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USER PERCEPTIONS OF THE SECURITY OF PERSONAL HEALTH DATA ON CHATGPT IN INDONESIA

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Abstract. This study aims to explore the relationship between perceptions of data security and privacy, awareness of cyberattacks, and other factors that influence users' trust in ChatGPT and their willingness to provide personal information. Data was collected via a questionnaire and analyzed using SmartPLS. This study examines eight main variables, namely: Privacy Concern (PC), Perceived Effectiveness of Government Regulation (PEGR), Trust in ChatGPT (TR), Moral Motive (MM), Perceived Intelligence (PI), Perceived Risk (PR), Perceived Benefit (PB), and Sharing Willingness (SW). This study tested nine hypotheses regarding the influence of these variables. Data were collected via a questionnaire using a 1–5 Likert scale and analyzed using SmartPLS to test the relationships among constructs using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. The analysis results indicate that four of the proposed hypotheses were supported, with p-values < 0.05, suggesting that the decision to share personal data is significantly influenced by perceived benefits, which are in turn influenced by perceptions of ChatGPT's intelligence and trust in the platform. Perceived Risk does not have a significant impact on Sharing Willingness; however, privacy concerns influence users' perceptions of risk. The results of this study indicate that the benefits of using ChatGPT, significantly influences their willingness to share personal health data. This study suggests that the sample size should be increased to conduct a more in-depth analysis of information-sharing decisions.

Keywords: ChatGPT, Data Privacy Calculus, Health Information, Willingness to Share

I. INTRODUCTION

CHATGPT (Generative Pre-trained Transformer) is one of the generative artificial intelligence (Gen AI) products that is widely used by the public. ChatGPT was launched by OpenAI in November 2022. The number of ChatGPT users reached 100 million within just two months of its release. This indicates that almost everyone with internet access has either used GenAI or knows someone who uses it [1]. ChatGPT has the potential to transform how people work and carry out their daily lives. For example, in the medical field, ChatGPT can be used to answer medical students' exam questions, write basic medical reports, enable patients to obtain better information about their treatment [2], compile summaries of patient discharge reasons based on concise patient profiles, facilitate access to specialized clinical information such as gynecology [3], and provide various other benefits [4].

ChatGPT is designed to mimic human interaction by providing responses to a wide range of user questions or statements, where the model is capable of interpreting and generating coherent and contextually relevant content [5]. Consequently, numerous studies have been conducted to leverage the convenience offered by ChatGPT. These include the development of a ChatGPT-based health consultation chatbot for cancer patients, as well as applications in drug discovery [4]. This healthcare chatbot program has shown promising results in understanding user intent, producing accurate responses, and maintaining readability, making it suitable for use by cancer patients [6]. There are also studies examining the reliability of ChatGPT's responses to questions posed by parents regarding commonly encountered pediatric urological conditions [7]. Although it has certain limitations, the continuously evolving ChatGPT platform is expected to play a significant role in the healthcare industry in the future [7]. The use of ChatGPT in healthcare practice requires sensitive patient information to generate recommendations, such as medication prescriptions [3]. Respondents in studies on the use of ChatGPT in the pharmaceutical field have expressed concerns regarding legal and ethical consequences if ChatGPT violates data privacy [3].

This technology can be likened to a double-edged sword: on one hand, it has the potential to enhance productivity, while on the other hand, it may pose risks such as cyberattack threats. These risks raise concerns about privacy security and user trust in ChatGPT. A data breach involving external entities that unlawfully accessed ChatGPT user conversations occurred in 2023 [1]. Confidential information leakage was also experienced by Samsung when its employees used ChatGPT to create or debug programming code. This activity caused the information to be stored in ChatGPT's data, making it potentially accessible to the public simply by querying it [1], [9]. When users create an account to use ChatGPT services, OpenAI provides a privacy statement indicating that various types of personal information will be collected, including account information, user content, communication information, and social media data. Additionally, OpenAI automatically collects log data, usage data, device information, and cookies. The privacy statement also notes that certain personal data may be shared with third parties, including cloud service providers, online analytics providers, government agencies, and business competitors. This privacy policy does not fully align with personal data protection regulations in some countries, such as the European Union's GDPR, which led to a temporary ban of ChatGPT in Italy [4]. Several other countries, including China, Iran, North Korea, and Russia, have also blocked ChatGPT [9]. These real-world concerns regarding the security of private or confidential data raise critical questions about the security protocols and data storage strategies implemented by ChatGPT [1]. Therefore, it is crucial to establish appropriate and comprehensive regulations for ChatGPT to fully protect patient data privacy and confidentiality, and to prevent the adverse impacts of data privacy breaches (such as those affecting insurance information, employment opportunities, and personal relationships) [3].

