Wearable health devices: the role of perceived complexity and effectiveness in shaping positive Word-of-Mouth (WOM). A study on Automated Insulin Delivery (AID) systems

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Wearable health devices are transforming the healthcare sector through the continuous expansion of their functionalities. In this context, this research analyzes the role of perceived complexity and effectiveness of wearable health devices in generating positive word of mouth (WOM). A survey-based quantitative study has been conducted among automated insulin delivery (AID) systems users. The results show that perceived complexity does not have a direct effect on WOM, but rather an indirect effect mediated by effectiveness perception. These findings have important implications for the design and promotion of devices, suggesting the need for a user-centered approach.

Keywords: Wearable health devices, complexity perception, effectiveness perception, Word-of-Mouth (WOM), diabetes, Automated Insulin Delivery (AID) system.

First submission: 14/07/2025, accepted: 17/10/2025

SUMMARY

1. Introduction

In recent years, wearable health devices have significantly transformed the healthcare sector thanks to their ability to monitor a wide range of physiological and biochemical parameters in a non-invasive, continuous, and real-time manner (Erdem *et al.,* 2024).

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MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

These devices, equipped with physical, chemical, and biological sensors, are designed to be worn on the body or integrated into accessories such as smartwatches, rings, bracelets, or adhesive patches (Babu *et al.*, 2024). Wearable health devices are becoming increasingly sophisticated, integrating cutting-edge sensors, artificial intelligence (AI), and machine learning algorithms. This enables them to analyze physiological data in real time, generate predictive health insights, and support individualized treatment strategies (Yang *et al.,* 2024; Wah, 2025). Intelligent systems are now able to detect cardiac anomalies, monitor metabolic markers, and even facilitate non-invasive glucose sensing through biofluids such as sweat and tears (Jafleh *et al.*, 2024).

Patients generally perceive wearable devices positively not only because they can efficiently manage health issues, but also because they collect valuable data related to glucose levels, physical activity, sleep, and heart rate (Rodríguez-Rodríguez *et al.,* 2024). Among older adults, wearables are appreciated for their comfort and non-invasiveness, yet concerns persist regarding costs, data reliability, and the psychological burden of constant self-monitoring (Ahn *et al.,* 2024). However, perceived effectiveness depends on factors such as ease of use, data accuracy, and compatibility with smartphones and digital systems Wang *et al.* (2020). Patients with diabetes particularly value the integration of wearable devices with mobile apps that facilitate self-management and motivate physical activity, although challenges remain in terms of interface usability and clarity of instructions (Karim *et al.,* 2024). This appreciation therefore appears to increase with the expansion of functionalities and features, although this relationship remains unclear. In fact, recent studies suggest that some features – such as those related to customization or interface – may not significantly impact perceived satisfaction (El-Gayar & Elnoshokaty, 2023). Another recent study supports this ambiguity. Adiyatma *et al.* (2022) and Benbunan-Fich (2020) highlight how satisfaction does not depend so much on the quantity or technological sophistication of the available functions, but rather on their coherence with the concrete needs and personal expectations of users, especially in the context of daily use. In this paper, "technological sophistication" refers to an advanced and coherent bundle of technological capabilities, achieved by deepening and broadening constituent capabilities and securing a tight integration among them (Rousseva, 2008). Considering this evidence, the need to adopt a theoretical frame capable of accurately investigating the user experience emerges.

Over the years, marketing theory has sought to classify product attributes. For example, the seminal research conducted by Kano *et al.* (1984) classifies the characteristics of a product based on their impact on perceived satisfaction, thus offering a useful interpretive framework, also in the healthcare context. According to the Kano model, attributes are divided into three main categories. *Must-Be* attributes are considered basic, their absence generates dissatisfaction, but their presence does not increase perceived satisfaction. *One-Dimensional* attributes produce satisfaction in proportion to their quality and performance. Finally, *Delighters*

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

attributes, being unexpected but appreciated, can positively surprise the user and generate enthusiasm. In the case of health wearable devices, safety requirements – such as one-key SOS calls and fall detection – emerge as *Must-Be* attributes. Performance features that simplify operation or daily management tend to behave as *One-Dimensional* (*e.g.*, video calls in wearables or large displays). More advanced or hedonic capabilities act as *Delighters*, such as voice memos and aesthetic/social components (Chen & Li, 2022; Yuan *et al.*, 2025). These features often increase perceived complexity but, when viewed as useful and relevant, can enhance the perception of effectiveness and become a source of value rather than a barrier.

More recently, Mao *et al.* (2022), have shown that, in an intelligent system for the management of elderly patients' medications, basic features such as reminders for taking medications or ease of use are considered essential (Must-Be), while more advanced features, such as integration with WeChat or longer battery life, positively influence the perception of the service's effectiveness when perceived as truly useful for health (Delighters). The systematic review by Wang *et al.* (2024) further strengthens this approach, showing how the application of the Kano model in the healthcare sector helps identify the most relevant attributes for patient satisfaction – particularly in terms of efficiency, reliability and empathy – and reveals a positive relationship between the presence of Delighters attributes and the overall evaluation of the healthcare experience.

In a broader sense, marketing theory affirms that the combination of all these attributes generates what can be described as perceived complexity (Ferreira *et al.,* 2021; Seneviratne *et al.*, 2017). This construct does not merely refer to the number of integrated functions or attributes, but rather to the cognitive and emotional effort required from users to make sense of the device's usefulness, usability, and consistency with their daily routines (Moore *et al.,* 2021; Jeong *et al.,* 2021). Even advanced features – *i.e.,* personalized health information or environmental activity recognition – may fail to generate satisfaction when perceived as difficult to access, interpret, or control (Ciabattoni *et al.*, 2018; Mehrotra *et al.,* 2024). In this view, perceived complexity is treated as an important proximal determinant of satisfaction because it aggregates the joint effect of multiple attributes experienced during everyday use. Analyzing the construct, rather than specific features, allows comparisons across devices that differ in their functions and interfaces, thereby improving the generalizability of the findings.

Understanding how users experience and interpret this complexity thus becomes crucial to predicting whether they are likely to perceive the device as effective and recommend or discourage its use. With this aim, the Word-of-Mouth (WOM) – *i.e.,* the informal exchange of opinions and experiences between individuals about a product or service (Bowman & Narayandas, 2001) – emerges as a key strategy to support adoption and prevent abandonment of a wearable device.

Although the role of WOM in shaping user behavior has been widely acknowledged, the existing literature has not produced a cohesive theoretical understanding of WOM in the context of

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

wearable devices (Abouzeid *et al.*, 2025; Ntumba & Budree, 2021). In particular, it remains unclear how positive WOM is generated, and which factors facilitate its emergence. This research aims to address the existing gap by exploring how factors such as the perception of device complexity and effectiveness affect WOM among users of wearable devices, with a particular focus on the experimental context of diabetes care. By examining the relationship between these variables, the research provides valuable insights into how user experiences with wearable devices can foster positive social influence and contribute to the broader adoption of these technologies in healthcare.

