Available at https://journalenrichment.com/index.php/jr/

Enrichment Journal of Multidisciplinary Research and Development

Enrichment: Journal of Multidisciplinary Research and Development

Analysis of Perceived Severity, Perceived Vulnerability, Attitude, Subjective Norms, and Perceived Behavioral Control on the Intention to Continue Using a Smartwatch, with Age as a Moderating Variable

Grace Intan Karlina Lidia Simanjuntak*, Mas Wahyu Wibowo
Universitas Mercu Buana, Indonesia
Email: 55124110078@student.mercubuana.ac.id*, mas.wahyu@mercubuana.ac.id

Keywords
protection motivation theory (pmt); theory of planned behavior (tpb); continued use intention; smartwatch; age.

Abstract
Smartwatches are wearable devices that are increasingly used to support health monitoring, physical activity, productivity, and healthy lifestyles. However, the sustained use of smartwatches remains a challenge because not all users continue using these devices over the long term. This study aims to examine the effects of perceived severity, perceived vulnerability, attitude, subjective norms, and perceived behavioral control on users' continuance intention to use smartwatches, with age serving as a moderating variable. The study integrates Protection Motivation Theory (PMT) and the Theory of Planned Behavior (TPB) and adopts a quantitative survey design. Data were collected from 303 smartwatch users in the Greater Jakarta area belonging to Generation Z and Generation Y and were analyzed using Partial Least Squares–Structural Equation Modeling (PLS-SEM). The results indicate that attitude, subjective norms, and perceived behavioral control have positive and significant effects on users' continuance intention to use smartwatches, whereas perceived severity and perceived vulnerability do not have significant effects. Furthermore, age significantly moderates the relationships between perceived vulnerability and continuance intention, and between perceived behavioral control and continuance intention, but does not moderate the relationships involving perceived severity, attitude, or subjective norms. These findings suggest that the sustained use of smartwatches is driven more by users' positive attitudes, social influences, and perceived behavioral control than by their perceptions of health threats.

INTRODUCTION

The rapid advancement of digital technology over the past decade has significantly transformed human behavior, as reflected in the growing use of sensor-based wearable devices and internet-connected technologies for independently monitoring personal health without direct intervention from healthcare professionals. One such device is the smartwatch, which has become an important tool for supporting healthy lifestyles. Modern smartwatches no longer function solely as timekeeping devices; they have evolved into sophisticated health-monitoring tools capable of tracking blood pressure, blood oxygen saturation, sleep patterns, calories burned, and physical activity in real time (Konstantinidis et al., 2022).

The primary purpose of using smartwatches is to help individuals continuously monitor their health and promote regular physical activity to reduce the risk of chronic conditions such as hypercholesterolemia, cardiovascular disease, hypertension, and other noncommunicable diseases (NCDs). According to the World Health Organization (WHO), noncommunicable diseases are the leading cause of disability and mortality worldwide, accounting for approximately 41 million deaths annually, or about 74% of all global deaths. Therefore, the use of smartwatches as personal health-monitoring devices represents an important component of global disease prevention efforts (Lennox et al., 2024). Kumar (2025) reported that there were more than 454.69 million smartwatch users worldwide, approximately 92% of whom used these devices to monitor their health and fitness.

Despite the continued popularity of smartwatches, Lennox et al. (2024) reported that more than half of users discontinued using their devices within the first six months, while fewer than 20% continued using them consistently over time. Similarly, an empirical study by Ranti and Roestam (2023) found that approximately 30% of users stopped using their smartwatches within a few months of purchase. This phenomenon highlights a gap between initial adoption and continuance intention, indicating the need for further research into the factors influencing the sustained use of smartwatches.

Global smartwatch adoption also varies across age groups. Recent data indicate that individuals aged 18–34 years constitute the largest user group, accounting for 40% of smartwatch users, followed by those aged 35–54 years (30%) and individuals aged 55 years and older (15%) (Pangarkar, 2025). Trends in global smartwatch ownership are presented in Tables 1 and 2.