This study addresses the following research question: How do privacy concerns, perceptions of government regulatory effectiveness, perceived risk, perceived intelligence of ChatGPT, trust, moral motives, and perceived benefits influence users' willingness to share health information on ChatGPT? The analysis is conducted empirically to ensure objective results. The findings of this study are expected to benefit academics by enriching the body of knowledge for further research on privacy and health data security issues related to ChatGPT users, particularly in Indonesia. It is hoped that broader research will assist organizations and policymakers in designing regulations to enhance personal data protection and public awareness, especially regarding health information.

II. RESEARCH METHODS

A. *Research Instruments*

The research instrument used in this study is a questionnaire. A questionnaire is a form used in surveys, which participants fill out to select answers to the questions provided and provide basic personal or demographic information [13]. The respondents in this study are members of the Indonesian public. This questionnaire contains 21 (twenty-one) statements and 4 (four) demographic questions. All statements will be measured using a Likert scale ranging from 1 to 5. The Likert scale is rated from 1 = strongly disagree to 5 = strongly agree.

Table 1. Questionnaire Statement

Code	Statement	Ref
***Trust* (TR)**		
TR1	I believe that ChatGPT keeps my health information confidential.	[15]
TR2	I believe that ChatGPT is reliable in providing accurate and secure health information.	[15]
TR3	I am confident that ChatGPT operates with a high degree of integrity.	[15]
***Perceived Benefit* (PB)**		
PB1	Sharing health data with ChatGPT can help me quickly find the health information I need.	[15]
PB2	Sharing health data with ChatGPT can help me find relevant health information.	[15]
PB3	Sharing health data can contribute to training the ChatGPT model, which benefits the community.	[15]

Table 2. Questionnaire Statement (continued)

Code	Statement	Ref
***Perceived Risk* (PR)**		
PR1	I feel unsafe sharing my medical history with ChatGPT because I'm afraid my information might be leaked.	[15]
PR2	I feel that the privacy risks of using ChatGPT outweigh the benefits.	[15]
PR3	I'm concerned that using ChatGPT could threaten my privacy.	[15]
***Privacy Concern* (PC)**		
PC1	I'm worried that others will discover my personal health data.	[22]
PC2	I feel that health information entered into ChatGPT could be misused, such as for commercial purposes or used by third parties without my consent.	[22]
PC3	I believe that the protection of personal health data is far more important than anything else.	[22]
***Perceived Effectiveness of Government Regulation* (PEGR)**		
PEGR1	I am confident that government regulations can prevent the leakage of personal data on the ChatGPT platform when sharing health information.	[15]
PEGR2	I believe that current government regulations are sufficiently transparent in managing and overseeing the use of my personal data on the ChatGPT platform.	[15]
PEGR3	I believe that if there is a privacy breach involving my health data, the government will impose strict penalties on the offending party.	[15]
***Sharing Willingness* (SW)**		
SW1	I feel comfortable sharing my health data with ChatGPT as long as the platform is transparent about how it is used.	[15]

Code	Statement	Ref
SW2	I am willing to provide my health data to ChatGPT if the benefits outweigh the privacy risks.	[15]
SW3	I am willing to share my personal health data with ChatGPT to obtain more accurate information.	[15]
***Moral Motive* (MM)**		
MM1	I feel that using ChatGPT to share health data aligns with my personal moral and ethical values.	[15]
MM2	Sharing personal health data allows me to do something meaningful for others.	[15]
MM3	I believe that the use of ChatGPT for health data must be conducted ethically and responsibly.	[15]
***Perceived Intelligence* (PI)**		
PI1	I feel that ChatGPT possesses strong analytical capabilities in understanding my health issues.	[19]
PI2	ChatGPT seems very intelligent in providing relevant health advice.	[19]
PI3	I believe that the technology behind ChatGPT is designed with superior intelligence to handle health-related questions.	[19]

B. Data Collection Procedures

Once finalized, the questionnaire was distributed to the general public. Distribution began on February 12, 2025, and concluded on March 8, 2026, after which data processing began.