2. Theoretical background and hypotheses

2.1. Wearable health devices perception

The growing diffusion of wearable health devices has attracted the attention of the healthcare literature not only for their technical functionalities, but also for the way they are perceived by users in the daily management of their health. Recent studies have highlighted that this perception is multidimensional, encompassing functional aspects – such as usability, comfort, and integration – as well as emotional, ethical, and social evaluations (Chong *et al.,* 2020; Cilliers, 2020; Guillén-Gámez & Mayorga, 2019; Segura Anaya *et al.,* 2018; Soliño-Fernandez *et al.,* 2020; Tran *et al.*, 2019). Chong *et al.* (2020), for example, emphasize experiential elements such as motivation, discretion, and a sense of responsibility in health monitoring. Alongside these positive assessments, concerns also emerge regarding privacy, transparency, and data ownership (Segura Anaya *et al.,* 2018; Cilliers, 2020). User perception varies according to demographic and psychological factors such as age, education level, technological self-efficacy, and interest in health all influence both the intention to use and the actual engagement with the technology (Chandrasekaran *et al.,* 2020; Lee & Lee, 2018). Even among highly motivated users, actual experiences may lead to misalignments with expectations, physical discomfort, poor data readability, and technical limitations can undermine engagement (Wen *et al.,* 2017). As noted by Lee & Lee (2020), only the perception of tangible clinical benefits seems to sustain long-term and conscious use. An additional relevant dimension concerns the relational aspect. As shown by Tran *et al.* (2019), the willingness to adopt wearable health devices does not necessarily correspond to unconditional acceptance. Many patients are only open to their use under human supervision, highlighting the continued importance of the care relationship even in digital health contexts.

Given the extensive multidimensionality of the perception of health wearable devices, it would be possible to unify the concept by drawing from the relationship between functionalities—as described in the Kano model—and perceived complexity. The sum of individual functionalities, each generating a specific perception, could be studied by examining how these are perceived in terms of complexity. In particular, attention should be directed to the extent to which this perceived complexity influences users' perception of the effectiveness of the healthcare service provided.

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

2.2. Health Device Complexity Perception

Device complexity is a central concept in the study of technology adoption behaviors, particularly in relation to innovative solutions such as wearable devices in healthcare. According to Adjei *et al.* (2010), the complexity of a device refers to a consumer's subjective perception of the difficulty of using a product or service. In healthcare and technological contexts, several studies have shown that perceived complexity (or Health Device Complexity Perception) is not necessarily interpreted as a barrier but may instead serve as a positive signal of reliability, accuracy, and technological sophistication. Dellaert & Stremersch (2005) found that, when users possess adequate motivation and expertise, complexity can enhance the perceived utility of a product. Similarly, Xie *et al.* (2021) demonstrate that regular use of wearable devices fosters mastery experiences that reinforce perceived self-efficacy and, indirectly, trust in the device itself. Along the same lines, Rupp *et al.* (2018) emphasize that complexity, when embedded in a functional and engaging design, can stimulate user engagement and increase trust in the technology. Yang *et al.* (2016) further confirm that attributes commonly associated with complexity, such as advanced functionality, device compatibility, and sophisticated aesthetics, contribute positively to perceived value and product adoption. Supporting this perspective, Lu *et al.* (2020) highlight that the ability of wearable devices to conduct real-time, multiparametric health monitoring conveys clinical value even to users who may not fully understand the underlying technical infrastructure. Based on these considerations, the following research hypothesis is proposed:

H1. Health Device Complexity Perception positively influences Health Treatment Effectiveness Perception.

2.3. Health Device Effectiveness Perception and WOM

In the context of wearable devices in healthcare, effectiveness goes beyond the technical functionality of the device. It also encompasses the patient's perception of the device's ability to deliver tangible benefits in daily life (Rodriguez-León *et al.,* 2021). According to Adjei *et al.,* 2010, the perceived effectiveness of a health device (or Health Device Effectiveness Perception) refers to the subjective perception of how effective a given health treatment is in curing or improving a clinical condition. For example, a continuous glucose monitoring device may be perceived as effective not only if it provides accurate readings, but also if it enables better dietary management, greater decision-making autonomy, and a reduction in glycemic spikes (Luo *et al.,* 2022; Moulaei *et al.,* 2021).

When users perceive a treatment as effective, both technically and experientially, they tend to develop a high level of satisfaction, which often translates into active sharing of their experiences through WOM (Gu *et al.*, 2018; Liang & Scammon, 2011). WOM can be either positive – when users share favorable impressions and satisfaction – or negative, when they express disappointment or warn others against adoption. Positive WOM (hereafter WOM) is particularly effective in enhancing perceived credibility

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

and encouraging engagement (Alexandrov *et al.,* 2013). Peer-to-peer exchanges, both offline and online, can reduce skepticism and strengthen trust in the technology (Kim *et al.,* 2024a; Yang *et al.,* 2024). WOM is fueled by personal testimonials, case studies, online reviews, and community forums, all of which play a crucial role in influencing the decisions of potential health device users (Aljawawdeh *et al.,* 2024a; Hasan & Stannard, 2022). In particular, a positive user experience, based on perceived value, quality, and ease of use, has been shown to strongly correlate with the willingness to recommend the device to others (Uzir *et al.,* 2023a). Therefore, a wearable device that is perceived as effective supports the informal dissemination of health information, fosters peer trust, and encourages further adoption behaviors. Turan *et al.* (2016) found that perceived healthcare service quality – including dimensions such as reliability, responsiveness, empathy, and tangibles – has a significant positive impact on patient satisfaction and WOM sharing. However, due to its inherent ambiguity, there is no straightforward relationship between perceived complexity and WOM. Perceived effectiveness plays a crucial role, as it allows users to reinterpret complexity as an indicator of clinical value rather than as a barrier to use (Lu *et al.*, 2020; Yang *et al.*, 2016).

Based on this evidence, it is possible to formulate the following research hypothesis integrating the conceptual framework depicted in Figure 1:

H2. Health Device Effectiveness Perception positively influences Word-of-Mouth (WOM).

H3. Health Device Effectiveness Perception positively mediates the relationship between Health Device Complexity Perception and Word-of-Mouth (WOM)

2.4. The moderation role of age

Age is a key factor in shaping user interactions with digital health technologies (Kim & Ho, 2021). The use of complex devices is more widespread among younger individuals, who demonstrate greater familiarity with innovation and the operation of advanced devices (Calderón *et al.*, 2022). Conversely, older users tend to experience greater difficulties in managing technology, partly due to lower perceived self-efficacy and greater resistance to change (Oh *et al.*, 2021). These differences are also reflected in how technological complexity is perceived and evaluated (Zhang *et al.*, 2022). Younger individuals tend to associate it with greater efficacy perception, interpreting it as an indicator of advanced functionality and potential clinical benefits (Ferreira *et al.*, 2021; Kyytsönen *et al.*, 2023). Conversely, older users may perceive many of the additional features as superfluous or redundant, even when objectively effective. Consequently, as age increases, there is a tendency to evaluate complexity more critically, attributing a lower perceived effectiveness to the device (Chandrasekaran *et al.*, 2021; Moore *et al.*, 2021).