Table 1. Global Smartwatch Ownership Percentage by Age Group (2025)

Age Group	Ownership Percentage	Categories
18 – 34 years old	40%	Highest
35 – 54 years old	30%	Intermediate
≥ 55 years old	15%	Lowest

Source: Smartwatch Statistics 2025 by Market.us Scoop (Pangarkar, 2025)

Table 2. Global Smartwatch Ownership Trends 2023–2025

Period	Global Ownership Percentage	Remarks
First Quarter 2023	23,2%	Starting point of observation
First Quarter 2025	27,6%	Significant improvement
Indonesia (2025)	19.2% (Ranked 49th Globally)	Great growth potential

Source: Katadata Insight Center by Databoks (Muhamad, 2025)

Global statistics indicate that smartwatch ownership has continued to increase, rising from 23.2% in the first quarter of 2023 to 27.6% in the first quarter of 2025. Indonesia ranked 49th globally, with a smartwatch ownership rate of 19.3%, indicating substantial market growth potential as interest in health-oriented wearable technology continues to increase (Muhamad, 2025).

To provide a comprehensive understanding of users' continuance intention to use smartwatches, this study integrates Protection Motivation Theory (PMT) through the constructs of perceived severity and perceived vulnerability, and the Theory of Planned Behavior (TPB) through the constructs of attitude, subjective norms, and perceived behavioral control. PMT explains individuals' motivation to adopt protective behaviors in response to perceived health threats, whereas TPB explains the psychological factors that shape behavioral intentions, including the intention to continue using a smartwatch (Luo et al., 2021). In addition, age was examined as a moderating variable to determine whether differences between Generation Z and Generation Y strengthened or weakened the relationships between these constructs and users' continuance intention (Siepmann & Kowalczuk, 2021).

To support the selection of the study variables and obtain preliminary insights into the factors influencing smartwatch continuance intention, a pre-survey was conducted among smartwatch users. The results are presented in Table 3.

Table 3. Pre Research Survey

No.	Indicator	Yes (%)	No (%)
1	*Perceived Vulnerability: Signs of body health need to be considered so that it is not too late to detect diseases.*	85,3%	14,7%
2	*Perceived Severity: Maintaining health with the help of a smartwatch can prevent high-risk diseases.*	81,0%	19,0%
3	*Attitude: A positive view of the use of smartwatches because of its useful and practical health features.*	94,1%	5,9%
4	*Subjective Norms: The surrounding environment uses smartwatches to monitor physical activity in real-time.*	82,3%	17,7%
5	*Privacy Concern: Personal health data can be misused through smartwatch apps.*	49,6%	50,4%
6	*Perceived Behavioral Control: Able to use and understand health features on smartwatches.*	91,2%	8,8%
7	*Comfort Barrier: Uncomfortable use of the smartwatch for a long time due to skin irritation.*	43,5%	57,0%
8	*Risk Barrier: The effects of smartwatch radiation are harmful to health in the long term.*	38,2%	61,8%
9	*Performance Expectancy: Consistent use of smartwatches increases the effectiveness of managing daily health.*	72,1%	27,9%

Source: Primary Data, Researchers, Processed (2025)

The results of the pre-survey indicated that five key variables received more than 80% affirmative ("Yes") responses: perceived vulnerability (85.3%), perceived severity (81.0%), attitude (94.1%), subjective norms (82.3%), and perceived behavioral control (91.2%). The selection of these variables was further supported by previous studies, which indicate that important research gaps remain regarding users' continuance intention to use smartwatches in the Indonesian context.

Protection Motivation Theory (PMT), developed by Rogers (1975), explains how individuals are motivated to adopt and maintain protective behaviors in response to perceived health threats. In the PMT framework, the primary constructs examined in this study are threat appraisal, which comprises two components: perceived severity and perceived vulnerability. A meta-analysis of 65 studies conducted by Hedayati et al. (2023) found that both perceived severity and perceived vulnerability had significant positive effects on protective behavior, confirming that the threat appraisal component is an important predictor of protective motivation.