C. Data Analysis Methods

The collected data will be analyzed using SmartPLS. SmartPLS is software used for data analysis employing the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, with the aim of testing and evaluating the reliability and validity of theoretical constructs, as well as estimating and verifying the relationships among the proposed constructs. SmartPLS is suitable for use when working with relatively small samples [16].

III. RESULT AND DISCUSSION

The study followed a structured procedure for data processing using SmartPLS. A total of 100 respondents participated; however, 13 respondents were excluded from the analysis because they did not meet the criteria, namely having never used ChatGPT to provide their health information. Therefore, a total of 87 responses were analyzed in this study. Excluding such respondents ensures that the data better represents the target population and that anomalies do not affect the overall findings. Identifying and removing respondents who have never used ChatGPT improves the validity of the study and produces more robust and reliable results. Consequently, the findings can be used to support appropriate decision-making and to draw accurate conclusions regarding the studied population.

Table 3. Respondent Data

Measurement	Item	Frequency	Percentage
Gender	Female	31	36%
	Male	56	64%
Age	<17 Years	2	2%
	18-25 Years	23	26%
	26-35 Years	55	63%
	36-45 Years	4	5%
	>45 Years	3	3%
Occupation	Freelancer	2	2%
	Housewife	1	1%
	Employee	50	57%
	Student	17	20%
	Pastor	1	1%
	Entrepreneur	14	16%
	Unemployed	2	2%

The table above presents the demographic characteristics of the participants. Of the 87 responses analyzed, male respondents constituted a higher proportion (64%) compared to female respondents (36%). The largest age group was 26–35 years (63%), followed by 18–25 years (26%). The profession that most frequently used ChatGPT was employees (57%), followed by students (20%). The most commonly selected purpose of use by respondents was to learn about diseases or other health-related knowledge.

The research instrument utilized eight main variables: Trust (TR), Perceived Benefit (PB), Perceived Risk (PR), Privacy Concern (PC), Perceived Effectiveness of Government Regulation (PEGR), Sharing Willingness (SW), Perceived Intelligence (PI), and Moral Motive (MM). The model fit results are presented in Figure 1.

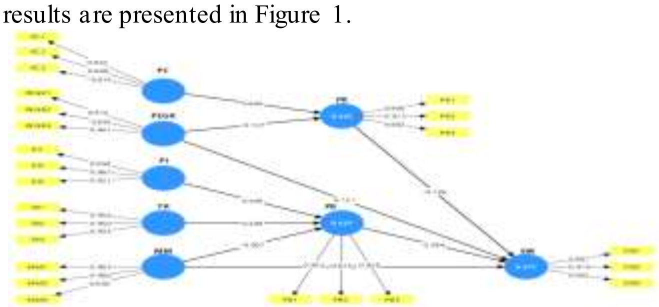

Figure 1. Model Fit Results

The measurement model evaluation, including construct reliability and validity, comprises factor loading (FL), composite reliability (CR), average variance extracted (AVE), and Cronbach's alpha (CA). Discriminant validity, as indicated by factor loading values, is expected to exceed 0.5, while values below 0.5 should be excluded. If the CR value exceeds 0.6, an AVE value of 0.5 is still considered acceptable. Meanwhile, both CR and CA values are expected to be greater than 0.6 [14].

Table 4. Construct Validity and Reliability

Construct	Item	*FL*	*CR*	AVE	*CA*
Moral Motive (MM)	MM1	0.963	0.898	0.752	0.884
	MM2	0.960			
	MM3	0.638			
	PB1	0.953	0.967	0.906	0.948

Perceived Benefit (PB)	PB2	0.975			
	PB3	0.928			
Privacy Concern (PC)	PC1	0.932	0.952	0.868	0.924
	PC2	0.949			
	PC3	0.914			
Perceived Effectiveness of Government Regulation (PEGR)	PEGR1	0.914	0.941	0.841	0.908
	PEGR2	0.895			
	PEGR3	0.941			
Perceived Intelligence (PI)	PI1	0.958	0.963	0.897	0.942
	PI2	0.962			
	PI3	0.921			
Perceived Risk (PR)	PR1	0.900	0.926	0.807	0.880
	PR2	0.912			
	PR3	0.882			
Trust (TR)	TR1	0.954	0.962	0.894	0.941
	TR2	0.950			
	TR3	0.933			
Sharing Willingness (SW)	SW1	0.967	0.965	0.902	0.946
	SW2	0.919			
	SW3	0.963			

