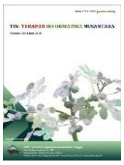

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Unveiling Barriers to Telehealth Adoption among Employees with Metabolic Syndrome: Innovation Resistance Theory Perspective

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Abstract–This study explores the key barriers hindering the adoption of telehealth services among employees diagnosed with Metabolic Syndrome (MetS), using the Innovation Resistance Theory (IRT) framework. The focus on office employees is justified, as this group is highly susceptible to MetS due to sedentary work routines that elevate cardiometabolic risks, making telehealth a potentially valuable tool for continuous monitoring and disease management. A quantitative approach was employed with data collected from 400 office-based employees with MetS in Indonesia via an online survey. Constructs related to usage, value, risk, tradition, and image barriers were measured and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that all five barriers significantly and negatively influence the intention to use telehealth, with usage barrier ($\beta = -0.274$; $p = 0.001$) and image barrier ($\beta = -0.196$; $p = 0.000$) exerting the strongest effects. The model demonstrates strong explanatory power, with R^2 values of 0.600 for intention to use and 0.515 for actual usage. Furthermore, intention to use was found to significantly predict actual usage and mediate the effects of resistance barriers on adoption behavior. These findings highlight the need to enhance system usability, increase perceived value, and build a credible telehealth image. This research contributes to telehealth literature by validating IRT in a chronic disease context and offering strategic insights for service developers, healthcare policymakers, and digital health marketers aiming to reduce resistance and boost adoption.

Keywords: Telehealth Adoption; Innovation Resistance Theory; Metabolic Syndrome; Usage Barriers; Image Barriers

1. INTRODUCTION

In Indonesia, digital transformation is rapidly accelerating, as reflected by the report from We Are Social & Meltwater (2024), which notes that out of 278.7 million people, approximately 185.3 million are internet users (66.5% of the population). Among them, 46.84 million individuals utilize digital health services, marking a 9.6% increase from the previous year. This surge highlights the growing importance of digital platforms in improving healthcare access. Telehealth, in particular, has become a prominent tool, enabling users to obtain personal health information and knowledge remotely, often serving as a preliminary source before formal diagnosis (Endalamaw et al., 2025; Gajarawala & Pelkowski, 2021).

As an emerging innovation, telehealth addresses systemic healthcare challenges by reducing medical errors and enhancing service delivery efficiency (Jeilani & Hussein, 2025; VanDeWiele et al., 2025). It holds considerable promise for managing chronic conditions such as Metabolic Syndrome (MetS), a cluster of risk factors—including hyperglycemia, obesity, dyslipidemia, and hypertension—that heighten the risk of cardiovascular disease and type 2 diabetes (Leppe Zamora et al., 2025; Najikh & Permatasari, 2023). Through consistent monitoring and patient education, telehealth supports effective disease management and complication prevention (Hudiyawati et al., 2025; H. S. Park et al., 2022).

Telehealth is a healthcare innovation that utilizes information and communication technologies to provide remote, real-time medical services via digital platforms such as smartphones, tablets, or computers (Endalamaw et al., 2025; Praswati & Ningsih, 2024). It facilitates virtual patient–provider interactions through applications, video calls, messaging, and online portals (Ameyaw et al., 2025). Telehealth encompasses a wide range of services, including medical consultations, preliminary diagnostics, chronic disease management, medication monitoring, and remote rehabilitation (Alkhuzaimi et al., 2024).

Initially designed to support remote and underserved communities, telehealth has expanded as a viable solution for individuals with limited time or access to traditional healthcare services, particularly among working populations (Osingada et al., 2025). It is especially relevant for managing chronic conditions such as Metabolic Syndrome (MetS), which require continuous monitoring, preventive care, and adherence to healthy routines (Kristinawati et al., 2024; Yuniartika & Hidayati, 2021).

Despite its advantages, telehealth adoption remains limited, hindered by issues such as low digital literacy, privacy concerns, doubts about service reliability, and insufficient organizational support (Alghamdi et al., 2022; Crowe et al., 2024). The IRT provides a relevant lens to analyze these barriers by categorizing them into functional obstacles—such as complexity, risk, and inconvenience—and psychological ones, including preference for conventional practices and negative perceptions (Chuang & Huang, 2025). In this context, concerns over usability, data security, and lack of personal interaction often led to resistance. Thus, applying IRT helps in identifying these barriers and shaping effective strategies to boost telehealth acceptance (Putinagari & Apriliantty, 2021; Talwar et al., 2024).

Employees diagnosed with MetS often encounter challenges in maintaining health due to occupational stress, time constraints, and limited healthcare access (Monico et al., 2025; Zhang et al., 2024). In this context, telehealth presents a convenient solution by offering accessible and remote healthcare services (Endalamaw et al., 2025).

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However, despite its potential benefits, adoption in Indonesia remains limited due to several barriers, including insufficient digital infrastructure (Hezer et al., 2024), low digital literacy (Aji & Ramadani, 2024), concerns over data privacy (Niazkhani et al., 2020), and behavioral resistance to change (Seppänen et al., 2025).