However, when older users recognize the effectiveness of a technological device, they tend to value it as a significant novelty, thus increasing their propensity for WOM. Conversely, among younger individuals – now accustomed to high levels of efficacy on digital devices – this characteristic tends to be taken for granted, with a

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

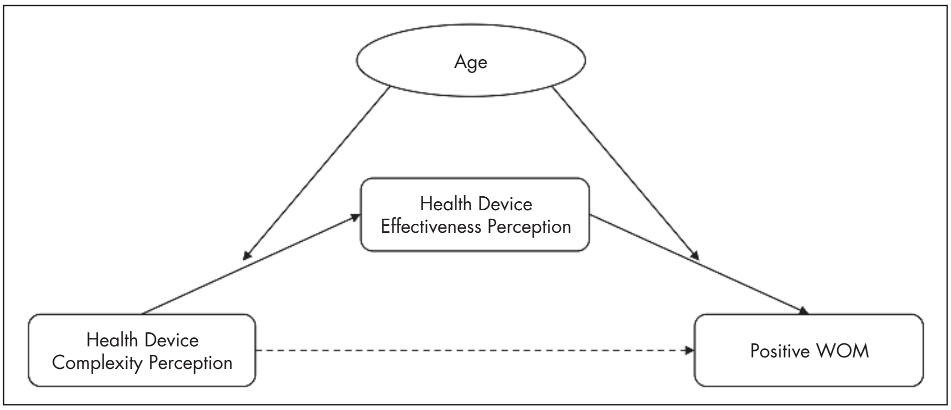

Fig. 1
The proposed conceptual framework

Covariates: Gender, Education.

lesser impact on the willingness to share the experience (Zhao *et al.*, 2024).

These observations suggest that age, on the one hand, attenuates the relationship between perceived complexity and perceived efficacy, and on the other, strengthens the relationship between perceived efficacy and WOM. Based on these premises, the following hypotheses are formulated:

H4a. Age negatively moderates the effect of Health Device Complexity Perception on Health Device Effectiveness Perception.

H4b. Age positively moderates the effect of Health Device Effectiveness Perception on Positive WOM.

3. Methodology and results

3.1. Diabetes management

The research was conducted within the context of diabetes management, focusing on the use of wearable devices by patients for the daily monitoring and treatment of the condition.

Diabetes is generally classified into two main types. Type 1 Diabetes (T1D) is an autoimmune condition in which the immune system attacks and destroys the insulin-producing beta cells in the pancreas, leading to a complete dependence on insulin therapy, whereas Type 2 Diabetes (T2D) is characterized by insulin resistance and a progressive decline in beta-cell function, often associated with lifestyle factors such as obesity and physical inactivity (Cnop *et al.,* 2005). Diabetes has become a global health challenge, with its prevalence steadily increasing worldwide and significant implications for health systems (Avilés-Santa *et al.,* 2020). Within the epidemiological context in Italy, the National Diabetes Network AMD (2023) reported 42,352 active adults with type 1 diabetes in 2023 (19,261 women; 23,091 men). The mean age was approximately 49 years (49.5 in women; 47.9 in men). Among patients seen in 2023, new diagnoses accounted for approximately 2.5-3.0% and first-time visits approximately 3.5-3.9%. These data contextualize the epidemiology observed in specialist care and frame our focus on adults with type 1 diabetes.

In the context of diabetes management, wearable devices have introduced a major shift, enabling glucose

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

monitoring through alternative biofluids such as sweat, saliva, tears, and interstitial fluid (Kim *et al.,* 2024b). Beyond offering more personalized, comfortable, and less invasive alternatives to traditional methods, technologies such as Automated Insulin Delivery (AID) system, consisting of a continuous glucose monitor (CGM), an insulin pump, and a control algorithm, have become essential in the daily routines of patients with T1D. However, this constant control may generate emotional stress, related to the need for continuous data interpretation and ongoing decision-making (Ahn *et al.,* 2024). The most recent scientific evidence highlights how AID systems significantly improve glycemic control, increase the time in the target range (Time in Range) and reduce the risk of hypoglycemia, especially during the night hours (Renard, 2023). The joint consensus of the American and European Diabetes Associations underlines that, although AID represents a clinical breakthrough, its effective adoption requires careful management of expectations, continuous support and patient education (Sherr *et al.,* 2022).

3.2. Sampling and measures

To test the model presented in Figure 1 and evaluate the proposed hypotheses, a structured questionnaire was developed using validated measurement scales for the relevant constructs. The questionnaire was administered to a sample of participants recruited from an Italian hospital. Following methodologies commonly used in similar research (Wong *et al.*, 2022), participants were selected through convenience sampling, ensuring voluntary and anonymous participation. While this sampling method can introduce potential biases due to its limited representativeness (Sedgwick, 2013), efforts were made to mitigate these biases. The sample was characterized with respect to national epidemiological and socio-demographic benchmarks (AMD, 2023; ISS, 2022). While overall gender alignment with Italian T1D estimates was noted, the age profile was younger, consistent with the predefined inclusion range (16-74 years) and recruitment to a single hospital clinic with an AID program. All participants had T1D and were users of AID systems. Therefore, age is included as a covariate in all analyses, and generalizability refers to T1D patients aged 16-74 years in a hospital setting.

The questionnaires were distributed in paper format by two interviewers over a four-week period between June and October 2024. Interviewers approached patients, explained the study procedure, and obtained informed consent before asking them to complete the questionnaire. To measure the variables defined in the framework, the questionnaire included standardized measurement scales. Additionally, to minimize cognitive biases and heuristics, the constructs were presented in a reverse order relative to their placement in the framework (Podsakoff *et al.*, 2003).

Health Device Complexity Perception (HDCP) was measured by adapting the three-item semantic differential Product Complexity scale (Adjei *et al.*, 2010). The items assessed perceptions of complexity in terms of difficulty and effort required to use the product, using bipolar adjectives such as "complicated/not complicated", "difficult to use/not difficult to use",

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

and "requires a lot of effort to use/ does not require a lot of effort to use". Health Device Effectiveness Perception (HDEP) was assessed using a five-item scale adapted from Cheng *et al.* (2017). The items evaluated participants' beliefs regarding the effectiveness, power, and usefulness of the treatment, as well as its perceived likelihood to provide a quick and thorough recovery. Following a well-established procedure in expectancy-value models (Ajzen and Fishbein, 1980), WOM was assessed by asking participants about the strength of their intention and the likelihood of recommending the device to others.

All items were rated on Likert-type scales ranging from 1 to 5. The wording of all items was translated from English to Italian following an iterative translation and back-translation approach (Douglas & Craig, 2007). Finally, the survey collected socio-demographic data – gender, age, and level of education – as well as the duration since their diagnosis.

To protect consumers' anonymity and reduce evaluation apprehension (Podsakoff *et al.*, 2003), the questionnaire assured participants that their responses would remain anonymous and that there were no right or wrong answers.

3.3. Sample

The sample consisted of 219 participants with a diagnosis of T1D, including 104 men (47.5%) and 115 women (52.5%), with age between 16 and 74 years (M = 35.49, SD = 16.58). Educational levels were well-balanced: 47 participants (21.5%) held a bachelor's degree, 108 (49.3%) had a high school diploma or equivalent, 51 (23.2%) had completed lower secondary education, and 13 (6%) had only primary education. Regarding diabetes history, 25 participants (11.4%) had been diagnosed with type 1 diabetes within the past five years, 42 (19.2%) between five and ten years ago, 39 (17.8%) between ten and fifteen years ago, and 113 (51.6%) more than fifteen years ago. In comparison with national epidemiological data on T1D (AMD, 2023; ISS, 2022;), the sample shows a younger age profile, consistent with the pre-specified inclusion range (16-74 years) and recruitment in a single hospital AID clinic. Sex is broadly aligned with national figures.

