

The Moderation of Health Motivation on The Adoption of Wearable Health Devices (WHD), Quantitative Study of Millennials in Indonesia

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Abstract: The rapid growth of wearable health devices (WHD) has not been matched by equivalent adoption, particularly in emerging economies such as Indonesia. Previous studies have primarily focused on technological determinants, while the moderating role of health motivation in linking behavioral intention to actual usage remains underexplored. This study extends the Technology Acceptance Model (TAM) by integrating perceived product value and health motivation to explain WHD adoption among Indonesian millennials. A quantitative approach with a cross-sectional survey design was employed. Data were collected from 350 millennial respondents in Indonesia and analyzed using Structural Equation Modeling-Partial Least Squares (SEM-PLS). The measurement model assessment confirmed that all variables met the criteria for validity and reliability. The findings reveal that health motivation significantly moderates the relationship between intention to use and actual usage of WHD. Perceived compatibility, perceived technology accuracy, and perceived usefulness positively and significantly influence perceived product value. In addition, perceived product value significantly affects intention to use, while intention to use and health motivation significantly affect actual WHD usage. Conversely, perceived cost, perceived personal privacy, and social image do not significantly influence perceived product value. These results indicate that WHD adoption among Indonesian millennials is primarily driven by functional factors, including device compatibility with users' lifestyles, technological accuracy, usefulness, perceived product value, and health motivation. This study contributes theoretically to the literature on health technology adoption and provides practical implications for WHD manufacturers in developing marketing strategies focused on product value and health motivation.

Keywords: *Health Motivation, Intention to Use, Actual Usage, Wearable Health Devices (WHD)*

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INTRODUCTION

The development of digital technology has impacted nearly every aspect of human life over the past two decades, including how individuals maintain and monitor their health. One form of technological innovation has emerged from wearable health devices (WHD), such as smartwatches, fitness trackers, and biometric sensors integrated with mobile applications. This technology allows users to monitor their heart rate, sleep patterns, daily step count, and blood oxygen levels in real-time (Mattison et al., 2022). In Indonesia, the trend of using wearable health devices increased significantly after the COVID-19 pandemic, which triggered a push to strengthen disease prevention and health awareness in the community. Studies show that despite high levels of awareness of the

importance of health, there is still hesitation in using wearable health devices due to issues of trust, perceived usefulness, and ease of use (Chandrasekaran et al., 2020).

In addition to supporting individual health monitoring, wearable health devices (WHD) also contribute to the broader transformation of healthcare systems toward preventive and data-driven healthcare. The integration of wearable technology with mobile applications and cloud-based systems enables users to store, analyze, and share health-related information more efficiently. This capability allows individuals to become more actively involved in managing their own health conditions and encourages continuous self-monitoring behavior. Furthermore, wearable devices are increasingly equipped with advanced features such as stress monitoring, electrocardiogram (ECG) analysis, calorie tracking, and exercise recommendations, making them more relevant to modern consumers who seek practical and personalized health solutions. The increasing popularity of wearable health devices is also influenced by changes in consumer lifestyles, particularly among younger generations who are highly familiar with digital ecosystems and mobile technologies. Millennials and digitally connected consumers tend to adopt technologies that provide convenience, flexibility, and immediate access to information. However, despite the growing awareness of the health benefits offered by wearable devices, many consumers still perceive these technologies as complementary lifestyle products rather than essential healthcare tools. As a result, the decision to adopt wearable health devices is often influenced not only by technological features, but also by users' perceptions regarding reliability, usefulness, comfort, and long-term value. Therefore, understanding the factors that encourage or hinder wearable health device adoption becomes increasingly important in supporting the development of digital healthcare innovation in Indonesia. Optimal adoption rates do not match the significant growth potential of the wearable health device market in Indonesia. Indonesians still view wearable health devices (WHD) as mere lifestyle products, rather than as health-supporting tools.

Although research on wearable health device (WHD) adoption has grown considerably over the last decade, several important research gaps remain. Previous studies have predominantly emphasized technological attributes, including perceived usefulness, compatibility, ease of use, and system quality, as the primary determinants of wearable health technology adoption (Chuah et al., 2016; Gao et al., 2015). More recently, a meta-analysis by (Peng et al. 2021) confirmed that technological characteristics consistently exert stronger effects on wearable health tracker adoption than most consumer-related factors across different countries. However, empirical findings regarding non-technological determinants remain inconsistent. Privacy concerns, for example, have been identified as an important factor influencing users' trust and intention to adopt wearable Internet of Medical Things (WIoMT) devices because secure handling of personal health information increases users' confidence in digital healthcare technologies (Thapa et al., 2023).

Nevertheless, other studies suggest that when users perceive substantial functional and health-related benefits, privacy concerns become less influential in the adoption decision, indicating a privacy–benefit trade-off in wearable healthcare technologies (Li et al., 2016). Furthermore, previous studies have largely concentrated on the direct effects of technological determinants. At the same time, limited attention has been devoted to understanding how psychological factors strengthen or weaken the relationship between behavioral intention and actual technology usage. This limitation is particularly evident

in emerging digital healthcare markets, where consumer behavior may differ because of variations in technological readiness, healthcare awareness, and socio-cultural characteristics. Therefore, further investigation is needed to examine wearable health device adoption by integrating both technological and psychological perspectives, particularly in emerging economies such as Indonesia, where empirical evidence remains relatively limited.

Based on data from Statista, the market size of fitness trackers, a type of wearable health device, in Indonesia in 2025 is projected to be USD 564.92 million, or IDR 9 trillion. The market size is also predicted to have a 4-year Compounding Annual Growth Rate (CAGR) of 7.07%, so that in 2029 it will have a market of USD 742.3 million, or IDR 12.25 trillion. Penetration of fitness-tracker use in Indonesia is 10.77% and is projected to reach 13.08% in 2029. Market players can utilize the large potential of the wearable health device market in Indonesia to optimize their product sales.

Health motivation is understood as a psychological tendency that drives individuals to actively maintain, preserve, and improve their health. Meanwhile, perceived benefits and the perception that wearable health devices are easy to use will increase user comfort and trust in the technology (Holden & Karsh, 2010).

In the context of wearable health device (WHD) adoption, health motivation plays an important role in encouraging individuals to use digital health technologies consistently in their daily lives. Individuals with strong health motivation are generally more concerned about maintaining physical fitness, preventing disease, and monitoring their health conditions regularly. As a result, they are more likely to perceive wearable health devices as useful tools that can support healthier lifestyles and improve self-management behavior. Furthermore, when users perceive wearable devices as beneficial, easy to operate, and capable of providing accurate health-related information, their level of trust and willingness to adopt the technology tends to increase.

Unlike previous studies, this research develops an extended Technology Acceptance Model (TAM) by simultaneously integrating Perceived Product Value as a mediating construct and Health Motivation as a moderating construct within a single conceptual framework. Rather than merely examining the direct effects of technological characteristics on adoption intention, this study investigates how health motivation strengthens the relationship between behavioral intention and actual wearable health device usage. Furthermore, this research provides empirical evidence from Indonesia, one of the fastest-growing digital healthcare markets in Southeast Asia, where studies investigating wearable health device adoption remain limited. By addressing the inconsistent findings regarding perceived cost, perceived personal privacy, and social image, this study provides a more comprehensive understanding of wearable health device adoption in emerging economies.