Previous studies have predominantly examined the facilitators of telehealth adoption using theoretical frameworks such as the Technology Acceptance Model (TAM), Information Acceptance Model (IAM), Theory of Planned Behavior (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Aji & Ramadani, 2024; Han & Han, 2023; van de Werken et al., 2025). However, limited attention has been directed toward understanding user resistance—an equally critical dimension of technology adoption—particularly in emerging markets where structural, cultural, and technological constraints remain pronounced. Existing telemedicine literature also tends to overlook the consumer's perspective, especially regarding concerns and barriers experienced when accessing remote healthcare services, which are essential considerations for marketers and technology professionals developing telehealth solutions. More importantly, research specifically addressing barriers or resistance to telehealth among employees with MetS, a population that stands to benefit greatly from continuous digital health monitoring, remains extremely scarce. To address this gap, the present study employs the Innovation Resistance Theory (IRT) to investigate both functional barriers (usability, value, risk, and tradition) and psychological barriers (image and social influence) (Kautish et al., 2023). By applying IRT to this underserved yet clinically relevant population, the study offers theoretical advancement in telehealth resistance research and provides practical insights for telehealth developers, policymakers, and healthcare marketers aiming to design user-centered strategies that enhance adoption.

Ram and Sheth (1989) define innovation resistance as a disruption or delay in adopting new innovations due to perceived threats to satisfaction or cultural norms. The theory is instrumental in explaining why many innovations fail to achieve widespread acceptance, attributing resistance to the psychological and behavioral disruptions caused by change (Wang et al., 2025). Resistance is considered a natural response to innovations that challenge established habits or values, often leading to rejection, hesitation, or postponement in adoption (Sobaih et al., 2025).

IRT has been applied in various contexts, including agriculture (Drewry et al., 2019), mobile payments (Kaur et al., 2020), electric vehicles (Xue et al., 2024), and digital finance (Talwar et al., 2024). However, telehealth presents unique complexities. Unlike many consumer technologies, telehealth often involves ongoing engagement and directly impacts personal health, potentially intensifying resistance due to privacy concerns, emotional discomfort, or fear of misdiagnosis. These distinct attributes make understanding telehealth resistance critical for promoting its acceptance, particularly in emerging markets where trust in digital health solutions remains limited (Kautish et al., 2023).

2. RESEARCH METHODOLOGY

2.1 Basic Research Framework

Ram and Sheth (1989) define innovation resistance as a disruption or delay in adopting new innovations due to perceived threats to satisfaction or cultural norms. The theory is instrumental in explaining why many innovations fail to achieve widespread acceptance, attributing resistance to the psychological and behavioral disruptions caused by change (Wang et al., 2025). Resistance is considered a natural response to innovations that challenge established habits or values, often leading to rejection, hesitation, or postponement in adoption (Sobaih et al., 2025).

In the context of technological innovation, a usage barrier refers to the users difficulties in understanding and utilizing the innovation (Drewry et al., 2019). The complexity level of a particular innovation can increase resistance to technology adoption (Ram & Sheth, (1989). Wang et al. (2025) found that the usage barrier is a significant factor shaping resistance to new technology. Users of telehealth applications are likely to encounter difficulties in navigating several of its functional features. Based on this understanding, the first hypothesis is proposed:

1. H1: Usage barrier has a significant negative effect on the intention to use telehealth among employees with MetS.
   The value barrier arises when consumers decline to adopt a new product or service due to a perceived lack of sufficient benefits compared to existing options. This perceived value is shaped by the degree to which consumers believe the innovation delivers financial gains or other forms of utility. When the price or associated costs are viewed as excessive relative to the benefits, adoption rates tend to decline. The value barrier represents a critical challenge to the widespread acceptance of innovations (Leong et al., 2021). Based on this premise, the second hypothesis is proposed:
2. H2: Value barrier has a significant negative effect on the intention to use telehealth among employees with MetS.
   The risk barrier reflects consumer skepticism and concerns about the potential adverse effects of innovation (Ram & Sheth, 1989). In healthcare, perceived risks typically include economic, physical, psychosocial, and time-related risks (Liu et al., 2021). Although some studies have shown that telehealth can reduce patient risks by minimizing exposure to infected individuals, other research has highlighted the risk of misdiagnosis and further medical complications when physical examinations are not conducted (Alexandra et al., 2021). Based on this insight, the third hypothesis is formulated as follows:
3. H3: Risk barrier has a significant negative effect on the intention to use telehealth among employees with MetS.
   The tradition barrier refers to consumers' reluctance to accept changes introduced by innovations that disrupt habitual routines (Ram & Sheth, 1989). The greater the deviation from societal routines, the stronger the resistance to innovation. Some studies attribute resistance due to tradition barriers to conflicts with existing user cultures

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(Putinagari & Aprilianty, 2021). In the context of telehealth, research has indicated that users may be unwilling to accept clinical services when medical professionals are not physically present (Frishammar et al., 2023). Based on this, the fourth hypothesis is proposed:

