Design and Usability Evaluation of AI-Enhanced Wearable Health Dashboards for Generation Z Users

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ABSTRACT

Wearable health technology is becoming increasingly common among Generation Z, but complicated user interfaces and unclear data presentation hinder adoption. This paper proposes and evaluates an AI-augmented wearable health dashboard prototype for Generation Z using a Concurrent Triangulation Mixed-Methods Usability Evaluation Design aligned with ISO 9241-11 criteria, specifying its predictive analytics, anomaly detection, personalized recommendations, and explainable AI assistant. Sixty-seven Generation Z participants completed five standardized usability tasks, after which they completed the System Usability Scale (SUS) and answered open questions. Participants achieved a 100.0% success rate on the tasks, took an average of 38.3 seconds to complete them, scored 3.68 on a 4.00-point scale (Strongly Agree), and rated the SUS at 89.3 (Grade A, Excellent Usability). They expressed trust in the AI rationale and satisfaction with the privacy management capabilities, which we attribute to the specific AI feature set evaluated in this study. They also identified information density and text contrast as areas of improvement. The findings indicate that a low-effort, transparent, AI-driven dashboard with clearly specified capabilities can achieve excellent usability.

Keywords: human-computer interaction, usability evaluation, system usability scale, wearable health dashboards, Generation Z, explainable AI

INTRODUCTION

Wearable health devices have been widely adopted, particularly by Generation Z (born between 1997 and 2012). Young people have started using smartwatches, fitness bands, and AI-enabled health apps to monitor their health and fitness, with common indicators including heart rate variability, sleep quality, activity volume, and stress. However, an easy-to-use, valued interface plays a pivotal role in continued use of these devices. Despite their initial popularity, many young users stop using wearables months after purchase because of complex visual design, too much raw data, and a lack of health recommendations.

The new health technology uses Artificial Intelligence (AI) to improve system usability. The introduction of AI in technology allows processing of complex biometric data, including heart rate variability, sleep cycles, and caloric consumption, to generate personal recommendations and notifications concerning potential risks: predictive analytics for wellness trends, anomaly detection for biometric readings outside the user's typical range, personalized recommendations, and an explainable AI assistant. AI dashboards enable a customizable user interface through human-computer interaction concepts. However, designing an interface for Generation Z requires addressing additional challenges, since Gen Z wants less information, more feedback loops, more customization options, and more useful information.

Although AI has become an important aspect of health monitoring systems, existing wearable dashboards fail to engage Generation Z because of complicated user interfaces and navigation. Existing solutions present users with a complex array of numbers without putting them in proper context to explain how the data connects to a person's daily routine. Moreover, existing interfaces do not consider younger generations' interaction preferences and can lead to misunderstandings of the data.

To address this problem, the current study focuses on the interactive design and usability evaluation of an AI-powered health dashboard for Generation Z. Using a user-centered design approach, the research conducts iterative prototyping and usability testing of the proposed dashboard to assess learnability, navigation efficiency, satisfaction, and user engagement. The evaluated prototype integrates four specific AI capabilities—trend prediction, anomaly detection, personalized recommendations, and an explainable AI assistant—while presenting heart rate variability, sleep quality, activity, and stress monitoring supported by mainstream smartwatch and fitness-band sensors.

The main contribution of this research is the prototype, which combines visual appeal and functional clarity, along with HCI design guidelines for AI-powered wellness applications for younger generations.

LITERATURE REVIEW

This study focuses on Generation Z as the primary demographic in evaluating interactive digital health interface designs. Wang et al. [29] found that continuous monitoring through wearables helps alleviate depression, anxiety, and stress in 32 randomized controlled trials, underscoring the importance of emotionally aware Gen Z dashboards for psychological monitoring.

Subramani et al. [24] identified health awareness, usefulness, and privacy issues as the most important factors for wearable use among 407 Gen Z participants, aligning with the Technology Acceptance Model and Theory of Reasoned Action and suggesting that sustained use of interactive dashboards depends on usability.

Wahyuni et al. [28] proved that tracking of vital signs, stress, sleep, and activity helps develop health literacy among digitally literate Gen Z members, who can easily use self-tracking via interactive dashboards. Sieniawska et al. [23] showed that fitness, stress, and sleep trackers with personalized suggestions help younger users develop healthy habits.