Perceived severity (PS) refers to an individual's assessment of the seriousness and potential consequences of a health threat. The greater the perceived seriousness of a health condition, the more likely an individual is to engage in protective behaviors (Chiu et al., 2025). In contrast, perceived vulnerability (PV) refers to the extent to which individuals perceive themselves to be susceptible to a disease or health threat. Individuals with higher levels of perceived vulnerability tend to demonstrate stronger motivation to engage in protective behaviors (Zhang et al., 2023).

The Theory of Planned Behavior (TPB), introduced by Ajzen (1991) as an extension of the Theory of Reasoned Action (TRA), proposes that actual behavior is primarily determined by behavioral intention, which is shaped by three core constructs: attitude, subjective norms, and perceived behavioral control. Attitude reflects an individual's positive or negative evaluation of a particular behavior, subjective norms represent perceived social pressure to perform or avoid the behavior, and perceived behavioral control refers to an individual's perception of their ability to perform the behavior. Studies by Chen et al. (2023) and Fragolia and Wibowo (2025) demonstrated that these three TPB constructs have positive and significant effects on behavioral intention across various technological contexts.

Continuance intention (CUI) refers to an individual's intention to continue using a technology after its initial adoption. Technology Continuance Theory (TCT), developed by Liao et al. (2009), provides a theoretical foundation for explaining the sustained use of technology by emphasizing the psychological mechanisms that develop after users interact with a technological system. Age, as a demographic characteristic, may moderate the relationships between psychological factors and behavioral intentions. Morris and Venkatesh (2020) demonstrated that age moderates the relationships between attitude, subjective norms, and perceived behavioral control and technology use. Similarly, Al Mamun et al. (2023) found that age moderates the relationship between behavioral intention and the actual adoption of wearable payment devices.

Based on the theoretical framework presented above, this study integrates PMT and TPB to explain users' continuance intention to use smartwatches, with age serving as the moderating variable. The proposed hypotheses are as follows:

METHOD

Research Design

This study employed a quantitative approach using a survey research design. A cross-sectional design was adopted, in which data were collected at a single point in time. The study involved no manipulation of the research variables, and data were collected from smartwatch users in their natural settings. The unit of analysis consisted of individual smartwatch users who provided responses through a structured questionnaire (Bougie & Sekaran, 2025).

Population and Sample

The study population is all individuals who use smartwatches in their daily activities and are in the productive age group in the Greater Jakarta area. The sampling technique used non-probability sampling using purposive sampling and snowball sampling methods. Respondent criteria: (1) active smartwatch users for at least the last three months, (2) domiciled in Greater Jakarta, and (3) aged between 17–44 years old (Gen Z: 17–28 years old; Gen Y: 29–44 years). The number of samples was determined using the G*Power application with the parameters of effect size = 0.15, α error probability = 0.05, power = 0.80, and 5 predictors, resulting in a minimum of 92 respondents per group. After the data cleaning, 303 valid respondents were obtained for analysis.

Variable Operationalization

This study consisted of five independent variables (Perceived Severity/PS, Perceived Vulnerability/PV, Attitude/ATT, Subjective Norms/SN, and Perceived Behavioral Control/PBC), one dependent variable (Continued Use Intention/CUI), and one moderation variable (Age). All indicators were measured using a seven-point Likert scale (1 = Strongly Agree to 7 = Strongly Agree) as presented in Table 4 and Table 5.

Table 4. Operationalization of Research Variables

No.	Variable	Indicator	Scale
1	*Perceived Severity (PS) Chiu et al. (2025)*	PS1: Severity of unmonitored health conditions. PS2: Increased severity of health problems. PS3: The impact of health issues on productivity.	Ordinal (Likert 1–7)
2	*Perceived Vulnerability (PV) Chiu et al. (2025)*	PV1: Risk of having health problems. PV2: The likelihood of having a health problem. PV3: Susceptibility to chronic diseases.	Ordinal (Likert 1–7)
3	*Attitude (ATT) Guo et al. (2023)*	ATT2: Positive assessment of the use of the smartwatch. ATT4: A favorite of using smartwatches for health.	Ordinal (Likert 1–7)
4	*Subjective Norms (SN) Guo et al. (2023)*	SN1: The influence of important people on the use of the smartwatch. SN3: Group support with similar interests or hobbies.	Ordinal (Likert 1–7)
5	*Perceived Behavioral Control (PBC) Guo et al. (2023)*	PBC1: Ability to use the smartwatch effectively. PBC2: The level of control over the use of the smartwatch. PBC3: Level of knowledge of using the smartwatch. PBC4: The ability to search for information related to your smartwatch.	Ordinal (Likert 1–7)
6	*Continued Use Intention (CUI) Siepmann & Kowalczuk (2021)*	CUI1: Intention to continue long-term use of the smartwatch. CUI2: Commitment to continue using the smartwatch. CUI3: Consistency of regular use of the smartwatch.	Ordinal (Likert 1–7)