This study examines the role of health motivation as a variable that strengthens or weakens the relationship between behavioral intention and actual use of wearable health devices (WHD) among millennials in Indonesia. The main focus is to examine whether higher health motivation encourages individuals to be more consistent in translating intention into action. The selection of respondents from the millennial generation was motivated by current lifestyle developments that tend to affect adults' health. Their relatively higher purchasing power also influenced the selection of millennial generation respondents during their productive age. This study also examines the formation of perceived product value (PPV) as a result of several main influencing factors, namely

compatibility, cost, personal privacy, accuracy, brand name, social image, and ease of use of wearable health devices (WHD), especially among millennials in Indonesia. This study can provide an understanding of millennial generation consumer behavior towards health technology, such as wearable health devices (WHD), while also providing strategic input for the development and marketing of wearable health devices (WHD) products in the domestic market. Theoretically, this study extends the Technology Acceptance Model (TAM) by incorporating Perceived Product Value and Health Motivation into an integrated framework explaining wearable health device adoption. The findings demonstrate that psychological motivation serves as an important boundary condition that strengthens the relationship between behavioral intention and actual technology usage, thereby enriching the literature on digital health technology adoption. Empirically, this study contributes by providing evidence from Indonesian millennials, a population that has received limited attention in previous wearable health technology research. The findings also offer practical implications for wearable health device manufacturers and healthcare service providers by highlighting the importance of enhancing functional value and users' health motivation rather than relying solely on technological features or social appeal when promoting wearable health devices.

RESEARCH METHODS

This study uses a quantitative approach with a cross-sectional survey design to test causal relationships between latent variables within a single data collection period. The research conceptual model is based on TAM, expanded with dimensions of perceived product value, perceived compatibility, perceived cost, perceived personal privacy, perceived technology accuracy, perceived usefulness, brand name, social image, intention to use, health motivation, and the use of wearable health devices (WHD).

The variables were operationalized based on previously validated measurement scales. Perceived Compatibility (PCM), Perceived Cost (PCT), Perceived Personal Privacy (PPP), Perceived Technology Accuracy (PTA), Perceived Usefulness (PUF), Perceived Product Value (PPV), Social Image (SI), Brand Name (BN), Intention to Use (IWD), Health Motivation (HMT), and Usage of Wearable Health Devices (UWD) were operationalized as reflective constructs. The measurement items were adapted from established studies, particularly Yang et al. (2016), Hayat et al. (2022), Sergueeva et al. (2020), Venkatesh (2003), Snell Jr et al. (1991), and Tian et al. (2025). Minor wording modifications were made to ensure that the items were appropriate for the Indonesian context while preserving the original conceptual meaning and content validity of each construct.

The population in this study was millennials who use wearable health devices (WHD), such as smartwatches, which are quite common in Indonesia. In Structural Equation Modeling (SEM) analysis, the minimum sample size is generally set at five to ten times the number of research indicators. With a total of 41 indicators used, this study set a minimum sample size of 205 respondents. The technique used in this study was non-probability sampling, with a purposive sampling approach. Millennials were selected as the target respondents because they represent one of the most active generations in adopting digital technologies and wearable health devices in Indonesia. As individuals in their productive age, millennials generally possess relatively higher purchasing power, greater familiarity with mobile technologies, and stronger awareness of preventive healthcare than older generations. Therefore, they constitute an appropriate population for examining the adoption of wearable health devices.

The questionnaire used a seven-point Likert scale, with responses ranging from strongly disagree (1) to strongly agree (7). Prior to the main survey, the questionnaire was reviewed by experts in digital technology and marketing research to assess content validity and language clarity. A pilot test involving respondents representing the target population was subsequently conducted to ensure that all questionnaire items were easily understood. Based on the pilot test results, minor wording revisions were made while maintaining the conceptual equivalence of the original measurement scales.

This research employs a quantitative explanatory approach, relying not only on primary data but also utilizing secondary data obtained through literature review. Furthermore, the approach used is Structural Equation Modeling based on Partial Least Squares (SEM-PLS) with the assistance of SmartPLS software.

Since all data were collected through self-administered questionnaires from the same respondents, several procedural remedies were implemented to minimize the potential for common method bias. Respondents were informed that their participation was voluntary and that all responses would remain anonymous and confidential. They were also assured that there were no right or wrong answers and were encouraged to provide honest responses based on their personal experiences. In addition, the questionnaire was carefully designed using clear, concise, and unambiguous wording adapted from previously validated measurement scales to reduce respondents' misunderstanding and response bias.

RESULTS AND DISCUSSION

Measurement model analysis (outer model) in PLS-SEM is conducted to evaluate the validity and reliability of variables before testing the structural model (Hair et al., 2019). The following validity tests cover two main aspects: convergent and discriminant validity.

Table 1. Outer Loading Values

	BN	HMT	IWD	PCM	PCT	PPP	PPV	PTA	PUF	SI	UW D	HMT x IWD
BN 1	0,85 2											
BN 2	0,82 9											
BN 3	0,78 7											
BN 4	0,81 7											
HMT 1		0,86 8										
HMT 2		0,88 3										
HMT 3		0,85 0										
HMT 4		0,82 8										
HMT 5		0,79 8										
IWD 1			0,89 3									
IWD 2			0,90 6									
IWD 3			0,90 4									

	BN	HMT	IWD	PCM	PCT	PPP	PPV	PTA	PUF	SI	UW D	HMT x IWD
IWD 4			0,86 1									
IWD 5			0,78 0									
PCM 1				0,89 7								
PCM 2				0,91 5								
PCM 3				0,87 8								
PCM 4				0,90 1								
PCT 1					0,58 9							
PCT 2					0,95 1							
PCT 3					0,91 7							
PPP 1						0,96 5						
PPP 2						0,92 8						
PPP 3						0,93 1						
PPV 1							0,89 3					
PPV 2							0,87 3					
PPV 3							0,86 6					
PPV 4							0,87 6					
PTA 1								0,86 7				
PTA 2								0,90 0				
PTA 3								0,91 7				
PTA 4								0,90 9				
PTA 5								0,83 5				
PUF 1									0,89 0			
PUF 2									0,92 7			
PUF 3									0,89 5			
SI 1										0,90 5		
SI 2										0,92 1		
SI 3										0,93 7		
SI 4										0,86 6		
UWD 1											0,91 4	
UWD 2											0,92 0	

	BN	HMT	IWD	PCM	PCT	PPP	PPV	PTA	PUF	SI	UWD	HMT x IWD
UWD 3											0,90	
HMT x IWD											2	1,000

Source: Researcher Processed Results using SmartPLS

The measurement model demonstrated satisfactory convergent validity. All constructs achieved AVE values above the recommended threshold of 0.50, while almost all indicator loadings exceeded 0.70. Although one indicator (PCT1 = 0.589) was slightly below the preferred level, it remained acceptable because the construct's AVE and composite reliability satisfied the recommended criteria. These findings indicate that the measurement model possesses adequate convergent validity; this value is still acceptable because it does not reduce the AVE value below the threshold and remains conceptually relevant (Hair et al., 2019).