Multi-metric monitoring faces equipment limitations; optical heart rate monitoring, ECG, and GPS provide meaningful biometrics, yet battery and sensor-accuracy issues can reduce trust in the equipment itself [21], making well-designed dashboards essential.

Holko et al. [13] identified cost, limited digital literacy, and weak onboarding as major adoption barriers among 1,007 patients, so AI-assisted dashboards must stay accessible to Gen Z users regardless of literacy.

Pandit et al. [16] reviewed emerging smart wearables and identified power consumption, data scalability, and regulatory limitations as the main technical barriers, making lightweight dashboards necessary for efficient data exchange.

Advances in materials science have expanded how biometric data can be captured and visualized. Yang et al. [31] introduced stretchable, flexible electronics that obtain dense data straight from the skin, while Chen et al. [6] miniaturized skin-interactive bioelectronics to receive high-frequency data streams in real time.

Dai et al. [9] showed that combining skin-like sensors with intelligent algorithms enables closed-loop preventive monitoring, and Han et al. [12] demonstrated that 24-hour skin-attachable systems with cloud transmission give a full-day view of physiological changes that supports health-trend visualization. Cusack et al. [8] found that while personalized feedback changes behavior, retaining users remains critical, so this study evaluates both efficiency and engagement.

Chandel et al. [5] studied the evolution of smartwatch technology and its persistent signal noise and battery challenges, underscoring the need for adaptive dashboards that adjust visualization quality to the data received.

Turning to artificial intelligence processing, Shafik [22] argued that AI in wearables depends on algorithmic interpretability, since users must comprehend how their health predictions were generated.

Esmaeilzadeh and Maddah [10] stressed federated learning and interpretable XAI as requirements for trust in health information systems. Assaad et al. [2] created an IoT wearable with React.js dashboards delivering over 85% accuracy, and Wang et al. [30] achieved 93% prediction accuracy in a cloud-based deep learning framework accessed through a mobile interface, providing a validated blueprint for intelligent dashboards.

Sabry et al. [19] identified memory constraints and computation latency as key difficulties of machine learning in consumer electronics, so AI-enhanced dashboards must perform well despite a complex backend. Yang [32] showed that real-time AI feedback from wearable sensor data increases user engagement and training effectiveness.

In front-end design, Graumann [11] found that interactive visualizations and conversational AI assistants make data more accessible and easier to navigate, while Zacheo et al. [33] showed on the FitYou dashboard that good layout and filters help users find connections among heart rate, activity, and sleep data.

Arun et al. [1] reported a SUS score of 71.5 for custom vital signs visualizations in RemoteHealthConnect, providing a benchmark for efficiency, errors, and satisfaction in AI-enhanced dashboards; Ramezani et al. [18] offered lightweight UI guidelines for small-screen smartwatch interfaces that inform companion designs aligned with full-fledged web dashboards.

Petek et al. [17] warned that algorithmically derived metrics can confuse users and cause unnecessary health anxiety, indicating that Gen Z dashboards should offer interactive tooltips with AI-generated explanations. Together, these studies provide the usability criteria and interface principles that guide this research.

Capulli et al. [4] identified privacy and inequity risks among six important ethical and legal aspects of wearable health technologies, so AI-powered dashboards should provide transparent data policies, consent control, and privacy features.

Previous studies reveal that wearable sensors [6], [12], artificial intelligence [2], [30], dashboard usability [1], [33], and data privacy issues [4], [24] are inherently linked, yet each topic has been studied independently. This study addresses the gap left by the lack of an empirical evaluation of real-time biometric telemetry, explainable AI guidance, and privacy controls in a single interactive health dashboard for Generation Z.

METHODOLOGY

This section presents the methodology: the design of the AI-enhanced wearable health dashboard prototype, the evaluation techniques, and the methods used to collect and analyze data.

A. Research Design

This study uses the Concurrent Triangulation Mixed-Methods Usability Evaluation Design [7], developed from the ISO 9241-11 ergonomic design [14]. The following measurable parameters evaluate the usability of the AI-powered health dashboard: success rate (SR), error rate, task completion time (T), and the 10-item System Usability Scale (SUS). In addition, qualitative assessments cover legibility, privacy access, and the interpretability of AI-generated health insights. [7], [14], [15]. The evaluation framework covers task completion (effectiveness), error rates (errors in interaction), learnability (SUS item Q7), satisfaction (SUS and feature-level Likert scales), accessibility (theme and readability checks), and perceived usefulness (AI assistant utility task), thereby aligning each usability measure with the ISO 9241-11 dimensions. The prototype was evaluated in a single usability testing round, so future work should include iterative refinement and prototype-variant comparisons. As a usability-centered evaluation, the study did not assess clinical accuracy, device measurement reliability, or long-term engagement, which would require clinical validation and longitudinal studies.