4. H4: Tradition barrier has a significant negative effect on the intention to use telehealth among employees with MetS.
   The image barrier is associated with consumers' rejection of an innovation due to the identity it conveys, which may be influenced by factors such as brand, country of origin, or product category. These perceptions often lead to the development of stereotypes that hinder adoption. Consumers form image barriers based on their perception of service quality, delivery time, and the complexity involved in operating a new innovation. Several studies have identified the image barrier as a significant factor contributing to resistance toward innovation adoption and diffusion (Kautish et al., 2023). Based on this understanding, the fifth hypothesis is formulated as:
5. H5: Image barrier has a significant negative effect on the intention to use telehealth among employees with MetS.
   Employees with MetS have specific health monitoring needs that make telehealth a practical solution. Their intention to use telehealth is influenced by the belief that such applications can help them manage their health conditions efficiently and securely. Intention to use is considered a key predictor of actual use in the context of technology adoption, including telehealth applications, particularly for employees with MetS. While intention to use plays a critical role in predicting actual use, certain barriers, such as technical challenges, privacy concerns, and adherence to traditional habits—may hinder the transition from intention to actual behavior (Kautish et al., 2023). Accordingly, the sixth and seventh hypotheses are proposed as follows:
6. H6: Intention to use has a significant positive effect on the actual use of telehealth among employees with MetS.
7. H7: Intention to use mediates the relationship between usage barrier (H7a), value barrier (H7b), risk barrier (H7c), tradition barrier (H7d), and image barrier (H7e) and the actual use of telehealth among employees with MetS.

2.2 Research Design

The research procedures followed a structured series of stages consisting of planning, data collection and processing, and the generation of research outputs. The planning stage began with reviewing prior studies, identifying the research problem, and conducting an extensive literature review to develop the conceptual framework. This was followed by the identification and operationalization of variables, hypotheses, and research questions, as well as the determination of the population and sampling methods. Prior to the main data collection, the research instrument underwent translation and expert validation, followed by a pilot test involving 30 respondents to assess reliability and ensure cultural appropriateness. After refining the instrument, the data collection phase proceeded with the distribution of questionnaires, retrieval of responses, and subsequent data cleaning and processing. The final stage involved statistical analysis and the interpretation of results, which produced the research findings and contributed to the overall conclusions of the study. The research procedures is explained in Figure 1.

This study applies a quantitative descriptive–correlational design to examine the barriers that hinder telehealth adoption among employees diagnosed with MetS. Guided by the Innovation Resistance Theory (IRT), the research focuses on five key dimensions of resistance, usage, value, risk, tradition, and image—and their influence on the intention and actual use of telehealth services. This approach is appropriate for testing hypotheses and validating theoretical assumptions with empirical evidence. Data were collected through a structured online questionnaire, which enabled efficient measurement of respondents' perceptions and attitudes toward telehealth services. The study used a cross-sectional design, with data obtained at a single point in time, reflecting current user experiences and resistance factors. To ensure rigorous analysis, the study employed Partial Least Squares Structural Equation Modeling (PLS-SEM), which is particularly suitable for models involving multiple constructs and indicators. This method allows systematic assessment of the measurement model (validity and reliability) and the structural model (causal relationships).

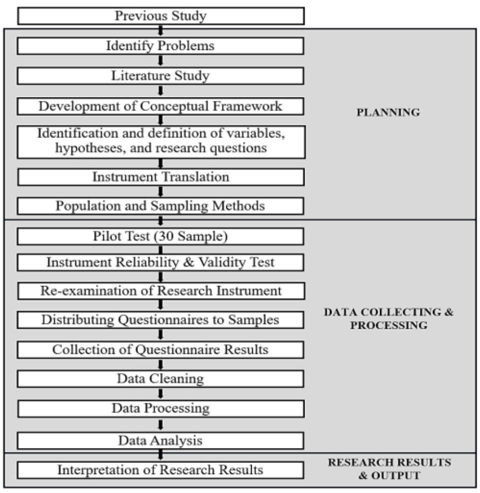

Figure 1. Research Procedures

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2.3 Sampling

The target population consists of office-based employees in Indonesia diagnosed with MetS, as they represent a segment with high potential benefit from telehealth services. Since the total population size is indeterminate, the Bernoulli formula with a 5% margin of error was applied, resulting in a minimum requirement of 385 respondents. To meet this target, the survey was distributed through digital platforms to reach employees familiar with online health services. A purposive non-probability sampling technique was used to ensure that only respondents meeting the predefined clinical and behavioral criteria were included. To verify the MetS condition within the constraints of an online survey, respondents were required to answer a set of screening questions adapted from the National Institute of Health (NIH) criteria. A key screening item asked whether respondents had been formally diagnosed by a physician as having at least three of the five established MetS risk factors, namely abdominal obesity, hypertension, hyperglycemia, elevated triglycerides, and reduced HDL cholesterol levels. Only respondents who confirmed a formal diagnosis proceeded to the main questionnaire.

Additionally, because the study investigates telehealth adoption, participants were also screened for basic exposure to digital health or teleconsultation services. Prior knowledge was assessed using a binary filter question: "Have you ever used or been introduced to any telehealth or digital health service in the past?" Respondents answering "yes" were categorized as having minimal exposure, while those answering "no" were provided a brief standardized description of telehealth to ensure baseline conceptual understanding before responding to the main survey. Participation was voluntary and anonymous, and respondents were informed of the research objectives, data confidentiality, and ethical considerations prior to completing the questionnaire.