Table 2. Average Variance Extracted Values

Variable	AVE	Value Parameters	Validity
Brand Name (BN)	0,675	> 0,5	Valid
Health Motivation (HMT)	0,716	> 0,5	Valid
Intention to use (IWD)	0,757	> 0,5	Valid
Perceived Compatibility (PCM)	0,806	> 0,5	Valid
Perceived Cost (PCT)	0,697	> 0,5	Valid
Perceived Personal Privacy (PPP)	0,887	> 0,5	Valid
Perceived Product Value (PPV)	0,769	> 0,5	Valid
Perceived Technology Accuracy (PTA)	0,785	> 0,5	Valid
Perceived Usefulness (PUF)	0,817	> 0,5	Valid
Social Image (SI)	0,824	> 0,5	Valid
Usage Wearable Health Device (UWD)	0,832	> 0,5	Valid

Source: Researcher's Processed Results using SmartPLS

Judging from the AVE values, all variables in this study are above the recommended minimum limit of 0.50, with values ranging from 0.675 to 0.887. Overall, the outer loading and AVE values indicate that the measurement model in this study meets the criteria for convergent validity.

Table 3. Heterotrait-Monotrait Ratio (HTMT) Values

Variable	BN	HMT	IWD	PCM	PCT	PPP	PPV	PTA	PUF	SI	UWD	HMT x IWD
Brand Name (BN)												
Health Motivation (HMT)	0,585											
Intention to use (IWD)	0,663	0,673										
Perceived Compatibility (PCM)	0,533	0,555	0,732									
Perceived Cost (PCT)	0,091	0,173	0,120	0,116								
Perceived Personal Privacy (PPP)	0,062	0,160	0,139	0,107	0,773							
Perceived Product Value (PPV)	0,714	0,680	0,855	0,776	0,124	0,151						
Perceived Technology Accuracy (PTA)	0,678	0,391	0,637	0,584	0,047	0,053	0,741					
Perceived Usefulness (PUF)	0,604	0,448	0,736	0,564	0,048	0,095	0,746	0,692				
Social Image (SI)	0,550	0,244	0,464	0,438	0,065	0,088	0,509	0,651	0,656			
Usage Wearable Health Device (UWD)	0,461	0,318	0,388	0,333	0,039	0,092	0,416	0,450	0,471	0,551		

Variable	BN	HMT	IWD	PCM	PCT	PPP	PPV	PTA	PUF	SI	UWD	HMT x IWD
HMT x IWD	0,275	0,556	0,420	0,305	0,078	0,065	0,302	0,042	0,219	0,026	0,072	

Source: Researcher's Processed Results using SmartPLS

Discriminant validity was confirmed because all HTMT values were below the recommended threshold of 0.90, which was further supported by the Fornell-Larcker criterion and cross-loading analysis. Therefore, each construct was empirically distinct from the others.

Table 4. Fornell-Larcker Criterion Values

Variable	BN	HMT	IWD	PCM	PCT	PPP	PPV	PTA	PUF	SI	UWD
Brand Name (BN)	0,822										
Health Motivation (HMT)	0,524	0,846									
Intention to use (IWD)	0,579	0,617	0,870								
Perceived Compatibility (PCM)	0,470	0,518	0,674	0,898							
Perceived Cost (PCT)	-0,018	-0,164	-0,122	-0,123	0,835						
Perceived Personal Privacy (PPP)	-0,003	-0,146	-0,136	-0,107	0,686	0,942					
Perceived Product Value (PPV)	0,623	0,626	0,779	0,708	-0,130	-0,148	0,877				
Perceived Technology Accuracy (PTA)	0,599	0,379	0,591	0,544	0,002	-0,051	0,679	0,886			
Perceived Usefulness (PUF)	0,524	0,417	0,667	0,513	-0,034	-0,086	0,670	0,630	0,904		
Social Image (SI)	0,491	0,245	0,434	0,409	0,042	0,078	0,470	0,607	0,599	0,908	
Usage Wearable Health Device (UWD)	0,402	0,307	0,352	0,303	0,024	0,081	0,373	0,411	0,422	0,504	0,912

Source: Researcher's Processed Results using SmartPLS

Based on the analysis, all diagonal values representing the square root of the AVE appear larger than the correlation values between variables in the same row and column. This indicates that each variable has a fairly clear level of differentiation. Each variable can distinguish itself from other variables in the model. These results indicate that the discriminant validity criteria based on the Fornell-Larcker approach have been met. Furthermore, the cross-loading values are shown in the following table.

Table 5. Cross-Loading Values

Item	BN	HMT	IWD	PCM	PCT	PPP	PPV	PTA	PUF	SI	UWD	HMT x IWD
BN 1	0,852	0,476	0,472	0,429	0,097	0,075	0,548	0,518	0,412	0,433	0,323	-0,184
BN 2	0,829	0,459	0,530	0,399	0,009	0,066	0,494	0,463	0,454	0,384	0,270	-0,257
BN 3	0,787	0,311	0,465	0,364	0,027	0,010	0,456	0,501	0,410	0,363	0,324	-0,136
BN 4	0,817	0,463	0,442	0,353	0,010	0,001	0,541	0,489	0,448	0,426	0,400	-0,252
HMT 1	0,469	0,868	0,542	0,477	0,097	0,091	0,532	0,358	0,455	0,254	0,312	-0,437
HMT 2	0,511	0,883	0,576	0,502	0,153	0,129	0,623	0,420	0,365	0,259	0,321	-0,431
HMT 3	0,386	0,850	0,505	0,421	0,168	0,145	0,502	0,195	0,313	0,128	0,200	-0,470
HMT 4	0,410	0,828	0,484	0,389	0,148	0,134	0,491	0,284	0,295	0,194	0,237	-0,480
HMT 5	0,402	0,798	0,481	0,352	0,151	0,141	0,455	0,277	0,280	0,140	0,149	-0,426
IWD 1	0,444	0,542	0,893	0,599	0,073	0,118	0,696	0,452	0,600	0,367	0,278	-0,380