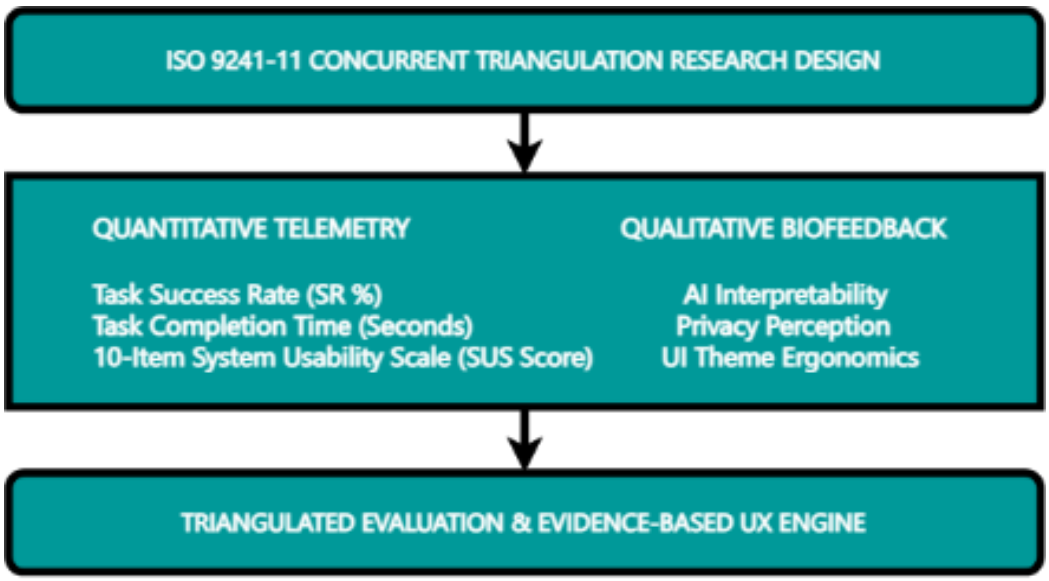


Figure 3.1 *illustrates the Concurrent Triangulation model that integrates quantitative telemetry (Task Success Rate, Execution Time, and SUS) with qualitative user biofeedback.*

B. Respondents

The participants were N = 67 Generation Z digital natives aged 12–27 residing in Metro Manila, composed of IT students, developers, wearable users, and digital health consumers, recruited through university and community networks, email, and social media messaging—a mix essential for evaluating the web dashboard interface.

C. Sampling Design

A non-probability, purposive sampling technique identified participants who regularly use smartphone health apps, biometric wearables, or web dashboards [20]. Inclusion criteria (age 12–27, active digital devices, prior health-tracking experience, and current use of a smartwatch, fitness band, or mobile health application capturing heart rate variability, sleep, activity, or stress data) ensured valid and knowledgeable evaluations of dashboard usability, privacy, and AI guidance [20].

D. Research Instrument

The test data were collected using both the telemetry logging tool and the post-test survey questionnaire [25], [26]. The questionnaire used the 10-item System Usability Scale (SUS) created by Brooke [3], a 4-point Likert scale measuring Navigation Structure, Metric Clarity, Privacy Control, and AI Assistant Usability, and four open-ended questions on AI explainability, readability, privacy, and personalization. Together, the telemetry logging tool for task success, error rate, and completion time, and the validated survey instruments constitute the measurement toolkit for the evaluation. [25], [26], [3].

Table 3.1: Standardized Usability Task Execution Protocols

Task ID	Operational Task Objective	Usability Metric Evaluated	Expected Path / Action
Task 1	Navigating the Daily Biometric Summary	Effectiveness & Visual Clarity	Visit HRV, Sleep, Activity, and Stress Cards from the Hero Dashboard.
Task 2	Review Interactive Tooltips for Sensors	Information Transparency	Hover/Click on PPG telemetry, sleep lab diagnosis indicators.
Task 3	Change Display Color Preference	Accessibility of Interface	Toggle between Cyber Navy Dark Theme and Light Theme.