2.4 Data and Instrumentation

Data were gathered through a structured questionnaire developed in Google Forms to ensure efficiency and avoid entry errors. The questionnaire was divided into two sections. Section A collected demographic information, including age, gender, education, occupation, income, geographic location, and health-related habits, in order to profile respondents. Section B measured the constructs of Innovation Resistance Theory. Measurement items for usage, value, risk, tradition, and image barriers were adapted from Kautish et al. (2023), while items for intention and actual use were adapted from Alexandra et al. (2021). All items were assessed on a five-point Likert scale, ranging from 1 = "strongly disagree" to 5 = "strongly agree," capturing the degree of respondents' agreement with each statement. Using established scales from prior literature enhanced construct validity and reliability, ensuring alignment with existing research on technology and healthcare adoption.

Data were collected using a structured questionnaire developed based on validated measurement items from the Innovation Resistance Theory (IRT) and prior telehealth adoption research. Because the instrument was adapted from English-language sources for use in Indonesia, a multi-step translation and validation procedure was employed. The questionnaire was first translated into Indonesian using a forward–backward translation method.

A pilot test was subsequently conducted with 30 respondents who met the basic MetS screening criteria. The pilot test examined the reliability and comprehension of the instrument, and items were refined based on internal consistency results and participant feedback. Only after the instrument demonstrated acceptable reliability (Cronbach's $\alpha > 0.7$) and content validity was the full survey distributed to the main sample. The final questionnaire measured usage, value, risk, tradition, and image barriers, along with intention to use and actual usage of telehealth, using a five-point Likert scale. Demographic variables and digital literacy were also included to contextualize the findings and support the interpretation of the results.

2.5 Data Analysis

Data analysis was performed using PLS-SEM with SmartPLS 4. This method was chosen over covariance-based SEM (CB-SEM) due to its advantages in prediction-oriented studies, ability to handle complex models with smaller sample sizes, and robustness against data non-normality. These conditions are often encountered in telehealth adoption research within emerging markets. The analysis was carried out in two stages. First, the measurement model was assessed for indicator reliability, internal consistency, convergent validity, and discriminant validity. Second, the structural model was tested by estimating path coefficients and evaluating hypotheses. Bootstrapping with 5,000 resamples was conducted to determine the significance of the proposed relationships. The coefficient of determination (R^2) was used to measure the explanatory power of resistance barriers in predicting intention and actual use of telehealth. This methodological approach ensures both statistical rigor and practical relevance in understanding the mechanisms of innovation resistance in digital healthcare (Hair & Alamer, 2022).

3. RESULTS AND DISCUSSION

3.1 Respondent Demographic

Table 1 presents the demographic characteristics of the 400 respondents included in this study, offering an overview of the sample profile and its relevance to the research context. A total of 400 individuals took part in the study, encompassing a wide range of demographic characteristics, including variations in age, gender, educational attainment,

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occupational roles, and socioeconomic levels. In terms of gender, the majority of respondents were female (207 individuals or 51.75%). The largest age group was 40–49 years (170 respondents or 42.50%). In terms of education, most participants held a bachelor's degree (243 individuals or 60.75%). Regarding occupation, private sector employees made up the largest group with 153 respondents (38.25%), followed by entrepreneurs with 83 respondents (20.75%). Monthly income data indicated that the majority of respondents earned between IDR 3,000,001 and IDR 6,000,000 (176 respondents or 44.00%). As for smoking habits, most respondents were non-smokers (202 individuals or 50.50%), while 198 respondents (49.50%) were smokers. Regarding alcohol consumption, the majority stated they did not consume alcohol (317 respondents or 79.25%), while 83 respondents (20.75%) reported that they did.

Table 1. Respondent Demographic

Demographic	Variables	Frequency	Percentage
Age	19-29 y.o	72	18.00%
	30-39 y.o	59	14.75%
	40-49 y.o	170	42.50%
	50-59 y.o	83	20.75%
	60-69 y.o	15	3.75%
	Over 69 y.o	1	0.25%
Gender	Male	193	48.25%
	Female	207	51.75%
Education	Junior High School	3	0.75%
	Senior High School	40	10.00%
	Diploma	76	19.00%
	Bachelor Degree	243	60.75%
	Master Degree	34	8.50%
	Doctoral Degree	4	1.00%
Profession	Academicians	20	5.00%
	Health Worker	12	3.00%
	State-owned Company	64	16.00%
	Civil Servant	50	12.50%
	Private Sector Worker	153	38.25%
	Indonesian National Armed Forces/ Indonesian National Police	18	4.50%
	Self-Employed	83	20.75%
Income	Under Rp3.000.000	33	8.25%
	Rp18.000.001-27.000.000	6	1.50%
	Rp3.000.001-6.000.000	176	44.00%
	Rp6.000.001-9.000.000	139	34.75%
	Rp9.000.001-18.000.00	43	10.75%
	Over Rp27.000.001	3	0.75%
Smoking Status	No	202	50.50%
	Yes	198	49.50%
Alcohol Consumption	No	317	79.25%
	Yes	83	20.75%

3.2 Measurement Model

The evaluation of the measurement model involved testing for convergent validity, discriminant validity, and reliability. Convergent validity examines how well the indicators of a particular construct correlate with each other, under the premise that they should be strongly associated with the underlying construct. This is commonly measured using factor loadings—considered acceptable when greater than 0.70, and the Average Variance Extracted (AVE), with a minimum acceptable value of 0.50 (Hair & Alamer, 2022). Table 2 presents the results of the construct reliability and validity assessment, which evaluates the internal consistency and convergence of the measurement model.