Item	BN	HMT	IWD	PCM	PCT	PPP	PPV	PTA	PUF	SI	UWD	HMT x IWD
IWD 2	0,548	0,524	0,906	0,607	-	-	0,726	0,544	0,607	0,391	0,297	-0,351
IWD 3	0,500	0,482	0,904	0,599	-	-	0,727	0,599	0,650	0,416	0,327	-0,294
IWD 4	0,502	0,582	0,861	0,594	-	-	0,635	0,473	0,525	0,361	0,346	-0,398
IWD 5	0,531	0,568	0,780	0,533	-	-	0,597	0,496	0,510	0,347	0,284	-0,326
PCM 1	0,409	0,498	0,565	0,897	-	-	0,594	0,406	0,386	0,326	0,249	-0,340
PCM 2	0,399	0,489	0,617	0,915	-	-	0,630	0,456	0,467	0,345	0,266	-0,259
PCM 3	0,406	0,451	0,598	0,878	-	-	0,626	0,522	0,476	0,421	0,290	-0,231
PCM 4	0,469	0,427	0,637	0,901	-	-	0,685	0,558	0,503	0,373	0,282	-0,222
PCT 1	0,098	0,054	-	0,017	0,589	-	-	0,029	0,036	0,043	0,031	-0,111
PCT 2	-	-	-	-	-	-	-	-	-	-	-	-
PCT 2	0,018	0,156	0,112	0,129	0,951	0,606	0,136	0,016	0,046	0,013	0,010	0,029
PCT 3	-	-	-	-	-	-	-	-	-	-	-	-
PCT 3	0,023	0,160	0,120	0,103	0,917	0,685	0,108	0,022	0,016	0,071	0,037	0,041
PPP 1	-	-	-	-	-	-	-	-	-	-	-	-
PPP 1	0,014	0,158	0,155	0,129	0,653	0,965	0,178	0,065	0,074	0,079	0,053	0,068
PPP 2	-	-	-	-	-	-	-	-	-	-	-	-
PPP 2	0,025	0,121	0,101	0,066	0,637	0,928	0,097	0,011	0,065	0,118	0,072	0,078
PPP 3	-	-	-	-	-	-	-	-	-	-	-	-
PPP 3	0,008	0,121	0,114	0,088	0,653	0,931	0,117	0,056	0,107	0,029	0,116	0,031
PPV 1	-	-	-	-	-	-	-	-	-	-	-	-
PPV 1	0,522	0,573	0,676	0,638	0,161	0,134	0,893	0,535	0,592	0,407	0,368	-0,277
PPV 2	-	-	-	-	-	-	-	-	-	-	-	-
PPV 2	0,521	0,554	0,717	0,640	0,064	0,123	0,873	0,605	0,576	0,384	0,282	-0,241
PPV 3	-	-	-	-	-	-	-	-	-	-	-	-
PPV 3	0,557	0,520	0,670	0,590	0,125	0,130	0,866	0,597	0,656	0,460	0,336	-0,223
PPV 4	-	-	-	-	-	-	-	-	-	-	-	-
PPV 4	0,587	0,547	0,670	0,615	0,108	0,131	0,876	0,646	0,527	0,399	0,326	-0,263
PTA 1	-	-	-	-	-	-	-	-	-	-	-	-
PTA 1	0,554	0,340	0,521	0,434	0,024	0,009	0,591	0,867	0,507	0,467	0,327	-0,009
PTA 2	-	-	-	-	-	-	-	-	-	-	-	-
PTA 2	0,490	0,337	0,475	0,520	0,017	0,064	0,602	0,900	0,535	0,531	0,322	-0,022
PTA 3	-	-	-	-	-	-	-	-	-	-	-	-
PTA 3	0,571	0,381	0,548	0,493	0,020	0,053	0,615	0,917	0,566	0,521	0,375	-0,070
PTA 4	-	-	-	-	-	-	-	-	-	-	-	-
PTA 4	0,534	0,377	0,572	0,506	0,036	0,052	0,651	0,909	0,574	0,545	0,400	-0,072
PTA 5	-	-	-	-	-	-	-	-	-	-	-	-
PTA 5	0,508	0,232	0,497	0,453	0,069	0,049	0,545	0,835	0,614	0,636	0,397	-0,007
PUF 1	-	-	-	-	-	-	-	-	-	-	-	-
PUF 1	0,427	0,345	0,573	0,448	0,043	0,074	0,538	0,522	0,890	0,531	0,349	-0,158
PUF 2	-	-	-	-	-	-	-	-	-	-	-	-
PUF 2	0,456	0,399	0,610	0,469	0,056	0,093	0,640	0,574	0,927	0,520	0,400	-0,218
PUF 3	-	-	-	-	-	-	-	-	-	-	-	-
PUF 3	0,531	0,382	0,623	0,471	0,006	0,066	0,630	0,605	0,895	0,573	0,391	-0,182
SI 1	-	-	-	-	-	-	-	-	-	-	-	-
SI 1	0,511	0,298	0,447	0,400	0,030	0,061	0,480	0,604	0,580	0,905	0,487	-0,038
SI 2	-	-	-	-	-	-	-	-	-	-	-	-
SI 2	0,409	0,194	0,414	0,413	0,001	0,042	0,408	0,558	0,591	0,921	0,451	-0,002
SI 3	-	-	-	-	-	-	-	-	-	-	-	-
SI 3	0,421	0,240	0,408	0,385	0,040	0,059	0,464	0,562	0,546	0,937	0,422	-0,003
SI 4	-	-	-	-	-	-	-	-	-	-	-	-
SI 4	0,429	0,136	0,287	0,273	0,086	0,129	0,336	0,464	0,446	0,866	0,467	0,047
UWD 1	-	-	-	-	-	-	-	-	-	-	-	-
UWD 1	0,367	0,223	0,339	0,246	0,026	0,052	0,343	0,391	0,395	0,453	0,914	-0,022
UWD 2	-	-	-	-	-	-	-	-	-	-	-	-
UWD 2	0,354	0,312	0,314	0,234	0,002	0,102	0,327	0,369	0,359	0,444	0,920	-0,078
UWD 3	-	-	-	-	-	-	-	-	-	-	-	-
UWD 3	0,381	0,302	0,310	0,350	0,038	0,066	0,352	0,364	0,401	0,481	0,902	-0,088
HMT x IWD	-	-	-	-	-	-	-	-	-	-	-	-
HMT x IWD	0,254	0,525	0,400	0,291	0,032	0,063	0,286	0,042	0,208	0,002	0,069	1,000

Source: Researcher's Processed Results using SmartPLS

The Perceived Cost (PCT) variable shows that item PCT1 has a loading of 0.589. This item has the highest value on the PCT construct compared to other constructs, thus still meeting the criteria for discriminant validity. Although the PCT1 value is relatively lower, this item can still be retained because it is still a stronger measure of the PCT construct than other variables.

The next test is reliability testing, which is conducted to determine whether the indicators in each variable can provide consistent measurement results. Reliability evaluation in this study uses three measures: Composite Reliability (rho_c) as the main indicator, supported by rho_A and Cronbach's Alpha, in accordance with recommendations in SEM-PLS (Hair et al., 2019).