3.4. Data Analysis

First the assumption of multivariate normality through Mardia's test (Cain *et al.*, 2017) was checked and was assessed the risk of Common Method Variance (CMV) bias using the Common Latent Factor (CLF) test (Fornell & Larcker, 1981; Podsakoff *et al.*, 2003). Using AMOS software a Confirmatory Factor Analysis (CFA) was then carried out, and the internal consistency of each scale was evaluated through Cronbach's α coefficient. After this preliminary analysis, reference was made to the literature (Diamantopoulos *et al.*, 2012) to average the item responses across all scales for hypothesis testing. Finally, a sequential moderated mediation analysis was conducted using the PROCESS macro for SPSS, Model 58 (Hayes, 2022), while considering age as moderator and gender and education as covariates.

3.5. Results

Mardia's test revealed a slight deviation from normality, with multivariate skewness (B = 4.49, p < .01) and mul-

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

tivariate kurtosis (B = 98.62, $p < .01$). Therefore, to ensure that indirect effect estimates remained robust without affecting direct effect results, a bootstrapping procedure with 5,000 resamples was employed (Cain *et al.*, 2017). The analysis of common method bias through the CLF test showed that the variance accounted for by the common factor was 41.3%, indicating that CMV bias was not a significant issue in this study (Fornell & Larcker, 1981; Podsakoff *et al.*, 2003). Regarding model fit, the CFA results suggested an adequate fit to the data (see Table 1), with the following indices: χ^2/d.f. = 3.533, $p < .001$; GFI = .859; CFI = .912; NFI = 0.871; SRMR = 0.081. Factor loadings and average variance extracted values were all above .50, while construct reliability and bivariate correlations exceeded .70. These findings confirmed the model's discriminant and convergent validity, with no evidence of multicollinearity (Fornell & Larcker, 1981; Grewal *et al.*, 2004; Hair *et al.*, 2012). Finally, internal consistency was assessed through Cronbach's α, with all coefficients above the recommend-

Table 1 – Measurement scales and Confirmatory Factor Analysis

Measurement scales and items	M	SD	FL	CR	AVE	α
Health Device Complexity Perception (HDCP)	2.82	.51		.80	.57	.83
HDCP1 – complicated/not complicated			.81			
HDCP2 – difficult to use/not difficult to use			.76			
HDCP3 – requires a lot of effort to use/does not require a lot of effort to use			.69			
Health Device Effectiveness Perception (HDEP)	3.21	.54		.88	.60	.89
HTEP1 – How effective do you think your Automated Insulin Delivery system is in treating diabetes?			.85			
HTEP2 – How powerful do you think your Automated Insulin Delivery system is in treating diabetes?			.76			
HTEP3 – How useful do you think your Automated Insulin Delivery system is in treating diabetes?			.81			
HTEP4 – If you use your Automated Insulin Delivery system to treat your diabetes, how likely do you think it will cure you quickly?			.75			
HTEP5 – If you use your Automated Insulin Delivery system to treat your diabetes, how likely do you think it will cure you thoroughly?			.69			
Word-of-Mouth (WOM)	3.30	.68		.82	.70	.91
WOM1 – I would strongly recommend the automated insulin pump therapy to a person with a similar form of diabetes in the future.			.89			
WOM2 – I am likely to talk positively about automated insulin pump therapy to a person with a similar form of diabetes in the future			.78			

Note: M = Mean, SD = Standard Deviation; FL = Standardized factor loading (all significant at a 0.01 level); CR = Construct Reliability; AVE = Average Variance Extracted; α = Cronbach's α; * = reverse items. N = 219. Fit statistics: χ^2/d.f. = 3.533, $p < .001$; GFI = .859; CFI = .912; NFI = .871; SRMR = .081.

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

ed threshold of .70, confirming the reliability of the measurement scales (Nunnally, 1994).
The estimation of the model confirms the hypotheses and provides insights into the relationships among the constructs. As predicted in H1, the perception of health device complexity (Health Device Complexity Perception) has a significant direct effect on the perception of health device effectiveness (Health Treatment Effectiveness Perception). Specifically, higher complexity perception is associated with greater perceived effectiveness of the device (B = .378, SE = .068; t = 5.522, $p < .001$; $R^2 = .374$). Moreover, the findings indicate that Education has a significant impact on how patients perceive the effectiveness of health devices relative to their complexity. Specifically, the results show a positive and significant effect (B = .174, SE = .086; t = 2.021, p = .045), suggesting that individuals with higher levels of education are inclined to view complex health devices as more effective.
Contrary to what might be intuitively expected, Health Device Complexity Perception does not have a direct influence on WOM, as the statistical test does not indicate significance ($p > .05$). Further supporting the theoretical framework, the results align with H2, showing that the perception of health treatment effectiveness plays a crucial role in shaping WOM. A higher Health Treatment Effectiveness Perception leads to a significant increase in the likelihood of WOM (B = .693, SE = .076; t = 9.140, $p < .001$; $R^2 = .582$). Finally, in support of H3, the findings indicate that the effect of Health Device Complexity Perception on WOM is mediated by the Health Device Effectiveness Perception. The indirect effect is statistically significant (B = .262, Boot SE = .050; Boot LLCI = .365, Boot ULCI = .365, $p < .05$), suggesting that while complexity perception does not directly influence WOM, it contributes to shaping it indirectly through its impact on device effectiveness perception. This mediation effect underscores the importance of perceived effectiveness as a key driver of patient communication behaviors.
Finally, results of moderation analysis confirm hypotheses H4a and H4b (Table 5). Specifically, Age appears to confirm that the older the age, the less the positive effect of Health Device Complexity Perception on Health Device Effectiveness Perception, although this moderating effect is not particularly impactful and approaches

Table 2 – Direct effect of Health Device Complexity Perception (HDCP) on Health Device Effectiveness Perception (HDEP) considering Gender and Education as covariates

Pathway	B	SE	t	p	LLCI	ULCI
HDCP – HDEP	*.378*	*.068*	*5.522*	*.000*	*.243*	*.513*
Gender	.048	.070	.695	.488	–.089	.186
Education	*.174*	*.086*	*2.021*	*.045*	.004	.343

HDCP = Health Device Complexity Perception; HDEP = Health Device Effectiveness Perception; WOM = Word-of-Mouth; R^2 = .374.

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

Table 3 – Direct effect of Health Device Effectiveness Perception (HDEP) and Health Device Complexity Perception (HDCP) on Word-of-Mouth (WOM) considering Gender and Education as covariates

Pathway	B	SE	t	p	LLCI	ULCI
HDEP – WOM	*.693*	*.076*	*9.140*	*.000*	*.543*	*.842*
HDCP – WOM	.080	.081	.998	.319	–.079	.241
Gender	–.114	.077	–1.479	.141	–.267	.038
Education	–.052	.096	–.540	.590	–.242	.138

HDCP = Health Device Complexity Perception; HDEP = Health Device Effectiveness Perception; WOM = Word-of-Mouth; R^2 *= .582.*

Table 4 – Indirect effect of Health Device Complexity Perception (HDCP) on Word-of-Mouth (WOM) through Health Device Effectiveness Perception (HDEP)

Pathway	B	Boot SE	Boot LLCI	BOOT ULCI	p
HDCP – HDEP – WOM	.262	.050	.168	.365	*< .05*

HDCP = Health Device Complexity Perception; HDEP = Health Device Effectiveness Perception; WOM = Word-of-Mouth.