The data collected from respondents plays a crucial role in addressing the research questions and providing a strong foundation for further analysis, particularly by considering the validity and reliability of the variables. Variable reliability ensures that the research results are consistent and stable over time. On the other hand, variable validity indicates that each variable truly measures what it is intended to measure. Both aspects are essential in research, as they enhance the credibility and dependability of the findings and conclusions. The validity and reliability of test results are also critical in determining the level of confidence in the research findings. If these two aspects are not met, the findings and conclusions may be inaccurate and may not contribute significantly to the advancement of knowledge. Therefore, validity and reliability testing are essential to ensure that the research results are trustworthy and can be used as reliable references [14]. As shown in Table 4, all constructs have met the criteria for convergent validity and reliability. All factor loading values are above 0.5, indicating that the indicators used adequately represent the constructs. In addition, the CR and CA values for all variables exceed 0.7, demonstrating that each construct has a good level of internal consistency. Overall, the results indicate that the indicators used are appropriate for representing the constructs in this study. Therefore, the analysis can proceed to structural model testing to examine the relationships among variables.

The next stage of testing employs bootstrapping in SmartPLS. The results of this test provide a clear depiction of the relationships among the variables studied and serve to validate the proposed hypotheses [14]. Figure 2 presents the results of the bootstrapping or hypothesis testing.

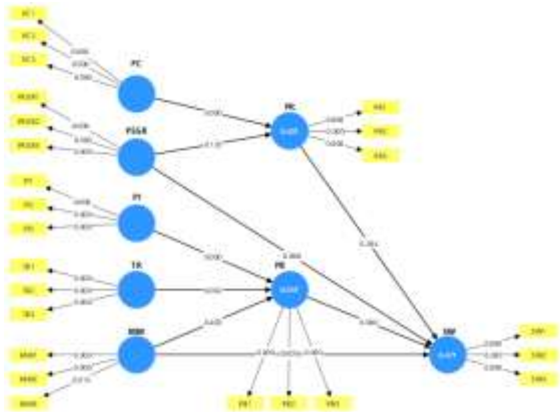

Figure 2. Hypothesis Testing

The results are also presented in the form of path coefficients in Table 5. Using this technique, researchers can assess the correlations among constructs. P-values less than 0.050 indicate statistical significance of the relationships represented, meaning that the constructs under study are interrelated and have a substantial influence on one another.

Table 5. Path Coefficient

Hipotesis	O	M	STDEV	T	P
H1: PR→SW	-0.126	-0.136	0.113	1.116	0.264
H2: PB→SW	0.544	0.536	0.101	5.375	0.000
H3: PEGR->SW	0.121	0.127	0.071	1.715	0.086
H4: PEGR→PR	-0.127	-0.131	0.082	1.555	0.120
H5: MM→SW	-0.073	-0.064	0.100	0.735	0.462
H6: MM→PB	-0.067	-0.060	0.080	0.837	0.403
H7: PC→PR	0.604	0.606	0.077	7.862	0.000
H8: TR→PB	0.408	0.400	0.130	3.153	0.002
H9: PI→PB	0.446	0.451	0.120	3.725	0.000

Based on the results of the P-values, the following can be interpreted:

1) The path coefficient from PR to SW has a p-value of 0.264, and the result is rejected.
2) The path coefficient from PB to SW has a p-value of 0.000, and the result is accepted.
3) The path coefficient from PEGR to SW has a p-value of 0.086, and the result is rejected.
4) The path coefficient from PEGR to PR has a p-value of 0.120, and the result is rejected.
5) The path coefficient from MM to SW has a p-value of 0.462, and the result is rejected.
6) The path coefficient from MM to PB has a p-value of 0.403, and the result is rejected.
7) The path coefficient from PC to PR has a p-value of 0.000, and the result is accepted.
8) The path coefficient from TR to PB has a p-value of 0.002, and the result is accepted.
9) The path coefficient from PI to PB has a p-value of 0.000, and the result is accepted.

The interpretation can be summarized in the results of the hypothesis analysis in Table 6.