Source: Researcher, Processed (2025)

Table 5. Likert Scale

Scale	Description
1	Strongly Disagree
2	Disagree
3	Simply disagree
4	Neutral
5	Simply Agree
6	Agree
7	Strongly agree

Source: Researcher, Processed (2025)

Data Analysis Methods

The data test method uses Partial Least Squares – Structural Equation Modeling (PLS-SEM) in SmartPLS 4.0 software. PLS-SEM was chosen because it is able to simultaneously evaluate measurement models (reliability and construct validity) and structural models (relationships between latent variables) without requiring strict assumptions of data normality

(Hair & Alamer, 2022). The analysis process involves: (1) testing the outer model through loading factor, composite reliability (CR), cronbach's alpha, average variance extracted (AVE), HTMT, and model fit (SRMR); (2) inner model testing through R^2, f^2, and Q^2; (3) direct hypothesis testing using bootstrapping; and (4) moderation testing through MICOM and PLS-MGA.

RESULTS AND DISCUSSION

Characteristics of Respondents

The research data was collected during the period of January 31–February 26, 2026. Of the 375 questionnaires collected, 303 were declared valid after the data cleaning process based on standard deviation (>0.5). The characteristics of the respondents are presented in Table 6.

Table 6. Characteristics of Respondents (n=303)

Characteristics	Categories	Quantity	Percentage (%)
Gender	Male	127	41,91%
	Women	176	58,09%
Age	Gen Z (17–28 years old)	147	48,51%
	Gen Y (29–44 years old)	156	51,49%
Education	Elementary Education (Elementary–High School)	23	7,59%
	Diploma (D1–D4)	42	13,86%
	Bachelor (S1)	206	68,00%
	Master (S2)	32	11,00%
Jobs	Civil Servant	22	7,26%
	Private Employees	211	69,64%
	Self-employed	42	13,86%
	Housewives	11	3,63%
	Student/Student	17	5,61%
Revenue/Month	< IDR 4,000,000	37	12,21%
	IDR 4,000,000 – IDR 8,000,000	113	37,29%
	IDR 9,000,000 – IDR 14,000,000	80	26,40%
	IDR 15,000,000 – IDR 20,000,000	24	7,92%
	> IDR 20,000,000	49	16,17%
Domicile	Jakarta	186	61,39%
	Tangerang	38	12,54%
	Bekasi	37	12,21%
	Bogor	28	9,24%
	Depok	14	4,62%
Smartwatch Brands	Apple	85	28,05%
Most Familiar	Huawei	74	24,42%
	Garmin	50	16,50%
	Xiaomi	48	15,84%
	Samsung	34	11,22%

Characteristics	Categories	Quantity	Percentage (%)
	Other Brands (Casio, Amazfit, etc.)	12	3,96%

Source: Researchers, Data processed (2026)

Descriptive Statistics of Research Variables

Table 7. Descriptive Statistics of Research Variables

Variable	Minimum	Maximum	Red	Std. Deviation
Perceived Severity	1,00	7,00	4,32	1,57
Perceived Vulnerability	1,00	7,00	3,17	1,72
Attitude	1,00	7,00	5,48	1,33
Subjective Norms	1,00	7,00	4,78	1,47
Perceived Behavioral Control	1,00	7,00	5,46	1,28
Continued Use Intention	1,00	7,00	5,44	1,33

Source: Researchers, Data processed (2026)

Based on Table 7, the attitude variable had the highest mean value (5.48), indicating that respondents tended to have a positive attitude towards the use of smartwatches. Perceived behavioral control and continued use intention also showed relatively high mean values. On the other hand, perceived vulnerability had the lowest mean value (3.17), indicating that the perception of vulnerability to health risks was still relatively low among respondents.