Table 5 – Moderation effects of Age on the relationship between Health Device Complexity Perception (HDCP) and Health Device Effectiveness Perception (HDEP) and Health Device Effectiveness Perception (HDEP) on Word-of-Mouth (WOM)

Interaction terms	Dependent Variable	B	SE	t	p	LLCI	ULCI
HDCP × Age	HDEP	–.011	.002	–1.992	.048	–.019	–.004
HDEP × Age	WOM	.220	.057	3.855	.000	.098	.343

HDCP = Health Device Complexity Perception; HDEP = Health Device Effectiveness Perception; WOM = Word-of-Mouth.

significance (B = – .011, SE = .002, t = – 1.992, p = .048).

Conversely, higher Age strengthens the relationship between Health Device Effectiveness Perception and WOM (B = – .220, SE = .057, t = 3.855, p < .001). This finding suggests that as individuals increase in age, their intention to engage in word-of-mouth communication is more strongly influenced by their perception of the device's effectiveness. However, despite this stronger link, older adults tend to engage in WOM less frequently than younger individuals. This may be explained by age-related differences in communication habits, social network size, and familiarity with digital sharing practices, which tend to decline with age.

4. Discussion

The aim of this research is to investigate the mechanisms that lead the users of wearable health devices to engage into WOM. Based on marketing literature, an analysis was conducted on the set of attributes of devices in terms of perceived complexity, evaluating how this may influence both perceived effectiveness and intention to speak favorably about them. The results of a survey-based study confirms that per-

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

ceived complexity interpreted as a signal of innovation and reliability, led users to strengthen their belief in the clinical value of the device. Moreover, the more a device is considered effective in improving one's condition, the more the propensity to share the positive experience and recommend it to others increases.

When patients perceive a health wearable device as effective – not only in providing accurate data but also in enhancing daily life quality, autonomy, and subjective well-being – they tend to develop an emotional bond with the device. This connection often leads to a form of "narration," that is, the desire to share their positive experience with others. Such a storytelling process marks the transition from an individual use of the device to a socially shared dimension of innovation (Aljawawdeh *et al.*, 2024b; Uzir *et al.*, 2023b). This is also consistent with the findings of Jeeyun Oh & Hyunjin Kang (2021), where the final stage of engagement with wearable devices is defined as "digital outreach", involving active sharing by users of their daily experiences with the device through social media or other digital platforms.

Moreover, the findings suggest that perceived technological complexity – typically regarded as a barrier – may actually be reinterpreted as a positive attribute when it signals reliability and innovation. This reinterpretation plays a critical role in fostering digital engagement, defined as a continuous, active, and aware relationship between users and technology (Graffigna *et al.*, 2020). In this context, digital engagement emerges as the key driver linking health wearable devices and positive WOM to the relational and social dimensions. Users who perceive themselves as part of a community – through apps, forums, or both online and offline discussion spaces – develop a sense of belonging and empowerment. This reduces the likelihood of device abandonment and encourages horizontal, peer-to-peer dissemination of the technology (Lupton, 2021; Veinot *et al.*, 2018). From this perspective, word-of-mouth acts both as an indicator of inclusion (when users feel motivated to communicate) and as a vehicle of inclusion (when individuals exposed to positive reviews are more inclined to adopt the technology with greater trust).

Furthermore, the results indicate that the level of education has a significant impact on how patients perceive the effectiveness of healthcare devices in relation to their complexity. Specifically, individuals with a higher level of education tend to interpret complex devices as more effective. This suggests that education does not merely act as a socio-demographic control variable but rather represents an active cognitive factor in shaping perceptions of technological complexity. This result is in line with the literature that identifies education as a facilitator in decoding technological affordances (Adjei *et al.,* 2010; Rogers, 2003), namely, the ability to recognize and interpret the functional potential embedded in complex artifacts. Goodyear *et al.* (2019) demonstrates that education contributes to the development of digital health literacy, understood as the ability to understand, evaluate, and effectively use health information mediated by digital technologies. This implication is further supported by the findings of Li *et al.* (2016), who show that the perception

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

of informational benefits and functional congruence in wearable devices is higher among users with greater technological competence – an attribute often correlated with higher educational levels. In this sense, a more advanced educational background not only strengthens the ability to interact with wearable health devices but also enables individuals to reframe complexity as a signal of perceived treatment effectiveness, rather than as a barrier to adoption.

Furthermore, the results highlight that age plays a significant moderating role in shaping how users interpret technological complexity and translate perceived effectiveness into communication behaviors. Specifically, the data show that younger users tend to associate device complexity with greater effectiveness, interpreting it as a signal of innovation and advanced features. In contrast, older users perceive complexity more critically and more readily associate it with difficulty of use, negatively impacting their perception of effectiveness.

However, the second moderated relationship reveals an opposite dynamic, when older users perceive a device as effective, they show a significantly greater propensity to share this experience through positive WOM. For these individuals, effectiveness often represents a relevant finding compared to expectations, capable of stimulating communication. In contrast, younger users, generally accustomed to high technological standards, tend to take effectiveness for granted and are less inclined to discuss it or recommend the device.

These findings offer a more nuanced interpretation than previous literature. While many studies have focused on generational differences in terms of digital literacy, self-efficacy and openness to innovation (Huedo-Martínez *et al.*, 2018; Šabić *et al.*, 2022; Staddon, 2020), this study shows that age not only affects adoption patterns, but also moderates the way complexity is interpreted in terms of perceived efficacy and, consequently, propensity for positive WOM.

5. Implications, limitation, and future research

The results of this research provide implications at both theoretical and managerial levels. From a theoretical perspective, the study highlights how the different attributes of the device should not be considered separately, but rather as components of a single overall perception, attributable to the concept of complexity. From this perspective, the research proposes a reinterpretation of perceived complexity, not as an objective obstacle to adoption, but as a cognitive and subjective synthesis that encompasses the user's global experience with the device. In line with the literature, perceived complexity takes on the role of a meta-construct capable of reflecting functional, symbolic, emotional and cognitive dimensions (Abouzeid, 2024; El-Gayar & Elnoshokaty, 2023). Complexity, if interpreted as "coherent" and "purpose-oriented", can become a facilitator of perceived effectiveness, strengthening user engagement and generating virtuous dynamics of social recommendation (e-WOM). This perspective is consistent with the results of the most recent studies on the adoption of wearable devices (Yang *et al.*, 2024), where perceived effectiveness is configured as a central element in determining not

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

only the initial adoption, but also loyalty over time. At the same time, human-factors evidence shows that reducing unnecessary complexity improves usability and is likely to support adherence (Gross *et al.*, 2023; Senders, 2006).