Task 4	Configure Privacy Settings for Data	Autonomy and Governance of the User	Change preferences to anonymize data, enable AI explanations, and sensors.
Task 5	Assess the Perceived Usefulness of the BYTECODE AI Assistant	Perceived Usefulness in Decision Making	Pose questions to the health chatbot engine.

Table 3.1 *shows the five standardized usability tasks participants executed, pairing each task's operational objective with the usability metric it evaluates and the expected path or action within the dashboard.*

E. Data Gathering Procedure

Data were collected in four stages on the live web application: participant familiarization and R.A. 10173 informed consent, during which participants were briefed on the study's purpose, the AI-generated nature and limitations of the dashboard's health insights, and their data privacy rights; sequential task performance, automatic telemetry logging, and the post-test SUS survey with database export (Figure 3.2) [27].



Figure 3.2 *outlines the four-step data collection process: participant familiarization and R.A. 10173 consent (Step 1), sequential task performance (Step 2), automated telemetry tracking in the background (Step 3), and SUS survey at the end of the test with database export (Step 4).*



Figure 3.3 *presents the web prototype's UI design, following the participant storyboard from live biometric telemetry visualization (PPG, HRV, circadian clock) to Explainable AI (XAI) assistance, themes, and privacy controls.*

The interface storyboard follows the participant's journey, illustrated in Figure 3.3. The participant's journey starts with the landing view on the BYTECODE AI Health mission control, which shows a hero summary and real-time metric cards of HRV, Sleep quality, Activity, and Stress. When a participant hovers over or clicks a card, an interactive sensor tooltip appears, and the participant can toggle between light and dark themes in the header. The privacy panel manages anonymized data sharing, AI explainability mode, and sensor permissions, and the BYTECODE AI assistant answers the participant's health questions.

F. Statistical Treatment of Data

The quantitative data were analyzed using Percentage Distribution, Weighted Mean ($\bar{X}$), and System Usability Scale (SUS) composite scoring equations $\overline{X}$ [3], [26].

1) Percentage Distribution

The percentage formula was employed to determine demographic frequency and task success rate (SR):

$$\text{Percentage } (\%) = \left(\frac{f}{n}\right) \times 100\%$$

Where f = frequency of responses or task successes, and n = total sample size (N = 67).

2) Weighted Mean

The Weighted Mean formula was calculated to determine the level of participants' agreement in Likert scale questions:

$$\bar{X} = \frac{\sum(f \cdot x)}{n}$$

- $\bar{X}$= weighted mean (average satisfaction score)
- f= frequency of responses in each Likert question
- x= Likert scale weight (1–4)
- n= total number of responses (sample size)

The above equation makes the calculation simpler for individual usability tests ($n = 1$). When calculating the weighted average using the equation above, the frequency distribution for the total sample ($N = 67$) is considered.

Table 3.2: 4-Point Likert Rating Continuum Scale & Interpretation

Scale Weight	Rating Range	Verbal Interpretation	Usability Level
4	3.26 – 4.00	Strongly Agree	Excellent Usability
3	2.51 – 3.25	Agree	Good Usability
2	1.76 – 2.50	Disagree	Fair Usability
1	1.00 – 1.75	Strongly Disagree	Poor Usability

Table 3.2 *shows the four-point Likert rating continuum used in the questionnaire, mapping every scale weight to its rating range, verbal interpretation, and corresponding usability level.*

3) System Usability Scale (SUS) Score Transformation

Global usability was benchmarked using Brooke's SUS transformation equations [3], [27]:

$$\text{Contribution}_i = \begin{cases} x_i - 1, & \text{for odd items } (1,3,5,7,9) \\ 4 - x_i, & \text{for even items } (2,4,6,8,10) \end{cases}$$

$$\bar{SUS} = \left(\sum_{i=1}^{10} \text{Contribution}_i \right) \times \frac{100}{30}$$

Where x_i is the raw rating (1–4) for item i.