The factor loadings, as shown in Table 2, ranged from 0.788 to 0.912, all exceeding the 0.70 benchmark, while AVE values for all constructs fell between 0.627 and 0.825. These results collectively confirm that the measurement model meets the required reliability and convergent validity standards and is therefore appropriate for subsequent structural model analysis.

Reliability analysis was performed to evaluate the precision, consistency, and stability of the measurement instruments using Cronbach's Alpha and Composite Reliability. As shown in Table 2, both Cronbach's Alpha and Composite Reliability are considered acceptable when exceeding a threshold of 0.70, particularly in confirmatory research settings (Hair & Alamer, 2022). In this study, the Cronbach's Alpha values ranged from 0.788 to 0.926, while the Composite Reliability scores varied between 0.882 and 0.967 for all constructs. These results demonstrate strong internal consistency and high measurement reliability.

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Table 2. Construct Reliability and Validity

Variables	Items	Outer Loading	VIF	Cronbach's alpha	Composite reliability	AVE
Actual Use	AU1	0.912	1.734	0.788	0.904	0.825
	AU2	0.905	1.734			
Image Barrier	IB1	0.909	2.610	0.806	0.885	0.720
	IB2	0.798	1.888			
	IB3	0.836	1.679			
Intention to Use	IU1	0.894	2.456	0.844	0.906	0.764
	IU2	0.833	1.667			
	IU3	0.892	2.483			
Risk Barrier	RB1	0.863	2.299	0.870	0.911	0.719
	RB2	0.822	1.907			
	RB3	0.846	2.080			
	RB4	0.861	2.268			
Tradition Barrier	TB1	0.869	3.156	0.926	0.944	0.772
	TB2	0.878	2.964			
	TB3	0.886	3.171			
	TB4	0.884	3.036			
	TB5	0.876	3.102			
Usage Barrier	UB1	0.829	2.264	0.821	0.882	0.651
	UB2	0.772	1.591			
	UB3	0.788	1.999			
	UB4	0.837	1.942			
Value Barrier	VB1	0.805	2.278	0.851	0.894	0.627
	VB2	0.787	1.999			
	VB3	0.787	1.910			
	VB4	0.782	1.908			
	VB5	0.798	2.099			

Discriminant validity confirms that each construct is unique and not overly similar to others. This was assessed using the Fornell-Larcker criterion. To complement this, the Heterotrait–Monotrait Ratio (HTMT) was also applied, as it offers a more precise evaluation of discriminant validity (Henseler et al., 2015). An HTMT value below 0.90 is generally considered acceptable. Table 3 presents the Fornell–Larcker Criterion results used to assess discriminant validity within the measurement model. As shown in Table 3, the square root of the Average Variance Extracted (AVE) for each construct is greater than its correlations with other constructs, indicating that each construct shares more variance with its own indicators than with indicators of other constructs. This confirms that the constructs are empirically distinct and measure unique conceptual domains within the Innovation Resistance Theory framework. The results demonstrate that discriminant validity has been satisfactorily achieved, ensuring that the latent variables do not overlap excessively and can be reliably used in the subsequent structural model analysis.

Table 3. Fornell Larcker Criterion

	Actual Use	Image Barrier	Intention to Use	Risk Barrier	Tradition Barrier	Usage Barrier	Value Barrier
Actual Use	0.908						
Image Barrier	-0.505	0.849					
Intention to Use	0.718	-0.623	0.874				
Risk Barrier	-0.482	0.707	-0.617	0.848			
Tradition Barrier	-0.469	0.583	-0.565	0.636	0.879		
Usage Barrier	-0.596	0.513	-0.652	0.501	0.420	0.807	
Value Barrier	-0.538	0.412	-0.581	0.407	0.367	0.694	0.792

Table 4 presents the HTMT values used as an additional criterion for assessing discriminant validity. As shown in Table 4, all HTMT values fall below the conservative threshold of 0.85, indicating that the constructs are sufficiently distinct from one another and do not exhibit problematic multicollinearity. These values further corroborate the discriminant validity established through the Fornell–Larcker Criterion, ensuring that each construct within the model measures a unique theoretical dimension. The satisfaction of the HTMT criterion reinforces the robustness of the measurement model and supports the reliability of subsequent structural path analyses.