From a managerial perspective, since perceived complexity, if well decoded, translates into perception of effectiveness, implications become particularly relevant. They concern first of all the role of designers, called to adopt a co-design logic, in which the end user is involved in the design of the device in order to guarantee not only the technical functionality, but also the perceived coherence between clinical objective and daily use (Abouzeid, 2024; El-Gayar & Elnoshokaty, 2023). In parallel, communication and marketing strategies should abandon merely descriptive strategies to adopt a narrative centered on personal impact, empowerment and everyday life, facilitating spontaneous storytelling dynamics, generating trust and emotional involvement (Abouzeid, 2024). Finally, institutional campaigns must promote personalized adoption paths and health and digital literacy programs, with the aim of reducing inequalities and making technologies truly accessible even to the most vulnerable segments of the population (El-Gayar & Elnoshokaty, 2023; Yang *et al.*, 2024).

However, the study has some limitations. First, the use of convenience sampling, limited to a single Italian hospital, may have introduced selection bias and limits the generalizability of the results to other populations or healthcare settings. Second, the survey focused exclusively on users of AID, without extending the analysis to other types of health wearable devices that, while sharing some functional characteristics, could be perceived differently by users. Third, by design the study included only adults with T1D who were current users of AID and fell within the 16-74 years inclusion range, all recruited from a single Italian hospital. This approach was adopted to avoid structural heterogeneity compared to T2D, for which care pathways and self-management routines differ significantly (Sempere-Bigorra *et al.*, 2021). Consequently, generalizability is limited to T1D adults aged 16-74 in hospital settings. Finally, although the literature cited underlines the importance of psychological, relational and contextual factors in shaping the user experience, these elements were not directly included in the analytical model, reducing the possibility of fully capturing the complexity of the dynamics that influence the diffusion and recommendation of digital health technologies.

In light of these considerations, future studies could integrate these dimensions and deepen the relationship between age and attitudes towards the use of wearable health devices, favoring their diffusion through a positive WOM. Additionally, future research should expand the sample to include cohorts aged 75 years and older as well as patients with T2D, thereby enabling a systematic comparison with T1D and testing the generalizability of the findings across settings. Moreover, despite recent scientific and technological advancements, significant challenges persist in the clinical management of diabetes, including the need for improved glycemic control, reduced complications, increased treatment adherence, and more equitable access

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

to care. Innovative health technologies – such as AID systems – play a crucial role in addressing these challenges by fostering patient empowerment and optimizing care processes. However, a key challenge remains, *i.e.*, understanding the role of such technologies not only in terms of their potential, but also in terms of their sustainable and equitable adoption.

Future research should therefore investigate the socio-economic, environmental, and technological factors driving the increasing prevalence of diabetes (mapping), with the aim of identifying the specific contribution of health wearable devices in tackling this trend. This approach may support the development of effective policy strategies (sharing) and guide the design of tailored interventions (acting) capable of resolving the tension between perceived complexity and clinical effectiveness, as evidenced in the case of AID systems. By adopting this broader perspective, researchers and policymakers can contribute to advancing digital health solutions that are not only innovative, but also inclusive, sustainable, and truly impactful in improving chronic disease management.

REFERENCES

Abouzeid D. Y. (2025). *Investigating the factors affecting users' and non-users' behavioral intention to use smartwatches for health-and fitness-specific purposes*. Universidade do Minho Escola de Economia e Gestão.

Adiyatma W., Oktavia T., Adhikara C. T., Gaol F. L., & Hosoda T. (2022). Evaluation Review on Wearable Technology Adoption for Sport Science. In: *Proceedings of 11th International Congress* (Vol. 81, pp. 464-473).

Adjei M. T., Noble S. M., & Noble C. H. (2010). The influence of C2C communications in online brand communities on customer purchase behavior. *Journal of the Academy of Marketing Science*, 38: 634-653.

Ahn J., Yang Y., & Park G. (2024). Advancing elderly diabetes care: exploring the usability and acceptance of continuous glucose monitoring (CGM). *Geriatric Nursing*, 59: 15-25.

Ajzen I., & Fishbein M. (1980). *Understanding attitudes and predicting social behavior*. Englewood Cliffs: Prentice-Hall.

Alexandrov A., Lilly B., & Babakus E. (2013). The effects of social-and self-motives on the intentions to share positive and negative word of mouth. *Journal of the Academy of Marketing Science*, 41: 531-546.

Aljawawdeh H., D'Auria A., Cavallone M., & Ferraris A. (2024b). eWOM in digital health innovation: The role of patient experience and online trust in the diffusion of wearable devices. *Journal of Business Research*, 171, 114266.

Aljawawdeh H., Dughmosh R., Almashaqbeh D., Alazzeh H., & Aldroubi A. (2024a). Smart Insulin Calculator: Technological Innovation for Type 1 Diabetes Management Revolutionising Insulin Management with Intelligent Health Technology. In: 2024 Global Digital Health Knowledge Exchange & Empowerment Conference (gDigiHealth. KEE) (pp. 1-6). IEEE.

Associazione Medici Diabetologi (AMD) (2023). *Annali AMD 2023. Profili assistenziali nei pazienti con diabete di tipo 1 e con diabete di tipo 2 in relazione al*

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

genere (Monografie). Fondazione AMD. -- Retrieved from https://aemmedi.it/nuova-monografia-annali-amd-2023-profili-di-assistenza-al-diabete-tipo-1-e-al-diabete-tipo-2-in-base-al-genere/.

Avilés-Santa M. L., Monroig-Rivera A., Soto-Soto A., & Lindberg N. M. (2020). Current state of diabetes mellitus prevalence, awareness, treatment, and control in Latin America: challenges and innovative solutions to improve health outcomes across the continent. *Current Diabetes Reports*, 20: 1-44.

Babu M., Lautman Z., Lin X., Sobota M. H., & Snyder M. P. (2024). Wearable devices: implications for precision medicine and the future of health care. *Annual Review of Medicine*, 75(1): 401-415.

Benbunan-Fich R. (2020). User satisfaction with wearables. *AIS Transactions on Human-Computer Interaction*, 12(1): 1-27.

Bowman D., & Narayandas D. (2001). Managing customer-initiated contacts with manufacturers: The impact on share of category requirements and word-of-mouth behavior. *Journal of Marketing Research*, 38(3): 281-297.

Cain M. K., Zhang Z., & Yuan K.H. (2017). Univariate and multivariate skewness and kurtosis for measuring nonnormality: Prevalence, influence and estimation. *Behavior Research Methods*, 49(5): 1716-1735.

Calderón D., Ortí A. S., & Kuric S. (2022). Self-confidence and digital proficiency: Determinants of digital skills perceptions among young people in Spain. *First Monday*, 27(4). DOI: 10.5210/fm.v27i4.12566.

Chandrasekaran R., Katthula V., & Moustakas E. (2020). Patterns of use and key predictors for the use of wearable healthcare devices by US adults: insights from a national survey. *Journal of Medical Internet Research*, 22(10), e22443.

Chandrasekaran R., Katthula V., & Moustakas E. (2021). Too old for technology? Use of wearable healthcare devices by older adults and their willingness to share health data with providers. *Health Informatics Journal*, 27(4), 14604582211058073.

Chen X., & Li S. (2022, June). Research on wearable smart products for elderly users based on Kano model. In: *International Conference on Human-Computer Interaction* (pp. 160-174). Cham: Springer International Publishing.

Cheng Y., Mukhopadhyay A., & Schrift R. Y. (2017). Do costly options lead to better outcomes? How the protestant work ethic influences the cost-benefit heuristic in goal pursuit. *Journal of Marketing Research*, 54(4): 636-649.