Measurement Model Test Results (*Outer Model*)

The outer model test was carried out to assess the validity and reliability of the construct. The results of the convergent validity test showed that all outer loading values were ≥ 0.70 (except PV3 in the Gen Y group of 0.678 which is still acceptable based on Hair et al., 2021), AVE > 0.50, and CR > 0.70 in all data groups. The results of the complete data set test are presented in Table 8.

Table 8. PLS Measurement Model: Outer Loading, CR, and AVE (Complete Data Set)

Variable	Indicator	Outer Loading	Cronbach's α	CR (rho_c)	AVE
Perceived Severity	PS1	0,902	0,882	0,927	0,808
	PS2	0,900			
	PS3	0,894			
Perceived Vulnerability	PV1	0,943	0,932	0,954	0,874
	PV2	0,965			
	PV3	0,895			
Attitude	ATT2	0,948	0,892	0,949	0,903
	ATT4	0,952			
Subjective Norms	SN1	0,883	0,763	0,894	0,808
	SN3	0,915			
Perceived Behavioral Control	PBC1	0,876	0,903	0,932	0,774
	PBC2	0,881			

Variable	Indicator	Outer Loading	Cronbach's α	CR (rho_c)	AVE
	PBC3	0,899			
	PBC4	0,863			
Continued Use Intention	CUI1	0,944	0,923	0,951	0,867
	CUI2	0,936			
	CUI3	0,913			

Source: SmartPLS Data Processing Results 4.1.1.6

All indicators are declared reliable and valid. Of the initial 21 indicator items, 4 indicators were excluded because they did not meet the requirements for outer loading (ATT1, ATT3, SN2, CUI4). The results of the discriminant validity test using HTMT show that all values are below 0.90, fulfilled in both the complete data set, Gen Y, and Gen Z, as presented in Table 9.

Table 9. Results of the Discriminant Validity Test – HTMT (Complete Data Set)

Variable	ATT	CUI	PBC	P.S.	PV	SN
ATT	–					
CUI	0,817	–				
PBC	0,768	0,780	–			
P.S.	0,641	0,539	0,505	–		
PV	0,108	0,062	0,109	0,212	–	
SN	0,829	0,809	0,725	0,684	0,147	–

Source: SmartPLS Data Processing Results 4.1.1.6

Table 10. Multicolonarity Test Results (VIF)

Variable Relationships	VIF Complete	LIVE Gen Y	VIF Gen Z
ATT → CUI	2,627	3,362	2,266
PBC → CUI	2,028	1,954	2,238
PS → CUI	1,643	1,993	1,396
PV → CUI	1,040	1,032	1,083
SN → CUI	2,185	2,914	1,674

Source: SmartPLS Data Processing Results 4.1.1.6 | Requirements: VIF < 5

All VIF values in Table 10 are below 5 in the complete data set, Gen Y, and Gen Z, indicating that there are no significant multicolonarity issues in the model.

Table 11. Model Fit (SRMR), Coefficient of Determination (R^2), Effect Size (f^2), and Predictive Relevance (Q^2)

Indicator	Complete	Gen Y	Gen Z
SRMR (< condition 0.08)	0.042 ✓	0.056 ✓	0.054 ✓
R^2 (CUI)	0.660 (Moderate)	0.696 (Moderate)	0.652 (Moderate)
Q^2predict (CUI)	0,640	0,663	0,615

Indicator	Complete	Gen Y	Gen Z
f² ATT → CUI	0.131 (Small)	0.204 (Medium)	0.059 (Small)
f² PBC → CUI	0.152 (Medium)	0.090 (Small)	0.318 (High)
f² PS → CUI	0.001 (Unaffected)	0.000 (Unaffected)	0.000 (Unaffected)
f² PV → CUI	0.004 (Unaffected)	0.028 (Small)	0.006 (Not Affected)
f² SN → CUI	0.082 (Small)	0.072 (Small)	0.067 (Small)