The composite SUS score varies from ~0 to 100, where scores represent Grade A / Excellent usability. 80.3

Table 3.3: Usability Metrics Framework (ISO 9241-11 alignment)

Usability Dimension	Operational Variable	Measurement Formula / Metric	Evaluation Goal
Effectiveness	Task Completion Success and Errors	$SR = \left(\frac{\text{Successful Tasks}}{\text{Total Tasks Attempted}} \right) \times 100\%$	$\geq$ 90.0% Success Rate
Efficiency	Mean Task Completion Time	$\bar{T} = \frac{1}{N} \sum_{p=1}^{N} T_p$ (Seconds)	$\leq$ 60.0 s (Rapid, low-friction task completion)
Satisfaction (Feature)	Likert Domain Mean	$\bar{X} = \frac{\sum (f \cdot x)}{n}$	$\bar{X} \geq 3.26$ (Excellent Rating)
Satisfaction (Global)	Composite SUS Score	$\bar{SUS} = \left(\sum_{i=1}^{10} \text{Score Contributions} \right) \times \frac{100}{30}$	$\bar{SUS} \geq 80.3$ (Grade A Usability)

Table 3.3 *shows the usability metrics framework aligned with ISO 9241-11, defining each usability dimension, its operational variable, measurement formula, and evaluation goal for this study.*

RESULTS AND DISCUSSION

This chapter presents the results of the usability evaluation conducted with sixty-seven participants. Table 4.1 presents the criteria from Table 3.3 along with the findings.

A. Usability Metrics Framework Summary

Table 4.1: Usability Metrics Framework Summary (ISO 9241-11 Alignment)

Usability Dimension	Operational Variable	Criterion (Evaluation Goal)	Result (Obtained)
Effectiveness	Task Completion Success and Errors	$\geq$ 90.0% Success Rate	100.0%
Efficiency	Mean Task Completion Time	$\leq$ 60.0 s (Rapid, low-friction task completion)	38.3 seconds
Satisfaction (Feature)	Likert Domain Mean	$\bar{X} \geq 3.26$ (Excellent Rating)	3.68/ 4.00 (Strongly Agree)
Satisfaction (Global)	Composite SUS Score	$\bar{SUS} \geq 80.3$ (Grade A Usability)	89.3 / 100 (Grade A Usability)

Table 4.1 *shows each usability dimension of the ISO 9241-11 framework, along with the criteria set in Table 3.3 and the results obtained during the evaluation.*

B. Demographic Profile of Respondents

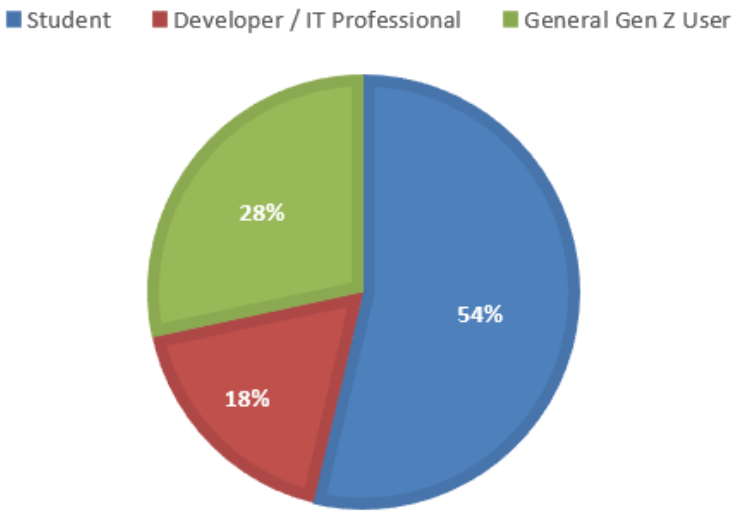


Figure 4.1 *charts the demographics of each respondent by percentage.*

In this Generation Z study, 67 people were interviewed. Students made up the largest group at 53.7%. Next came general users of technology at 28.4% and developers or IT professionals at 17.9%. Most respondents were 18 to 21 years old (46.3%). About a quarter were 25–27 (26.9%), while 22–24 accounted for 22.4%, and only 4.5% were under 18. Age groups ranged from 12 to 27 years old, covering the full Generation Z range. Gender was male-dominated, with 67.2% men and 20.9% women, while 11.9% did not disclose their gender.