Chong K. P., Guo J. Z., Deng X., & Woo B. K. (2020). Consumer perceptions of wearable technology devices: retrospective review and analysis. *JMIR mHealth and uHealth*, 8(4), e17544.

Ciabattoni L., Foresi G., Monteriù A., Pagnotta D.P., Romeo L., Spalazzi L., De Cesare A. (2018). Complex activity recognition system based on cascade classifiers and wearable device data. In: *2018 IEEE Int Conf Consum Electron (ICCE) IEEE 1-2*.

Cilliers L. (2020). Wearable devices in healthcare: Privacy and information security issues. *Health information management journal*, 49(2-3): 150-156.

Cnop M., Welsh N., Jonas J. C., Jorns A., Lenzen S., & Eizirik D. L. (2005). Mechanisms of pancreatic β-cell death in type 1 and type 2 diabetes: many differences, few similarities. *Diabetes*, 54(suppl_2): S97-S107.

Dellaert B. G., & Stremersch S. (2005). Marketing mass-customized products: Striking a balance between utility and complexity. *Journal of Marketing Research*, 42(2): 219-227.

Diamantopoulos A., Sarstedt M., Fuchs C., Wilczynski P., & Kaiser S. (2012). Guidelines for choosing between multi-item and single-item scales for construct measurement: A predictive validity perspective. *Journal of the Academy of Marketing Science*, 40(3): 434-449.

Douglas S.P., Craig C.S., 2007. Collaborative and iterative translation: an alternative approach to back translation. *Journal of International Marketing*, 15(1): 30-43.

El-Gayar O., & Elnoshokaty A. (2023). Factors and design features influencing the continued use of wearable devices. *Journal of Healthcare Informatics Research*, 7(3): 359-385.

Erdem A., Eksin E., Senturk H., Yildiz E., & Maral M. (2024). Recent developments in wearable biosensors for healthcare and biomedical applications. *TrAC Trends in Analytical Chemistry*, 171, 117510.

Ferreira J. J., Fernandes C. I., Rammal H. G., & Veiga P. M. (2021). Wearable technology and consumer interaction: A systematic review and research agenda. *Computers in human behavior*, 118, 106710.

Fornell C., & Larcker D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1): 39-50.

Goodyear V. A., Armour K. M., & Wood H. (2019). Young people learning about health: the role of apps and wearable devices. *Learning, Media and Technology*, 44(2): 193-210.

Graffigna G., Barello S., Bonanomi A., & Lozza E. (2020). Measuring patient engagement: Development and psychometric properties of the Patient

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

Health Engagement (PHE) Scale. *Frontiers in Psychology*, 11, 1253.

Grewal R., Cote J. A., & Baumgartner H. (2004). Multicollinearity and measurement error in structural equation models: Implications for theory testing. *Marketing Science*, 23(4): 519-529.

Gross M., Roberts C., Stinson K., & Wiltman S. (2023). Improving medical device usability by reducing complexity using a novel predictive models-based user interface assessment tool. *Human Factors in Healthcare*, 3, 100041.

Gu D., Yang X., Li X., Jain H. K., & Liang C. (2018). Understanding the role of mobile internet-based health services on patient satisfaction and word-of-mouth. *International journal of environmental research and public health*, 15(9), 1972.

Guillén-Gámez F. D., & Mayorga-Fernández M. J. (2019). Empirical study based on the perceptions of patients and relatives about the acceptance of wearable devices to improve their health and prevent possible diseases. *Mobile Information Systems*, (1), 4731048.

Hair J. F., Sarstedt M., Ringle C. M., & Mena J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, 40(3): 414-433.

Hasan M. N. U., & Stannard C. R. (2023). Exploring online consumer reviews of wearable technology: the owlet smart sock. *Research Journal of Textile and Apparel*, 27(2): 157-173.

Hayes A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (3rd ed.). New York: Guilford Publications.

Huedo-Martínez S., Molina-Carmona R., & Llorens-Largo F. (2018, May). *Study on the attitude of young people towards technology. In International Conference on Learning and Collaboration Technologies* (pp. 26-43). Cham: Springer International Publishing.

ISS (Istituto Superiore di Sanitá) (2022). -- Available on: https://www.epicentro.iss.it/diabete/epidemiologia-italia.

ISTAT (2024). -- https://www.epicentro.iss.it/diabete/epidemiologia-italia.

Jafleh E. A., Alnaqbi F. A., Almaeeni H. A., Faqeeh S., Alzaabi M. A., Al Zaman K., ... & Alzaabi M. (2024). The role of wearable devices in chronic disease monitoring and patient care: a comprehensive review. *Cureus*, 16(9).

Jeong J., Kim Y., & Roh T. (2021). Do consumers care about aesthetics and compatibility? The intention to use wearable devices in health care. *SAGE Open*, 11(3), 21582440211040070.

Kano N., Seraku N., Takahashi F., & Tsuji S. (1984). Attractive quality and must-be quality. Hinshitsu: *The Journal of the Japanese Society for Quality Control*, 41: 39-48.

Karim M. Z. A., Thamrin N. M., Shauri R. L. A., Jailani R., Manaf M. H. A., & Mustapa N. A. (2024). Evaluating Telemedicine Diabetes Mellitus: A Mobile Health App for Type-2 Diabetes. *International Journal of Advances in Applied Sciences*, 13: 787-795.

Kim T. B., & Ho C. T. B. (2021). Validating the moderating role of age in multi-perspective acceptance model of wearable healthcare technology. *Telematics and Informatics*, 61, 101603.

Kim T. Y., De R., Choi I., Kim H., & Hahn S. K. (2024b). Multifunctional nanomaterials for smart wearable diabetic healthcare devices. *Biomaterials*, 122630.

Kim Y., Godino J. G., Cheung F. L. T., Multhaup M., Chan D. K. C. K., Chen Z., ... & Griffin S. (2024a). Effect of communicating genetic risk of type 2 diabetes and wearable technologies on wearable device-measured behavioural outcomes in East Asians: protocol of a randomised controlled trial. *BMJ open*, 14(12), e082635.

Kyytsönen M., Vehko T., Anttila H., & Ikonen J. (2023). Factors associated with use of wearable technology to support activity, well-being, or a healthy lifestyle in the adult population and among older adults. *PLOS Digital Health*, 2(5), e0000245.

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

Li H., Wu J., Gao Y., & Shi Y. (2016). Examining individuals' adoption of healthcare wearable devices: An empirical study from privacy calculus perspective. *International Journal of Medical Informatics*, 88: 8-17.

Liang B., & Scammon D. L. (2011). E-Word-of-Mouth on health social networking sites: An opportunity for tailored health communication. *Journal of Consumer Behaviour*, 10(6): 322-331.

Lu L., Zhang J., Xie Y., Gao F., Xu S., Wu X., & Ye Z. (2020). Wearable health devices in health care: narrative systematic review. *JMIR mHealth and uHealth*, 8(11), e18907.

Luo J., Zhang K., Xu Y., Tao Y., & Zhang Q. (2022). Effectiveness of wearable device-based intervention on glycemic control in patients with type 2 diabetes: a system review and meta-analysis. *Journal of Medical Systems*, 46(1), 11.

Lupton D. (2021). Wearable devices: Sociocultural and ethical implications of self-tracking. *The Lancet Digital Health*, 3(11): e635-e636.