Source: SmartPLS Data Processing Results 4.1.1.6

Test of the Direct Relationship Hypothesis (H1–H5)

Table 12. Direct Hypothesis Test Results (H1–H5)

Hypothesis	Relationships	Path Coeff.	T-Statistics	P-Values	Results
H1	*PS → CUI*	0,018	0,418	0,338	Positive, insignificant. Hypothesis REJECTED
H2	*PV → CUI*	-0,039	1,110	0,134	Negative, insignificant. Hypothesis REJECTED
H3	*ATT → CUI*	0,342	4,085	0,000	Positive and significant. Hypothesis ACCEPTED
H4	*SN → CUI*	0,247	4,184	0,000	Positive and significant. Hypothesis ACCEPTED
H5	*PBC → CUI*	0,324	4,132	0,000	Positive and significant. Hypothesis ACCEPTED

Source: SmartPLS Data Processing Results 4.1.1.6 | Significant if the T-Statistics > 1.96 and the P-Values < 0.05

Moderation Effect Testing (MICOM and MGA)

Prior to MGA, the Measurement Invariance of Composite Models (MICOM) test was carried out to ensure that the measurement model was invariant between the Gen Z and Gen Y groups.

Table 13. MICOM Test Results Step 2 (Compositional Invariance)

Variable	Orig. Correlation	Perm. Red	5,0%	P-Value
ATT	1,000	1,000	1,000	0,218
CUI	1,000	1,000	1,000	0,506
PBC	1,000	1,000	0,999	0,700
P.S.	1,000	0,999	0,998	0,864
PV	0,871	0,891	0,386	0,200
SN	1,000	0,999	0,997	1,000

Source: SmartPLS Data Processing Results 4.1.1.6 | P-Value > 0.05 indicates a met compositional invariance

All constructs have a p-value above 0.05, indicating that compositional invariance is met. The results of MICOM Step 3a showed that ATT and PBC had significant differences in composite mean between groups ($p < 0.05$). However, because the partial measurement invariance is met, the MGA analysis can be continued. The results of the moderation hypothesis test (H6–H10) using PLS-MGA with a one-tailed test are presented in Table 14.

Table 14. Moderation Hypothesis Test Results – PLS-MGA (H6–H10)

Hypothesis	Relationships	Gen Y	Gen Z	Diff.	PLS-MGA	Param. Test	Supported
H6	*PS→CUI*	-0,007	0,000	-0,007	0,471	0,471	Yes
H7	*PV→CUI*	-0,093	0,048	-0,141	0,027	0,021	Yes
H8	*ATT→CUI*	0,456	0,216	0,240	0,058	0,053	Yes
H9	*SN→CUI*	0,252	0,198	0,054	0,331	0,323	Yes
H10	*PBC→CUI*	0,232	0,498	-0,266	0,033	0,030	Yes

Source: SmartPLS Data Processing Results 4.1.1.6 | H7 and H10: p-value < 0.05 (significant)

The Effect of Perceived Severity and Perceived Vulnerability on CUI. The results showed that PS had a positive but insignificant effect (H1 was rejected), while PV had a negative and insignificant effect (H2 was rejected). This condition can be explained through the characteristics of respondents who are in the productive age group (Gen Z and Gen Y) who are generally still socially and professionally active, so that physical health threats such as chronic diseases have not been perceived as urgent conditions. Respondents tend to use smartwatches not because they feel threatened by disease, but because of functional benefits and digital habits. These findings are in contrast to Zhang et al. (2023) and Lennox et al. (2024) who found PS to have a significant effect on the elderly population and adult users, indicating that differences in age context greatly influence this relationship.

The Influence of Attitude, Subjective Norms, and Perceived Behavioral Control on CUI. ATT (H3), SN (H4), and PBC (H5) have been shown to have a positive and significant effect on the CUI of smartwatches. The highest mean ATT value (5.48) indicates a strong positive attitude among respondents. The positive experience and high perception of smartwatch benefits reinforce the desire to continue using it (Guo et al., 2023; Chen et al., 2023). Significant SN shows that support from family, friends, co-workers, and the sports community is an important factor that strengthens smartwatch usage habits in Greater Jakarta's active urban community. While significant PBC indicates that users who feel able to operate smartwatch features tend to be more committed to using them sustainably, in line with the findings of Lee & Lee (2020) and Rekha & Timothy (2020).