Table 6. Composite Reliability and Cronbach's Alpha Reliability Test Values

Variable	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Parameter	Reliability
<i>Brand Name (BN)</i>	0,840	0,844	0,893	> 0,7	Reliable
<i>Health Motivation (HMT)</i>	0,903	0,939	0,926	> 0,7	Reliable
<i>Intention to use (IWD)</i>	0,919	0,923	0,940	> 0,7	Reliable
<i>Perceived Compatibility (PCM)</i>	0,920	0,922	0,943	> 0,7	Reliable
<i>Perceived Cost (PCT)</i>	0,818	0,928	0,869	> 0,7	Reliable
<i>Perceived Personal Privacy (PPP)</i>	0,938	1,048	0,959	> 0,7	Reliable
<i>Perceived Product Value (PPV)</i>	0,900	0,900	0,930	> 0,7	Reliable
<i>Perceived Technology Accuracy (PTA)</i>	0,931	0,934	0,948	> 0,7	Reliable
<i>Perceived Usefulness (PUF)</i>	0,888	0,895	0,930	> 0,7	Reliable
<i>Social Image (SI)</i>	0,929	0,938	0,949	> 0,7	Reliable
<i>Usage of Wearable Health Device (UWD)</i>	0,899	0,899	0,937	> 0,7	Reliable

Source: Researcher's Processed Results using SmartPLS

All constructs exhibited satisfactory reliability, with Cronbach's Alpha, Composite Reliability, and rho_A values exceeding 0.70, indicating strong internal consistency. Although several rho_A values exceed 1, this condition is still acceptable in the context of PLS estimation as long as the Composite Reliability and AVE values remain within the recommended limits (Hair et al., 2019).

After the measurement model meets the validity and reliability criteria, the analysis continues with the structural model. Structural model analysis (inner model) is conducted to assess the quality of the relationships between latent variables in the structural model.

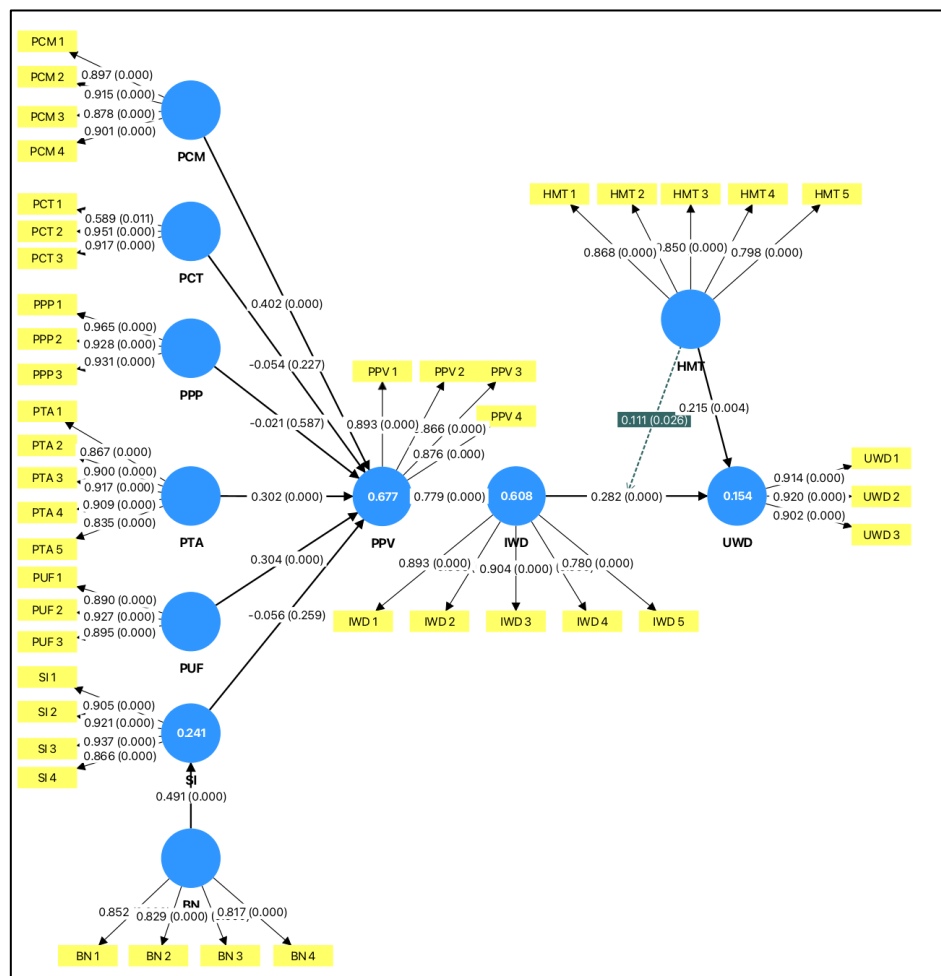


Figure 1. Structural Model of Research

The Variance Inflation Factor (VIF), R-square, Q-square Predictive, and F-square values in this study are shown in the following table.

Table 7. Variance Inflation Factor (VIF) Values

Variable	Variance Inflation Factor (VIF)
BN → SI	1,000
HMT → UWD	1,895
HMT × IWD → UWD	1,399
IWD → UWD	1,635
PCM → PPV	1,557
PCT → PPV	1,930
PPP → PPV	1,964
PPV → IWD	1,000
PTA → PPV	2,130
PUF → PPV	2,029
SI → PPV	1,873

Source: Researcher's Processed Results using SmartPLS

Table 8. R-square and Q-square Predictive Values

Variable	R-square	Result	Q ² predict	Result
Intention to use (IWD)	0,608	Moderate	0,571	The model has predictive relevance
Perceived Product Value (PPV)	0,677	Moderate to strong	0,648	The model has predictive relevance
Social Image (SI)	0,241	Weak	0,229	The model has predictive relevance
Usage Wearable Health Device (UWD)	0,154	Weak	0,166	The model has predictive relevance

Source: Researcher's Processed Results using SmartPLS

Table 9. F-square values

Variable	f-square	Effect Size
BN → SI	0,317	Medium effect
HMT → UWD	0,029	Small effect
HMT x IWD → UWD	0,021	Small effect
IWD → UWD	0,058	Small effect
PCM → PPV	0,321	Medium effect
PCT → PPV	0,005	No meaningful effect
PPP → PPV	0,001	No meaningful effect
PPV → IWD	1,548	Large effect
PTA → PPV	0,133	Small to medium effect
PUF → PPV	0,141	Small to medium effect
SI → PPV	0,005	No meaningful effect

Source: Researcher's Processed Results using SmartPLS

Based on Tables 7–9, the structural model showed no multicollinearity issues, as all VIF values were below the recommended threshold of 5. The model also demonstrated acceptable explanatory and predictive capability, with R^2 values ranging from weak to moderate and all Q^2 values exceeding zero. Furthermore, effect size analysis indicated that perceived product value exerted the strongest influence on intention to use. In contrast, perceived cost, perceived personal privacy, and social image contributed only negligible effects on perceived product value.

Table 10. Model Fit Values

	Saturated model	Estimated model
SRMR	0,051	0,109
d_ULS	2,421	11,304
d_G	1,244	1,492
Chi-square	2501,410	2863,584
NFI	0,819	0,793

Source: Researcher's Processed Results using SmartPLS

Based on the test results, the standardized root mean square residual (SRMR) value in the saturated model is 0.051, while in the estimated model it is 0.109. The standardized root mean square residual (SRMR) value in the saturated model is below the general limit of 0.08, thus indicating that the model has a good level of fit in the correlation structure

between variables. Meanwhile, the standardized root mean square residual (SRMR) value in the estimated model is above 0.08, thus indicating that there is still a difference between the estimated model and the empirical data. The path coefficients, t-statistics, and p-values are shown in the table.