C. Usability Evaluation Results

The research indicated that the dashboard was highly effective, efficient, and satisfying to use. All sixty-seven participants completed the five tasks without assistance, producing a 100.0% task success rate and a 0.0%

observed error rate, since no participant made an unrecovered error or required assistance. The mean task completion time was 38.3 seconds, well within the 60-second benchmark; the feature-level weighted mean was 3.68 out of 4.00 (Strongly Agree); and the composite SUS score was 89.3/100 with Grade A.

Table 4.2: SUS Item Matrix (N = 67)

SUS Item	Type	Weighted Mean	Interpretation
Q1. I would like to use this dashboard frequently	Odd (positive)	3.81	Strongly Agree
Q2. The system is unnecessarily complex	Even (negative)	3.6	Strongly Agree
Q3. The system is easy to use	Odd (positive)	3.64	Strongly Agree
Q4. I would need technical support to use it	Even (negative)	3.61	Strongly Agree
Q5. The functions are well integrated	Odd (positive)	3.7	Strongly Agree
Q6. There is too much inconsistency	Even (negative)	3.64	Strongly Agree
Q7. Most people would learn it quickly	Odd (positive)	3.76	Strongly Agree
Q8. The system is cumbersome to use	Even (negative)	3.64	Strongly Agree
Q9. I felt very confident using the system	Odd (positive)	3.79	Strongly Agree
Q10. I needed to learn a lot to get going.	Even (negative)	3.58	Strongly Agree

Table 4.2 *shows the ten SUS statements in questionnaire order, listing each item's type, weighted mean, and verbal interpretation based on the responses of the sixty-seven participants.*

Note: Even (negative) items were inverted (5 − raw) before computing the weighted mean, so all means are expressed on the positive usability scale; higher values indicate more favorable responses.

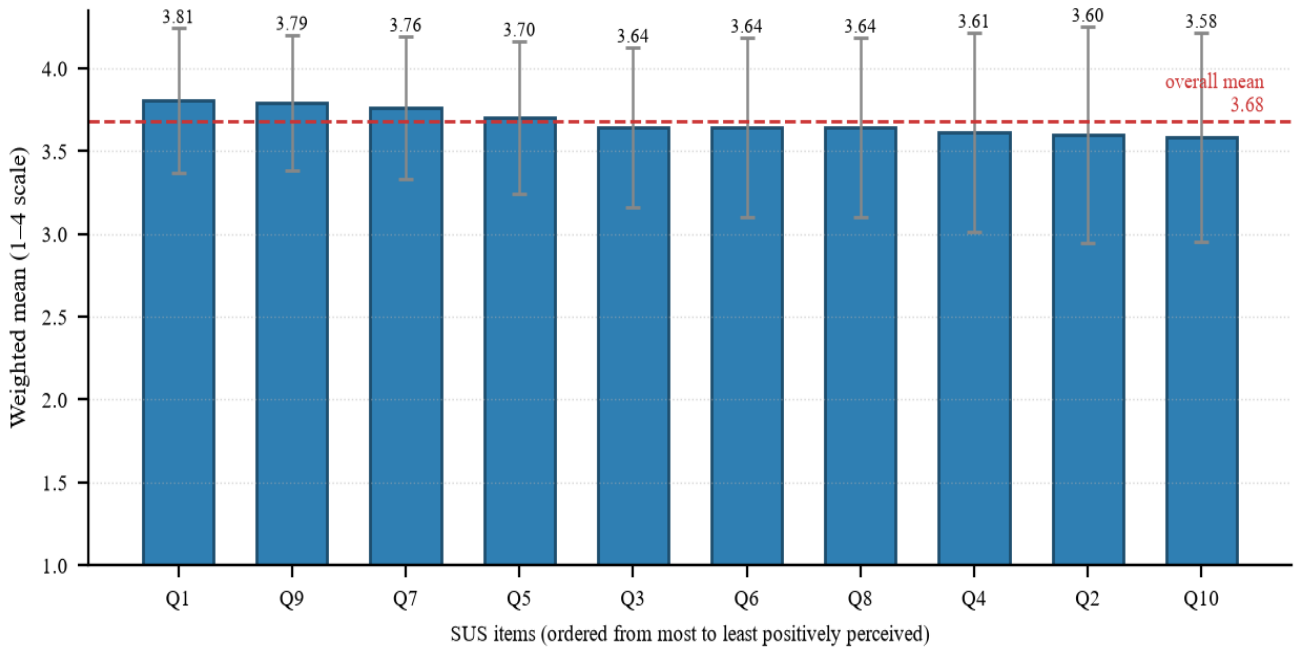


Figure 4.2 *charts the mean of every SUS item after inversion; the whiskers show the standard deviation, and the dashed line the overall mean.*