The Role of Age as Moderation. Age was not shown to moderate the relationship of PS, ATT, and SN to CUI (H6, H8, H9 was rejected), but it was shown to moderate the relationship between PV and PBC to CUI (H7 and H10 were accepted). On H7, the influence of PV is stronger on Gen Z than on Gen Y, because Gen Z is more responsive to health information such as fatigue, stress, and lack of sleep, and more quickly translates this feeling of vulnerability into the intention to use a smartwatch as a real-time self-monitoring device (Widyawati, 2020). In H10, the influence of PBC is stronger on Gen Z than on Gen Y. Gen Z who are already accustomed to the digital ecosystem, when they feel able to operate and integrate smartwatches in daily activities, the perception of control is stronger and encourages the intention of continuous use. These findings are in line with Morris & Venkatesh (2020) who prove that age moderates the relationship of PBC to technology use, as well as Al Mamun et al. (2023) who recommend further exploration of age differences in the context of wearable health devices.

CONCLUSION

This study examined the effects of perceived severity (PS), perceived vulnerability (PV), attitude (ATT), subjective norms (SN), and perceived behavioral control (PBC) on users' continuance intention (CUI) to use smartwatches, with age serving as a moderating variable. The analysis was conducted using Partial Least Squares–Structural Equation Modeling (PLS-SEM) based on data collected from 303 Generation Z and Generation Y smartwatch users in the Greater Jakarta area. The hypothesis testing results indicated that attitude, subjective norms, and perceived behavioral control had positive and significant effects on continuance intention, whereas perceived severity and perceived vulnerability did not have significant direct effects. These findings suggest that users' intentions to continue using smartwatches are influenced more strongly by favorable evaluations of the devices' benefits, social influence, and confidence in their ability to use the technology than by perceptions of health threats. Regarding the moderating effect, age significantly moderated the relationships between perceived vulnerability and continuance intention, and between perceived behavioral control and continuance intention, with stronger effects observed among Generation Z users. However, age did not moderate the relationships between perceived severity, attitude, or subjective norms and continuance intention. The managerial implications of this study highlight the importance for smartwatch manufacturers and service providers to strengthen positive user attitudes by enhancing functional and enjoyable user experiences, fostering user communities through social influence, and ensuring that smartwatch features are easy to use and provide users with a strong sense of control, particularly among the Generation Z segment. These efforts can support the sustainable adoption of wearable health technologies while contributing to Sustainable Development Goal (SDG) 3 (Good Health and Well-Being), SDG 9 (Industry, Innovation and Infrastructure), and SDG 12 (Responsible Consumption and Production). Future research is recommended to examine gender as a moderating variable, incorporate the PMT constructs of response efficacy and self-efficacy, expand the geographical scope of the study, and employ longitudinal research designs to better understand changes in smartwatch use over time.

REFERENCES

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211.

Al Mamun, A., Naznen, F., Yang, M., Yang, Q., Wu, M., & Masukujjaman, M. (2023). Predicting the intention and adoption of wearable payment devices using hybrid SEM-neural network analysis. Scientific Reports, 13(1), 11217.

Bougie, R., & Sekaran, U. (2019). Research methods for business: A skill building approach. John Wiley & Sons.

Bougie, R., & Sekaran, U. (2025). Research Methods for Business, with eBook Access Code: A Skill Building Approach. John Wiley & Sons.

Chen, J., Li, T., You, H., Wang, J., Peng, X., & Chen, B. (2023). Behavioral interpretation of willingness to use wearable health devices in community residents: a cross-sectional study. International Journal of Environmental Research and Public Health, 20(4), 3247.

Chiu, W., Won, D., & Chen, J. (2025). Older adults' adoption behavior of mobile health (mHealth) apps: integrating technology readiness with protection motivation theory. Asia Pacific Journal of Marketing and Logistics.