Table 11. Path Coefficients, T-statistics, and P-values

Variable	Path Coefficients	T-statistics	P-values	Decision
BN → SI	0,491	10,966	0,000	Supported
HMT → UWD	0,215	2,869	0,004	Supported
HMT x IWD → UWD	0,111	2,225	0,026	Supported
IWD → UWD	0,282	3,789	0,000	Supported
PCM → PPV	0,402	6,432	0,000	Supported
PCT → PPV	-0,054	1,209	0,227	Not Supported
PPP → PPV	-0,021	0,544	0,587	Not Supported
PPV → IWD	0,779	22,840	0,000	Supported
PTA → PPV	0,302	4,091	0,000	Supported
PUF → PPV	0,304	4,615	0,000	Supported
SI → PPV	-0,056	1,128	0,259	Not Supported

Source: Researcher's Processed Results using SmartPLS

The results further reveal that brand name (BN) has a positive and significant effect on social image (SI). At the same time, perceived compatibility (PCM), perceived technology accuracy (PTA), and perceived usefulness (PUF) are proven to have a positive and significant effect on perceived product value (PPV). These findings indicate that the value of wearable health devices (WHD) products is mainly formed by the suitability of the device to lifestyle, technological accuracy, and benefits perceived by respondents. In addition, perceived product value (PPV) has a positive and significant effect on intention to use (IWD), so that the higher the perceived product value, the greater the respondents' intention to use wearable health devices (WHD).

At the actual use stage, health motivation (HMT) and intention to use (IWD) were proven to have a positive and significant effect on the usage of wearable devices (UWD), and the moderating effect of health motivation (HMT) x intention to use (IWD) on the usage of wearable devices (UWD) was also significant. These results indicate that health motivation strengthens the relationship between usage intention and actual use of wearable health devices. Meanwhile, the relationship between perceived cost (PCT), perceived personal privacy (PPP), and social image (SI) and perceived product value (PPV) was not significant, so respondents in the study assessed wearable health devices (WHD) more based on functional aspects than on cost, personal privacy, or social image.

This study also tested the specific indirect effects between variables. The specific indirect effects tested in this study are shown in the table.

Table 12. Original Samples, Mean, Std. Deviation, T-statistics, and P-values

Specific Indirect Effect	Original samples	Mean	Standard deviation	T-statisticss	P-values
PPP → PPV → IWD	-0,017	-0,017	0,030	0,545	0,585
PTA → PPV → IWD	0,236	0,233	0,055	4,308	0,000
PCM → PPV → IWD → UWD	0,088	0,088	0,030	2,977	0,003
PUF → PPV → IWD	0,237	0,238	0,056	4,251	0,000

PCT → PPV → IWD → UWD	-0,012	-0,012	0,011	1,118	0,263
SI → PPV → IWD	-0,043	-0,041	0,039	1,121	0,262
BN → SI → PPV → IWD	-0,021	-0,020	0,020	1,091	0,276
PPV → IWD → UWD	0,220	0,220	0,060	3,661	0,000
SI → PPV → IWD → UWD	-0,012	-0,011	0,012	1,042	0,297
PUF → PPV → IWD → UWD	0,067	0,067	0,025	2,703	0,007
PTA → PPV → IWD → UWD	0,067	0,065	0,023	2,913	0,004
PPP → PPV → IWD → UWD	-0,005	-0,005	0,009	0,524	0,600
BN → SI → PPV	-0,027	-0,026	0,025	1,098	0,272
BN → SI → PPV → IWD → UWD	-0,006	-0,006	0,006	1,013	0,311
PCM → PPV → IWD	0,313	0,312	0,054	5,750	0,000
PCT → PPV → IWD	-0,042	-0,042	0,035	1,215	0,224

Source: Researcher's Processed Results using SmartPLS

These findings indicate that perceived compatibility (PCM) has a positive and significant effect on perceived product value (PPV). This finding indicates that the greater the suitability of wearable health devices (WHD) with the respondent's lifestyle, routine, work, and health management, the higher the perceived product value. This result is in line with Rogers (2003), who explained that compatibility is an important factor in innovation adoption, and with Hayat et al. (2022), who found that compatibility plays a role in shaping perceived product value because devices that match user needs are perceived as having higher value. This finding is also supported by Gao et al. (2015), who stated that compatibility is one of the main determinants in the acceptance of wearable healthcare technology. Similarly, Canhoto & Arp (2017) emphasized that wearable devices are more likely to be adopted when they align with users' lifestyles and health management routines. Thus, compatibility is one of the main factors in shaping the product value of wearable health devices (WHD).

The test results show that perceived cost (PCT) does not significantly influence perceived product value (PPV). This means that in this study, perceived cost was not a primary factor determining the value of wearable health devices for respondents. This finding differs from the perceived value perspective proposed by Yang et al. (2016), who stated that perceived value is formed from a comparison between the benefits received and the sacrifices incurred, including costs. However, in the context of this study, the device's benefits and functionality appear to outweigh price considerations. This finding is consistent with Lunney et al. (2016), who found that users of wearable fitness technology tend to prioritize perceived benefits and functionality over financial sacrifice. Similarly, Talukder et al. (2019) explained that consumers are more likely to adopt wearable healthcare technology when they perceive strong utility, usability, and health-related benefits despite the associated costs. This finding may reflect the purchasing behavior of Indonesian millennials, who tend to perceive wearable health devices as long-term health investments rather than luxury products. As a result, respondents prioritize functional benefits, such as health monitoring accuracy and convenience, over monetary considerations. This characteristic may explain why perceived cost does not significantly reduce perceived product value despite the relatively high price of wearable devices. Furthermore, this result suggests that in an emerging market such as Indonesia, the

perceived value of wearable health devices is driven more by expected health outcomes than by financial sacrifice.

This evidence confirms that perceived personal privacy (PPP) does not significantly influence perceived product value (PPV). This means that respondents' concerns about the risks of sharing personal health data have not been statistically proven to influence perceived product value (PPV). This finding aligns with Sergueeva et al. (2020), who found that privacy concerns are not always a significant factor in the adoption of wearable technology for personal health management. Similarly, Wu et al. (2016) argued that users often conduct a risk-benefit assessment in which the perceived health benefits of wearable devices outweigh privacy concerns. Nevertheless, privacy remains important because wearable health devices (WHD) deal with sensitive health data. One possible explanation is that Indonesian millennials generally have higher trust in well-established wearable device brands and tend to assume that these products already provide adequate data security mechanisms. This finding may also indicate increasing consumer trust in established wearable technology ecosystems, where respondents perceive that reputable manufacturers have implemented adequate privacy protection and data security mechanisms, thereby reducing privacy concerns during adoption decisions. In addition, awareness of personal health data protection remains relatively low compared with developed countries, leading respondents to place greater emphasis on functional benefits than on privacy concerns. Consequently, privacy considerations become less influential in shaping perceived product value.