D. Responses to the Open-Ended Questions

All sixty-seven participants answered all four open-ended questions. Theme-based analysis identified four themes. Explanation of AI and trust. Most participants found the AI explanation understandable and valuable:

"clear, structured, and dependable explanations which were easy to trust"; however, several said trust increases over time. Readability, density, darkness of theme. Many participants found the dashboard overloaded and recommended putting metrics on separate pages; at the same time, some described the dashboard as "too colorful" and difficult to read; however, most preferred the dark theme because it was more comfortable. Privacy, control, and transparency (Republic Act No. 10173). The privacy settings were considered safe and aligned with data protection requirements, "giving confidence in control." All participants reported feeling safe and in control because of the privacy settings; however, some asked for additional guarantees, and most needed personalization and accessibility.

E. Discussion

The findings show that all four criteria in Table 4.1 have been met. With a SUS score of 89.3, the dashboard falls into Grade A (Excellent) on the adjective scale proposed by Bangor et al. [27], surpassing the 71.5 recorded by Arun et al. [1]. The evaluation framework met each usability measure: task completion and error rates (effectiveness), completion time (efficiency), the SUS and Likert domain means (satisfaction), theme and readability checks (accessibility), and the AI assistant task (perceived usefulness). Thematic analysis confirmed the results and identified areas for improvement, including AI trust, information density, and text contrast. Although the study used purposive sampling and self-reported satisfaction, consensus across measures strengthens the results.

CONCLUSION

This study addressed the usability of AI-enhanced wearable health dashboards for Generation Z, whose complex interfaces and unclear data presentation discourage sustained use. Using a concurrent triangulation mixed-methods design aligned with ISO 9241-11, sixty-seven Generation Z participants evaluated the develop-

ped dashboard prototype through five standardized tasks followed by a SUS and Likert-scale survey. The design embedded privacy and responsible presentation through R.A. 10173-informed consent, visible privacy controls, and AI explanations for every generated insight. The main limitation is that the evaluation covered only a purposive sample in Metro Manila and relied partly on subjective self-assessment of satisfaction. The scope was likewise limited to interface usability: clinical accuracy, device measurement reliability, and sustained engagement were beyond the evaluation and remain directions for future research.

1. The dashboard had a Task Success Rate of 100.0%, exceeding the 90.0% effectiveness criterion.
2. The mean task completion time was 38.3 seconds, well within the 60.0-second efficiency criterion.
3. The feature-level Likert Domain Mean was 3.68 (rated as Strongly Agree), which was higher than the 3.26 criterion.
4. The composite SUS score was 89.3/100, or Grade A, and was better than the benchmark of 80.3.

These findings indicate that the prototype met all four ISO 9241-11 targets and surpassed comparable dashboards, such as the 71.5 SUS reported by Arun et al. [1], placing it in Grade A on Bangor et al.'s [27] adjective rating scale. The results carry two implications: first, explainable AI guidance, visible privacy controls, and Generation Z-adapted visual design improve perceived usability and trust; second, dashboard developers should prioritize these features to sustain engagement among younger users.

RECOMMENDATIONS

Based on the findings, the dashboard needs dedicated, more spacious areas so metrics can be viewed without distractions. Additionally, the AI assistant needs further improvement, including in-place tooltips. The R.A. 10173 privacy control mechanisms should remain visible, with enhanced privacy-guarantee notifications. Personalization and accessibility options would allow users to configure the dashboard. Further research may include implementing the prototype on other devices, such as wearables and mobile devices, and replicating the evaluation with a larger, multinational sample of participants. Researchers may also conduct a quantitative or mixed-methods study with a larger population to analyze AI-driven interface design, privacy control, and

user satisfaction. Future work may also strengthen the design process by comparing alternative prototype variants and adding iterative user testing with instrumentation focused on task completion, errors, learnability, satisfaction, accessibility, and perceived usefulness. These recommendations target dashboard developers and health information designers, with Generation Z users as the main beneficiaries.

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