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Table 4. Heterotrait–monotrait ratio (HTMT) Criterion

	Actual Use	Image Barrier	Intention to Use	Risk Barrier	Tradition Barrier	Usage Barrier	Value Barrier
Actual Use							
Image Barrier	0.625						
Intention to Use	0.879	0.747					
Risk Barrier	0.582	0.834	0.719				
Tradition Barrier	0.542	0.666	0.632	0.708			
Usage Barrier	0.736	0.623	0.778	0.589	0.476		
Value Barrier	0.654	0.490	0.682	0.472	0.408	0.829	

3.3 Structural Model

As outlined by Hair and Alamer (2022), the coefficient of determination (R^2) is used to measure how much of the variance in the dependent variable can be accounted for by the independent (or latent) variables in the structural model. Expressed on a scale from 0 to 1, higher R^2 values indicate greater explanatory power. R^2 values are typically categorized as weak (≤ 0.5), moderate (0.5–0.75), or strong (≥ 0.75) in terms of predictive capability. In addition, Hair & Alamer (2022) classifies effect sizes (f^2) into small (0.02), medium (0.15), and large (0.35). The R^2 and Q^2 statistics obtained in this study are summarized in Table 5, providing insights into the model's predictive accuracy and relevance.

Table 5. Hypothesis Test

Hypothesis	Coef	T statistics	P values	Hypothesis	R^2	f^2	Effect Size
IB -> IU	-0.196	3.448	0.000	*Accepted*	0.600	0.043	Strong
RB -> IU	-0.159	2.451	0.007	*Accepted*		0.026	Moderate
TB -> IU	-0.167	3.014	0.001	*Accepted*		0.038	Moderate
UB -> IU	-0.274	3.035	0.001	*Accepted*		0.083	Strong
VB -> IU	-0.184	2.317	0.010	*Accepted*		0.043	Strong
IU -> AU	0.718	15.075	0.000	*Accepted*	0.515	1.061	Strong

*UB = Usage Barrier, VB = Value Barrier, RB = Risk Barrier, TB = Tradition Barrier, IB = Image Barrier, IU = Intention to Use, AU = Actual Use

The structural model assessment is presented in Figure 2, which illustrates the magnitude and direction of the hypothesized relationships, while Table 5 reports the corresponding statistical outputs, including path coefficients, p-values, t-statistics, and effect sizes. Figure 2 visually demonstrates that all relationships among the constructs are negative as theorized, whereas Table 5 confirms the statistical significance of each path, with all p-values falling below the 0.05 threshold and t-statistics exceeding 1.96.

The results of the PLS-SEM method, as shown in Table 5, indicate that all hypothesized relationships in the proposed model are statistically significant, with p-values below 0.05 and t-statistics exceeding 1.96, confirming support for all proposed hypotheses. The innovation resistance dimensions—Usage Barrier (UB), Image Barrier (IB), Value Barrier (VB), Tradition Barrier (TB), and Risk Barrier (RB)—were found to have significant negative impacts on users' Intention to Use (IU) telehealth services. Among them, Usage Barrier exerted the most substantial negative effect ($\beta = -0.274$, $p = 0.001$, $f^2 = 0.083$), followed by Image Barrier ($\beta = -0.196$, $p = 0.000$, $f^2 = 0.043$). Other significant influences were observed from Value Barrier ($\beta = -0.184$, $p = 0.010$, $f^2 = 0.043$), Tradition Barrier ($\beta = -0.167$, $p = 0.001$, $f^2 = 0.038$), and Risk Barrier ($\beta = -0.159$, $p = 0.007$, $f^2 = 0.026$). The model explains 60% of the variance in Intention to Use ($R^2 = 0.600$). These results, when interpreted together, emphasize that functional and psychological barriers meaningfully shape resistance toward telehealth adoption among employees with Metabolic Syndrome.

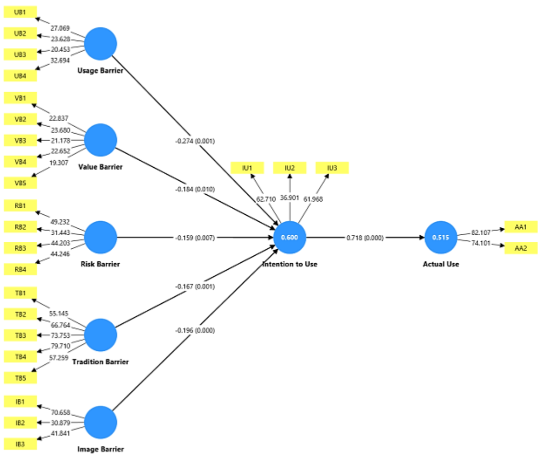

Figure 2. Measurement Models

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In addition, Intention to Use had a highly significant positive effect on Actual Use ($\beta = 0.718$, $t = 15.075$, $p = 0.000$, $f^2 = 1.061$), explaining 51.5% of the variance ($R^2 = 0.515$). These findings affirm the applicability of the Innovation Resistance Theory in identifying key psychological and functional barriers to telehealth adoption. Strategic interventions should particularly focus on minimizing Usage and Image Barriers to boost adoption rates.