The test results show that perceived technology accuracy (PTA) has a positive and significant effect on perceived product value (PPV). This finding indicates that the higher respondents' perceptions of the technological accuracy of wearable health devices (WHD), the higher the perceived product value. This result is in line with Hayat et al. (2022), who showed that technological accuracy influences the perceived product value (PPV) of wearable health devices (WHD). Furthermore, Mattison et al. (2022) explained that wearable devices have the potential to support health monitoring, especially if they produce relevant information that can be used in health decision-making. This finding is also supported by Gao et al. (2015), who highlighted that technological reliability and system performance significantly increase users' trust and acceptance of wearable healthcare technology. In addition, Gao et al. (2015) emphasized that technological performance and system reliability are critical in increasing consumer confidence toward wearable devices. Thus, technological accuracy is an important factor in building trust and product value.

The test results show that perceived usefulness (PUF) has a positive and significant effect on perceived product value (PPV). This finding indicates that the higher the benefits perceived by respondents from using wearable health devices (WHD), the higher the perceived product value (PPV) formed. This result is in line with the Technology Acceptance Model (TAM) theory developed by Davis (1989), which explains that perceived usefulness is a major factor in technology acceptance. This finding also supports Yang et al. (2016), who stated that perceived usefulness is part of the perceived benefit that can increase the perceived value of wearable devices. Similarly, Chuah et al. (2016) found that usefulness and visibility positively influence smartwatch adoption behavior. Kim & Shin (2015) also demonstrated that perceived usefulness is among the strongest predictors of smartwatch acceptance. This finding is also supported by Bhattacharjee & Hikmet (2007), who emphasized that perceived usefulness is a critical

determinant of users' continuance intention toward health-related technologies. Because the respondents consisted of Indonesian millennials who are generally familiar with digital technology and mobile applications, they tended to evaluate wearable health devices based on their practical usefulness and compatibility with daily activities. Consequently, functional attributes became more influential than symbolic or economic considerations in shaping perceived product value.

This evidence confirms that social image (SI) does not significantly influence perceived product value (PPV). This result indicates that social image has not been a major factor in shaping the value of wearable health devices (WHD) products for respondents. Positively, this finding shows that millennial consumers in this study do not merely view wearable health devices (WHD) as status symbols or lifestyle products, but as devices that are valuable if they provide real benefits. This result differs from Yang et al. (2016), who stated that social image can be one component of perceived benefits in wearable devices. However, in the context of wearable health devices (WHD) in Indonesia, especially among the millennial generation, health value and usage function seem to be more important than social image. This finding contrasts with Dehghani et al. (2018), who found that social influence and enjoyment may encourage continued intention to use wearable technologies. It also differs from Chuah et al. (2016), who suggested that visibility and social exposure may positively affect smartwatch adoption. The insignificant effect of social image indicates that Indonesian millennials increasingly perceive wearable health devices as functional healthcare tools rather than status symbols. Following the COVID-19 pandemic, consumers have become more health-conscious. They are more likely to evaluate wearable devices based on their practical benefits for monitoring and maintaining health rather than their ability to enhance social prestige. Therefore, symbolic value becomes less important than functional value in determining perceived product value.

This evidence confirms that brand name (BN) has a positive and significant effect on social image (SI). This finding indicates that the stronger the respondents' perception of the wearable health device (WHD) brand, the higher the perceived social image (SI). This result is in line with Yang et al. (2016), who explained that product attributes and perceived social benefits can influence the acceptance of wearable devices. Similarly, Kim & Shin (2015) argued that brand-related perceptions and design aesthetics contribute to users' attitudes toward wearable technologies. Dehghani et al. (2018) also emphasized that brand reputation and social influence can strengthen users' intention to continue using wearable devices. Thus, brand name (BN) plays an important role in shaping the social image of wearable health device (WHD) users.

These findings indicate that perceived product value (PPV) has a positive and significant effect on intention to use (IWD). This finding indicates that the higher the product value perceived by respondents, the greater their intention to use wearable health devices (WHD). This result is in line with Yang et al. (2016), who stated that perceived value is an important predictor of intention to use wearable devices, and supports Hayat et al. (2022), who found that perceived product value influences intention to use wearable medical devices. Likewise, Hsiao & Chen (2018) explained that perceived value and convenience significantly increase smartwatch purchase intention and wearable technology adoption. More importantly, the present findings suggest that perceived product value functions as a higher-order evaluative construct that integrates users' assessments of multiple technological attributes into a single cognitive judgment.

Rather than forming behavioral intention directly from isolated technological perceptions, such as perceived usefulness or compatibility, consumers first evaluate whether the overall benefits offered by wearable health devices outweigh the perceived sacrifices associated with their adoption. This integrative evaluation explains why perceived product value demonstrates stronger explanatory power than individual Technology Acceptance Model (TAM) constructs in predicting intention to use. Consequently, perceived product value represents the immediate cognitive mechanism through which technological perceptions are translated into adoption intentions, thereby extending the explanatory capability of the traditional TAM in the context of wearable health devices. Thus, perceived product value (PPV) serves not only as an important bridge between consumers' perceptions of product attributes and intention to use but also as the central mechanism that consolidates multiple technological evaluations into adoption decisions.

These findings indicate that health motivation (HMT) has a positive and significant effect on the usage of wearable health devices (UWD). This finding indicates that the higher the respondents' health motivation, the greater their tendency actually to use wearable health devices (WHD). This result is in line with Hayat et al. (2022), who showed that health motivation is an important psychological factor in the use of wearable medical devices. Furthermore, Mattison et al. (2022) explained that wearable devices can support health monitoring and self-management, especially for individuals who are concerned about their health conditions. This finding is also supported by Nelson et al. (2016), who found that motivational affordances in wearable fitness devices encourage users to engage more actively in healthy behaviors. Similarly, Mercer et al. (2016) found that individuals with stronger health awareness and self-monitoring motivation are more likely to use wearable health technologies consistently in their daily lives. Thus, health motivation is an important factor in encouraging the actual use of wearable health devices (WHD).

These findings indicate that intention to use (IWD) has a positive and significant effect on the usage of wearable health devices (UWD). This finding indicates that the stronger respondents' intention to use wearable health devices (WHD), the more likely they are actually to use the devices. This result is consistent with the Theory of Planned Behavior (TPB) developed by Ajzen (1991), which explains that intention is the main predictor of actual behavior. In the context of technology acceptance, Davis (1989) and Venkatesh (2003) also emphasized that intention to use is an important factor that drives technology use. Similarly, Talukder et al. (2019) found that intention to recommend and actual usage behavior are strongly associated with acceptance of wearable healthcare technology. In addition, Krey et al. (2019) explained that users with stronger behavioral intention and perceived technological benefits are more likely to integrate wearable technologies into their daily routines. Thus, increasing intention to use is an important step in encouraging the adoption or actual use of wearable health devices (WHD).

