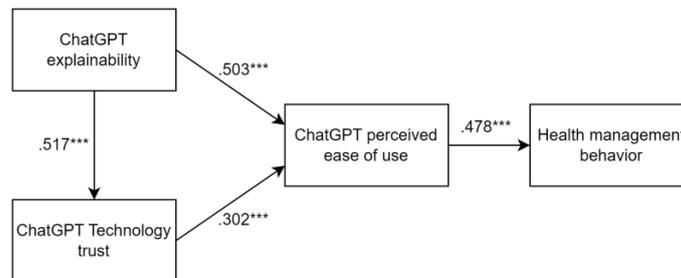


Figure 2: Structural path estimates model.

Note: All path estimates are standardized. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The explanatory and predictive power of the model is summarized in Table 7. The R^2 values indicate moderate explanatory power for CPEOU (0.49), and weak to moderate levels for CTT (0.26) and HMB (0.22). The corresponding Q^2 values are all positive, confirming the model's predictive relevance. Furthermore, we assess the effect sizes and report in Table 8. The results imply that the impact of CTT on HMB (0.30) and on CPEOU (0.13) are notable, while the influence of CPEOU on HMB (0.30) and of CE on CPEOU (0.37) also show substantive effects. Overall, the results support the model's adequacy in both explaining and predicting the endogenous constructs.

Table 7: R-squared and Q-squared values.

Construct	R-square	Q-square
CPEOU	0.49	0.30
GTT	0.26	0.19
HMB	0.22	0.11

Table 8: F-square values.

CTT	HMB	CPEOU
0.37	0.30	0.13
-	-	0.37

5. Conclusion

Based on a PLS-SEM analysis of 106 Chinese health and social work practitioners, this study validates a conceptual model in which ChatGPT's explainability fosters technical trust and perceived ease of use, collectively promoting health management behaviors. The results confirm a sequential mediation pathway, with perceived ease of use as the key proximal driver. This underscores that enhancing explainability is fundamental to building trust and usability, which are critical for ChatGPT's effective integration into healthcare. These findings provide insightful directions for increasing users' health practices through better knowledge and AI tools.

Certain aspects of our study merit further exploration, incorporating perceived usefulness, testing the model in diverse cultural settings, and employing longitudinal designs to establish causal, long-term effects. These avenues are essential for deepening the understanding of AI-enabled health management.

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Appendix

Scale Content

ChatGPT Explainability

1. I find ChatGPT's algorithm easy to understand
2. I think ChatGPT's algorithm is explainable
3. I can figure out ChatGPT's internal mechanism

ChatGPT Technical Trust

1. I trust the recommendations generated by ChatGPT
2. The decision recommendations derived through the ChatGPT algorithm process are trustworthy
3. I believe ChatGPT's results are reliable

ChatGPT Perceived Ease of Use

1. My interaction with ChatGPT is flexible
2. I find it easy to get the GPT system to do what I want it to do
3. It is easy for me to understand the interaction with the GPT system
4. I can easily remember how to perform tasks using the GPT system

Self-health Management Behavior

1. After experiencing the GPT intelligent AI health service, it affects your decision on how to treat the disease
2. After experiencing the GPT intelligent AI health service, it changes your overall view on staying healthy or caring about the health of your relatives and friends
3. After experiencing the GPT intelligent AI health service, it changes your approach to preventing chronic diseases
4. After experiencing the GPT intelligent AI health service, it affects the decision of whether to see a doctor
5. After experiencing the GPT intelligent AI health service, it changes your view on diet, exercise, or stress management