Fragolia, I., & Wibowo, M. W. (2025). Exploring Purchase Intention Toward Sustainable Fashion: The Role of Attitude, Norms, and Control. [Journal Publication].

Guo, Z., Liu, G., Liu, Z., & Khan, A. (2023). Evaluating the determinants of young runners' continuance intentions toward wearable devices. HighTech and Innovation Journal, 4(4), 720–738.

Ha, J., Park, J., Lee, S., Lee, J., Choi, J.-Y., Kim, J., Cho, S., & Jeon, G.-S. (2023). Predicting habitual use of wearable health devices among middle-aged individuals with metabolic syndrome risk factors in South Korea: cross-sectional study. JMIR Formative Research, 7, e42087.

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. Research Methods in Applied Linguistics, 1(3), 100027.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). Partial least squares structural equation modeling (PLS-SEM) using R: A workbook. Springer.

Hedayati, S., Damghanian, H., Farhadinejad, M., & Rastgar, A. A. (2023). Meta-analysis on application of Protection Motivation Theory in preventive behaviors against COVID-19. International Journal of Disaster Risk Reduction, 94, 103758.

Konstantinidis, D., Iliakis, P., Tatakis, F., Thomopoulos, K., Dimitriadis, K., Tousoulis, D., & Tsioufis, K. (2022). Wearable blood pressure measurement devices and new approaches in hypertension management: the digital era. Journal of Human Hypertension, 36(11), 945–951.

Kumar, N. (2025). Smartwatch Statistics 2025: Users & Market Share. Demand Sage. https://www.demandsage.com/smartwatch-statistics/

Lee, S. M., & Lee, D. (2020). Healthcare wearable devices: an analysis of key factors for continuous use intention. Service Business, 14(4), 503–531.

Lennox, A., Müller, R., & Coffie, I. S. (2024). Encouraging continuous use of wearable activity trackers: The interplay of perceived severity, susceptibility and social media influencers. International Journal of Environmental Research and Public Health, 21(12), 1549.

Liao, C., Palvia, P., & Chen, J.-L. (2009). Information technology adoption behavior life cycle: Toward a Technology Continuance Theory (TCT). International Journal of Information Management, 29(4), 309–320.

Luo, Y., Wang, G., Li, Y., & Ye, Q. (2021). Examining protection motivation and network externality perspective regarding the continued intention to use m-health apps. International Journal of Environmental Research and Public Health, 18(11), 5684.

Morris, M. G., & Venkatesh, V. (2020). Age differences in technology adoption decisions: Implications for a changing work force. Personnel Psychology, 53(2), 375–403.

Pangarkar, T. (2025). Smartwatch Statistics 2025 By Wearables, Technology, Devices. Market.Us Scoop. https://scoop.market.us/smartwatch-statistics/

Ranti, S. D., & Roestam, R. (2023). Analysis of Sustainability Factors for IoT Wearable Use Using UTAUT2 and TTF Methods. JUSTIN, 11(2), 230–236.

Rekha, I. S., & Timothy, P. S. (2020). Understanding the antecedents to smart watch user's continuance intention. International Journal of Business, 25(4), 367–381.

Rogers, R. W. (1975). A protection, motivation, theory of fear appeals and attitude change. The Journal of Psychology, 91(1), 93–114.

Sekaran, U., & Bougie, R. (2016). Research methods for business: A skill building approach. John Wiley & Sons.

Siepmann, C., & Kowalczuk, P. (2021). Understanding continued smartwatch usage: the role of emotional as well as health and fitness factors. Electronic Markets, 31(4), 795–809.

Wang, H., Tao, D., Yu, N., & Qu, X. (2020). Understanding consumer acceptance of healthcare wearable devices: An integrated model of UTAUT and TTF. International Journal of Medical Informatics, 139, 104156.

Widyawati. (2020). Non-Communicable Diseases Now Threaten Young Age. Ministry of Health. https://kemkes.go.id

Zhang, Q., Khan, S., Khan, S. U., & Khan, I. U. (2023). Assessing the older population acceptance of healthcare wearable in a developing Country: an extended PMT model. Journal of Data, Information and Management, 5(1), 39–53.