Table 6. Mediation Effect

Hypothesis	Coefficient	T statistics	P values	Hypothesis
Risk Barrier -> Intention to Use -> Actual Use	-0.114	2.460	0.007	Accepted
Tradition Barrier -> Intention to Use -> Actual Use	-0.120	2.980	0.001	Accepted
Usage Barrier -> Intention to Use -> Actual Use	-0.196	2.884	0.002	Accepted
Value Barrier -> Intention to Use -> Actual Use	-0.132	2.261	0.012	Accepted
Image Barrier -> Intention to Use -> Actual Use	-0.141	3.418	0.000	Accepted

Statistically, all indirect paths (moderation effect) presented in Table 6 were found to be significant ($p < 0.05$; t-statistics > 1.96), confirming that all five barriers—Risk Barrier, Tradition Barrier, Usage Barrier, Value Barrier, and Image Barrier —indirectly influence Actual Use through the mediation of Intention to Use. The highest indirect effect was observed for the path UB → IU → AU ($\beta = -0.196$; $t = 2.884$; $p = 0.002$), followed by IB → IU → AU ($\beta = -0.141$; $t = 3.418$; $p = 0.000$), indicating strong mediating effects.

3.4 Discussion

This study confirms that both functional and psychological barriers contribute to innovation resistance in the context of telehealth adoption (Frishammar et al., 2023; Kautish et al., 2023). In line with prior, digital transformation in healthcare presents challenges that stem from user perceptions of complexity, uncertainty, and disruption to existing practices research (Niazkhani et al., 2020; Zobair et al., 2020). Using the IRT as a framework, the study identified five key barriers significantly and negatively impact users' intention to adopt telehealth services.

3.4.1 Usage Barrier and Intention to Use

This study identifies the Usage Barrier as the most influential factor negatively affecting the Intention To Use telehealth services among employees with MetS, with a path coefficient of $\beta = -0.274$ ($p = 0.001$). This finding underscores that perceived difficulty, inconvenience, and the high cognitive effort required to adapt to new technologies are major contributors to resistance toward telehealth (Kautish et al., 2023). It supports Scott et al. (2018), who emphasized that higher complexity and effort needed to understand an innovation increase user resistance. For employees with MetS, using telehealth not only demands digital adaptation but also understanding of complex health-related interfaces. If the platform is seen as unintuitive or misaligned with users' routines, it deters adoption (Putri et al., 2022). This barrier is particularly relevant for non-digital natives who may struggle with poor system usability (Alfian et al., 2024; Hartono et al., 2024). Furthermore, usage barriers not only weaken the intention to use but also indirectly reduce actual usage by undermining user motivation. To address this, telehealth providers must focus on improving usability through intuitive design, clear navigation, and robust support systems (Endalamaw et al., 2025). Additionally, offering user education and training could help minimize perceived complexity and facilitate greater adoption (Parthasarathi et al., 2024).

3.4.2 Image Barrier and Intention to Use

The image barrier was identified as the second most influential factor negatively affecting intention to use telehealth services ($\beta = -0.196$; $p = 0.000$), with a notable indirect effect on actual use through intention. This barrier captures users' unfavorable perceptions regarding the credibility, quality, and reliability of telehealth (Jacob et al., 2020; Talwar et al., 2024). Many perceive telehealth as an underdeveloped or unprofessional service, often seen as a low-cost substitute for conventional healthcare. For employees managing MetS, who prioritize consistent and dependable care, such perceptions can severely undermine trust in telehealth solutions (Kautish et al., 2023). Contributing factors may include lack of familiarity, unappealing platforms, or weak branding, all of which can erode users' confidence in the service's legitimacy (Chakraborty et al., 2022). The image barrier thus becomes a psychological hindrance, deterring users from forming a positive intention toward telehealth adoption. Addressing this challenge requires telehealth providers to reinforce professional branding, involve certified healthcare practitioners, and communicate success stories to enhance credibility. Highlighting institutional support and showcasing user satisfaction can help reshape public perception, ultimately reducing image-related resistance and fostering broader acceptance of telehealth services (Listyorini, 2021; Paradilla et al., 2022).

3.4.3 Value Barrier and Intention to Use

The value barrier emerged as the third most significant factor negatively influencing employees' intention to use telehealth services for managing MetS, with a path coefficient of $\beta = -0.184$ ($p = 0.010$). This barrier reflects users' perception that the benefits offered by telehealth are not equivalent to the effort, cost, or trade-offs involved (Leong et al., 2021). Many respondents viewed telehealth as lacking the core benefits associated with traditional healthcare, such as accurate diagnoses, in-person interaction, and established trust with medical professionals (Wasi Abbas et al., 2024).

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For employees with MetS, who require continuous monitoring and tailored health advice, the perception that telehealth compromises care quality reduces its perceived value (H. S. Park et al., 2022). This perception not only directly reduces intention to use but also indirectly affects actual usage. Overcoming this barrier requires telehealth providers to highlight the tangible advantages of their services—such as increased convenience, reduced travel time, flexible scheduling, and long-term cost-effectiveness (Maleka & Matli, 2024). Emphasizing these unique benefits may help reshape user perceptions and strengthen both the perceived value and adoption of telehealth solutions.