Table 6. Hypothesis Test Results

Hypothesis	O	P-Values	Result
H1: **PR → SW**	-0.126	0.264	Not Supported
H2: **PB → SW**	0.544	0.000	Supported
H3: PEGR → SW	0.121	0.086	Not Supported
H4: PEGR → PR	-0.127	0.120	Not Supported
H5: MM → SW	-0.073	0.462	Not Supported
H6: MM → PB	-0.067	0.403	Not Supported
H7: PC → PR	0.604	0.000	Supported
H8: TR → PB	0.408	0.002	Supported
H9: PI → PB	0.446	0.000	Supported

Here is an explanation of the analysis for each hypothesis:

H1: Perceived Risk has a negative effect on Sharing Willingness:

An O-value of -0.126 indicates that Perceived Risk has a negative effect on Sharing Willingness. The p-value of 0.722 indicates that this hypothesis is not supported. This suggests that respondents are aware of potential risks related to privacy or data security, but they prioritize other factors. Perceived risk is not the primary factor determining respondents' willingness to share their health data on ChatGPT.

H2: Perceived Benefit has a positive effect on Sharing Willingness:

A p-value of 0.000 indicates that this hypothesis is supported. An O-value of 0.544 indicates that Perceived Benefit has a positive effect on Sharing Willingness. This means that the perceived benefits of using ChatGPT are a key factor driving respondents to share their personal data.

H3: Perceived Effectiveness of Government Regulation has a positive effect on Sharing Willingness.

An O-value of 0.121 indicates that Perceived Effectiveness of Government Regulation has a positive effect on Sharing Willingness. A p-value of 0.086 indicates that this hypothesis is not supported. This suggests that users' perceptions of the effectiveness of government regulations are not a primary consideration when deciding to share data with ChatGPT. The existence of regulations regarding personal data protection does not directly influence respondents' decisions to provide personal information.

H4: Perceived Effectiveness of Government Regulation has a negative effect on Perceived Risk.

An O value of -0.127 indicates that Perceived Effectiveness of Government Regulation has a negative effect on Perceived Risk. A p-value of 0.120 indicates that this hypothesis is not supported. This means that the hypothesis regarding users' perceptions of the effectiveness of government regulation does not influence the level of risk perceived by respondents.

H5: Moral Motive has a positive effect on Sharing Willingness.

An O-value of -0.073 indicates that Moral Motive has a negative effect on Sharing Willingness. A p-value of 0.462 indicates that this hypothesis is rejected. This suggests that users' moral motivations, such as a desire to contribute to research development, are not strong enough to drive the willingness to share information; thus, other factors, such as personal benefit, are more relevant in determining the decision to share personal data.

H6: Moral Motive has a positive effect on Perceived Benefit. An O-value of -0.067 indicates that Moral Motive has a negative effect on Perceived Benefit. A p-value of 0.403 indicates that this hypothesis is rejected. This suggests that users' moral motives do not influence respondents' assessment of the benefits of using ChatGPT.

H7: Privacy Concern has a positive effect on Perceived Risk. A p-value of 0.000 indicates that this hypothesis is accepted. An O-value of 0.604 indicates that Privacy Concern has a positive effect on Perceived Risk. This suggests that the higher users' level of concern about privacy, the higher their perceived risk when sharing personal data on ChatGPT.

H8: Trust has a positive effect on Perceived Benefit.

A p-value of 0.002 indicates that this hypothesis is accepted. An O-value of 0.408 indicates that Trust does not have a positive effect on Perceived Benefit. This suggests that users' level of trust in the platform directly influences their perception of perceived benefit.

H9: Perceived Intelligence has a positive effect on Perceived Benefit.

A p-value of 0.000 indicates that this hypothesis is accepted. An O-value of 0.446 indicates that Trust has a positive effect on Perceived Benefit. This suggests that when respondents perceive ChatGPT as an intelligent system capable of providing accurate information, they will perceive greater benefits.

IV. CONCLUSIONS

This study aims to identify and analyze the relationship between various constructs that influence users' willingness to share health information on ChatGPT, focusing on several variables such as Trust, Perceived Benefit, Perceived Risk, Privacy Concern, Perceived Effectiveness of Government Regulation, Moral Motive, Perceived Intelligence, and Sharing Willingness. Based on the results of the data analysis obtained from 87 respondents, this study found that the four proposed hypotheses were supported by the statistical test results. Respondents indicated that privacy concerns influence perceived risk. However, risk factors do not significantly influence willingness to provide personal data on the ChatGPT platform. Respondents are more focused on the benefits they receive, especially if they trust the platform and believe ChatGPT is capable of providing health information effectively. Thus, if the information provided by ChatGPT is deemed beneficial, respondents are more likely to be willing to share their personal data. Future research could increase the number of respondents to strengthen these findings. A larger sample size could provide deeper insights into ChatGPT users' behavior regarding privacy issues in sharing health data.

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