These findings indicate that the interaction between Health Motivation and Intention to Use (HMT x IWD) has a positive and significant effect on the usage of wearable devices (UWD). This finding indicates that health motivation strengthens the relationship between intention to use and actual use of wearable health devices (WHD). This result is in line with Hayat et al. (2022), who found that health motivation moderates the relationship between intention to use and actual usage of wearable medical devices. This finding also strengthens the view that the use of health technology is influenced not only

by technological factors but also by an individual's psychological drive to maintain and improve health. In line with this, Kalantari (2017) explained that wearable technology adoption is strongly associated with users' health-oriented lifestyles and personal motivation toward self-monitoring behavior. Hsiao & Chen (2018) also emphasized that health beliefs and perceived convenience can strengthen consumers' willingness to adopt wearable healthcare technologies. Thus, health motivation plays a reinforcing role in the adoption and actual use of wearable health devices (WHD).

Beyond the empirical findings, the moderating role of health motivation can also be explained from a theoretical perspective. From the perspective of Self-Determination Theory (Ryan & Deci, 2020), health motivation reflects an intrinsic psychological orientation that encourages individuals to maintain behaviors consistent with their personal health goals. Users with stronger intrinsic health motivation are more likely to transform favorable intentions into sustained technology usage because wearable health devices become instruments for achieving long-term health outcomes rather than merely technological products. Consequently, health motivation strengthens behavioral consistency by reducing the intention–behavior gap that frequently occurs in technology adoption studies. This theoretical perspective provides a deeper explanation for the moderating effect observed in this study, indicating that the successful adoption of wearable health devices depends not only on users' intention to use the technology but also on their intrinsic motivation to maintain a healthy lifestyle.

Overall, these findings reflect the current characteristics of the Indonesian wearable health device market, which remains in a growth stage. Consumers primarily seek products that deliver tangible health benefits rather than symbolic or hedonic value. Consequently, compatibility, usefulness, and technology accuracy become the dominant drivers of perceived product value, whereas perceived cost, privacy concerns, and social image play relatively minor roles. This pattern indicates that wearable health device adoption in Indonesia is primarily function-oriented rather than prestige-oriented.

The findings extend the Technology Acceptance Model (TAM) by demonstrating that perceived product value acts as a key mechanism linking technological attributes to behavioral intention. While the original TAM emphasizes perceived usefulness and perceived ease of use, this study shows that compatibility and technology accuracy also contribute significantly to product value, which subsequently strengthens intention to use wearable health devices. Therefore, perceived product value represents an important extension of the traditional TAM framework in explaining wearable health device adoption in emerging markets. Furthermore, this study contributes to the development of TAM by demonstrating the moderating role of health motivation in the relationship between intention to use and actual usage. The findings indicate that behavioral intention alone is insufficient to explain technology adoption unless individuals possess strong intrinsic motivation to maintain their health. Therefore, health motivation functions as a boundary condition that strengthens the intention–behavior relationship, enriching the explanatory power of TAM in the context of digital health technology.

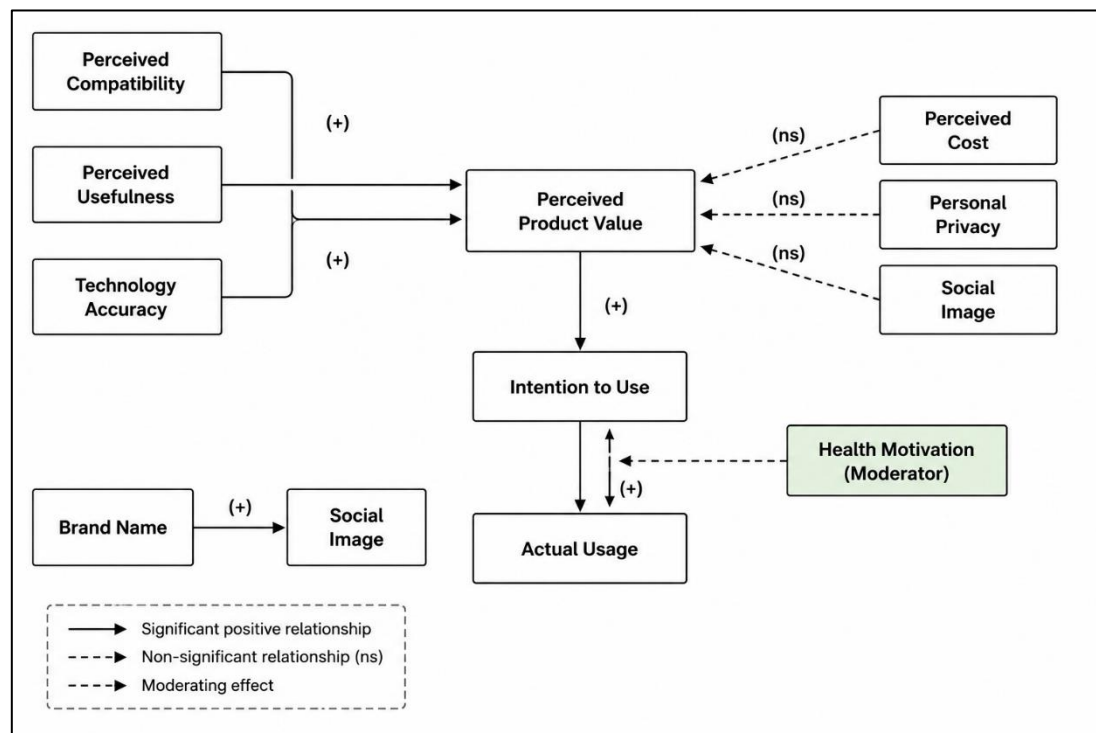


Figure 2. Final Validated Research Model of Wearable Health Device Adoption

CONCLUSION AND RECOMMENDATIONS

This study concludes that wearable health device (WHD) adoption among Indonesian millennials is mainly driven by perceived product value, which is influenced by perceived compatibility, perceived technology accuracy, and perceived usefulness. Perceived product value significantly increases intention to use, while health motivation strengthens the relationship between intention and actual WHD usage. Conversely, perceived cost, perceived personal privacy, and social image do not significantly influence perceived product value.

Theoretically, this study extends the Technology Acceptance Model (TAM) by integrating perceived product value and health motivation into a single framework, highlighting the important role of psychological motivation in transforming behavioral intention into actual technology usage. Practically, the findings suggest that manufacturers and healthcare providers should prioritize improving product functionality, technological accuracy, and users' health motivation rather than focusing primarily on price or social image.

This study is limited by its cross-sectional design and its focus on Indonesian millennials, which may limit the generalizability of the findings. In addition, although the proposed structural relationships were statistically significant, the relatively modest coefficient of determination ($R^2 = 0.154$) for actual usage indicates that wearable health device adoption is influenced by additional behavioral and environmental factors beyond the variables examined in this study. Factors such as facilitating conditions, habit, physician recommendations, digital health literacy, health status, and technological readiness may further explain actual usage behavior and should therefore be incorporated into future research. Future research is encouraged to employ longitudinal designs, involve more diverse populations, and incorporate additional variables, such as

trust, digital health literacy, or facilitating conditions, to obtain a more comprehensive understanding of wearable health device adoption.

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