3.4.4 Risk Barrier and Intention to Use

The risk barrier demonstrated a significant negative influence on employees' intention to adopt telehealth services ($\beta = -0.159$; $p = 0.007$). This barrier represents user concerns over potential negative outcomes from using new technologies, such as functional disruptions, psychological discomfort, social repercussions, and privacy breaches (Ram & Sheth, 1989). In the digital healthcare setting, users frequently express apprehensions about diagnostic inaccuracies, technical malfunctions, compromised personal health data, and the impersonal nature of virtual consultations (Maleka & Matli, 2024). These concerns are particularly relevant for employees with MetS who require precise and consistent health assessments (K. S. Park & Hwang, 2024). Reluctance may stem from mistrust in the system's security, especially when handling confidential medical information, or anxiety over potential misdiagnosis due to the absence of physical examinations (Wasi Abbas et al., 2024). The study also found that this barrier affects actual usage behavior indirectly, through a decline in the intention to use telehealth. Therefore, reducing perceived risk is critical to improving both intent and actual adoption. Telehealth providers should address this by reinforcing system security, ensuring service reliability, and enhancing the professionalism of care delivery. Strategies such as adhering to cybersecurity standards, providing clear privacy policies, and engaging certified medical personnel may foster user trust and alleviate risk-based resistance (Amelia & Simanjuntak, 2024).

3.4.5 Tradition Barrier and Intention to Use

The study reveals that the tradition barrier significantly hinders employees with MetS from intending to use telehealth services ($\beta = -0.167$; $p = 0.001$). This barrier refers to users' resistance toward innovations that disrupt established routines or cultural norms—particularly the preference for face-to-face consultations with healthcare professionals (Ram & Sheth, 1989). Such resistance emerges when digital innovations clash with longstanding beliefs about effective medical care, especially those rooted in physical interaction, emotional reassurance, and visible engagement with physicians. Among Indonesian office workers, direct consultations are often considered more trustworthy and comforting, allowing patients to observe nonverbal cues and undergo hands-on assessments (Tian et al., 2025; Wang et al., 2025). Telehealth, despite its convenience, may be perceived as impersonal and lacking the human connection central to healthcare experiences. Social influences and prevailing norms further strengthen this resistance, questioning the legitimacy and effectiveness of remote services (Kautish et al., 2023). This barrier not only affects users' intention to adopt telehealth but also indirectly reduces actual usage. To mitigate tradition-based resistance, awareness campaigns involving community outreach, trusted healthcare professionals, and user testimonials are essential (Candra et al., 2024; Purwanti et al., 2021). Such efforts can reframe telehealth as a valuable, supplementary tool rather than a replacement for in-person care (Alviani et al., 2023).

3.4.6 Intention to Use and Actual Use

The results indicate that Intention to Use exerts a strong and significant positive influence on Actual Use of telehealth services ($\beta = 0.718$; $p = 0.000$), confirming the predictive relationship commonly emphasized in technology adoption literature. This finding suggests that when users develop a clear intention to adopt telehealth—driven by perceived usefulness, reduced barriers, and favorable attitudes—they are more likely to translate that intention into actual behavioral engagement (Kautish et al., 2023). The strength of this relationship highlights the critical role of psychological readiness and motivational commitment in shaping real-world utilization patterns, particularly among employees with Metabolic Syndrome who stand to benefit from continuous digital health monitoring (Schlottke et al., 2024). The empirical evidence reinforces the theoretical assertion that intention functions as a proximal determinant of behavioral enactment, demonstrating that efforts to enhance user intention—through reducing resistance, improving system usability, and strengthening the perceived credibility of telehealth—can substantially increase actual adoption levels.

3.4.7 Mediation Effect of Intention to Use

The mediation analysis demonstrates that Intention to Use plays a significant and substantive role in transmitting the effects of innovation resistance barriers onto Actual Use of telehealth services. The significant indirect paths indicate that although the resistance dimensions do not directly influence actual behavior, they shape users' adoption outcomes through their impact on intention formation. This finding reinforces the theoretical view that intention operates as a central mediating mechanism within technology adoption processes, particularly in contexts where perceived barriers undermine user motivation (Kautish et al., 2023). In the case of employees with Metabolic Syndrome, the mediation effect suggests that overcoming psychological and functional barriers is essential for strengthening intention, which subsequently increases the likelihood of actual telehealth utilization (Chuang & Huang, 2025). These results highlight

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that interventions aimed at reducing user resistance, such as improving usability, enhancing perceived value, and reinforcing a credible service image, can indirectly drive adoption by first elevating users' intention to engage with telehealth systems.

4. CONCLUSION

This study concludes that multiple dimensions of innovation resistance—namely usage, value, risk, tradition, and image barriers—significantly hinder the intention of employees with Metabolic Syndrome to adopt telehealth services, with usage and image barriers emerging as the most influential. Intention to Use is confirmed as a strong predictor of Actual Use and functions as a key mediating mechanism through which resistance barriers indirectly affect adoption outcomes. While the findings offer robust theoretical contributions by extending the Innovation Resistance Theory within a chronic disease context, the study also provides practical insights for telehealth developers and policymakers to prioritize usability enhancements, strengthen service credibility, and address patient concerns to improve digital health engagement. Nevertheless, the use of purposive non-probability sampling and the focus on Indonesian office-based employees limit the generalizability of the results. Future research is encouraged to employ probability sampling, incorporate diverse population groups, and further investigate demographic moderators to provide a more comprehensive understanding of resistance and adoption behavior in telehealth ecosystems.

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