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

Mao J., Xie L., Zhao Q., Xiao M., Tu S., Sun W., & Zhou T. (2022). Demand analysis of an intelligent medication administration system for older adults with chronic diseases based on the Kano model. *International Journal of Nursing Sciences*, 9(1): 63-70.

Mehrotra S., Rai P., Saxena A., Priya S., & Sharma S. K. (2024). Advancements in enzyme-based wearable sensors for health monitoring. *Microchemical Journal*, 200, 110250.

Moore K., O'Shea E., Kenny L., Barton J., Tedesco S., Sica M., ... & Timmons S. (2021). Older adults' experiences with using wearable devices: qualitative systematic review and meta-synthesis. *JMIR mHealth and uHealth*, 9(6), e23832.

Moulaei K., Malek M., & Sheikhtaheri A. (2021). A smart wearable device for monitoring and self-management of diabetic foot: A proof of concept study. *International Journal of Medical Informatics*, 146, 104343.

Ntumba D., & Budree A. (2021). The Effect of Social Media Based Electronic Word of Mouth on Propensity to Buy Wearable Devices. In: HCI International 2021-Late Breaking Papers: Design and User Experience: 23rd HCI International Conference, HCII 2021, Virtual Event, July 24-29, 2021, Proceedings 23 (pp. 310-325). Springer International Publishing.

Nunnally J. C., & Bernstein I. H. (1994). *Psychometric Theory*, third ed., New York: McGraw-Hill.

Nutbeam D. (2008). The evolving concept of health literacy. *Social Science & Medicine*, 67(12): 2072-2078.

Oh S. S., Kim K. A., Kim M., Oh J., Chu S. H., & Choi J. (2021). Measurement of digital literacy among older adults: systematic review. *Journal of medical Internet research*, 23(2), e26145.

Podsakoff P.M., MacKenzie S.B., Lee J.Y., Podsakoff N.P., 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5): 879-903.

Renard E. (2023). Automated insulin delivery systems: from early research to routine care of type 1 diabetes. *Acta Diabetologica*, 60(2): 151-161.

Rodriguez-León C., Villalonga C., Munoz-Torres M., Ruiz J. R., & Banos O. (2021). Mobile and wearable technology for the monitoring of diabetes-related parameters: Systematic review. *JMIR mHealth and uHealth*, 9(6), e25138.

Rodríguez-Rodríguez I., Campo-Valera M., Rodríguez J. V., & Woo W. L. (2024). IoMT innovations in diabetes management: Predictive models using wearable data. *Expert Systems with Applications*, 238, 121994.

Rogers E. M. (2003). *Diffusion of Innovations.* New York: The Free Pree.

Rousseva R. (2008). Identifying technological capabilities with different degrees of coherence: The challenge to achieve high technological sophistication in latecomer software companies (based on the Bulgarian case). *Technological Forecasting and Social Change*, 75(7): 1007-1031.

Rupp M. A., Michaelis J. R., McConnell D. S., & Smither J. A. (2018). The role of individual differences on perceptions of wearable fitness device trust, usability, and motivational impact. *Applied Ergonomics*, 70: 77-87.

Šabić J., Baranović B., & Rogošić S. (2022). Teachers' self-efficacy for using information and communication technology: The interaction effect of gender and age. *Informatics in education*, 21(2): 353-373.

Sedgwick P. (2013). Convenience sampling. *BMJ*, 347, f6304.

Segura Anaya L. H., Alsadoon A., Costadopoulos N., & Prasad P. W. C. (2018). Ethical implications of user perceptions of wearable devices. *Science and Engineering Ethics*, 24: 1-28.

Sempere-Bigorra M., Julián-Rochina I., & Cauli O. (2021). Differences and similarities in neuropathy in type 1 and 2 diabetes: a systematic review. *Journal of Personalized Medicine*, 11(3), 230.

Senders J. W. (2006). On the complexity of medical devices and systems. *BMJ Quality & Safety*, 15(suppl 1): i41-i43.

Seneviratne S., Hu Y., Nguyen T., Lan G., Khalifa S., Thilakarathna K., ... & Seneviratne A. (2017). A survey of wearable devices and challenges. *IEEE Communications Surveys & Tutorials*, 19(4): 2573-2620.

Sherr J. L., Heinemann L., Fleming G. A., Bergenstal R. M., Bruttomesso D., Hanaire H., ... & Evans M. (2022). Automated insulin delivery: benefits, challenges, and recommendations. A Consensus Report of the Joint Diabetes Technology Working Group of the European Association for the Study of Diabetes and the American Diabetes Association. *Diabetes Care*, 45(12): 3058-3074.

Soliño-Fernandez D., Ding A., Bayro-Kaiser E., & Ding E. L. (2019). Willingness to adopt wearable devices with behavioral and economic incentives by health insurance wellness programs: results of a US cross-sectional survey with multiple consumer health vignettes. *BMC Public Health*, 19(1), 1649.

Staddon R. V. (2020). Bringing technology to the mature classroom: age differences in use and attitudes. *International Journal of Educational Technology in Higher Education*, 17(1), 11.

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030

Tran V. T., Riveros C., & Ravaud P. (2019). Patients' views of wearable devices and AI in healthcare: findings from the ComPaRe e-cohort. *NPJ Digital Medicine*, 2(1), 53.

Turan A., & Bozaykut-Bük T. (2016). Analyzing perceived healthcare service quality on patient related outcomes. *International Journal of Quality and Service Sciences*, 8(4): 478-497.

Uzir M. U. H., Al Halbusi H., & Thurasamy R. (2023b). Why do users spread eWOM on wearable health devices? The role of utilitarian and hedonic values. *Technology in Society*, 72, 102169.

Uzir M. U. H., Bukari Z., Al Halbusi H., Lim R., Wahab S. N., Rasul T., ... & Eneizan B. (2023a). Applied artificial intelligence: Acceptance-intention-purchase and satisfaction on smartwatch usage in a Ghanaian context. *Heliyon*, 9(8).

Veinot T. C., Mitchell H., & Ancker J. S. (2018). Good intentions are not enough: How informatics interventions can worsen inequality. *Journal of the American Medical Informatics Association*, 25(8): 1080-1088.

Wah J. N. K. (2025). Wear the Future of Healthcare: Revolutionizing Healthcare with AI-Driven Wearables for Enhanced Health and Wellness. *Wear*, 70(02).

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.

Wang X., Tang P., Jiang Y., Zhao Y., Tang L., Qiao S., ... & Chen D. (2024). The application value of Kano Model in quality of healthcare: a scoping review. *medRxiv*, 2024-03.

Wen D., Zhang X., & Lei J. (2017). Consumers' perceived attitudes to wearable devices in health monitoring in China: A survey study. *Computer Methods and Programs in Biomedicine*, 140: 131-137.

Wong E. L., Ho K., Wong S. Y., Cheung A. W., Yau P. S., Dong D. and Yeoh E. (2022). Views on Workplace Policies and its Impact on Health-Related Quality of Life During Coronavirus Disease (COVID-19) Pandemic: Cross-Sectional Survey of Employees. *International Journal of Health Policy and Management*, 11(3): 344-353.

Xie Z., Yadav S., & Jo A. (2021). The association between electronic wearable devices and self-efficacy for managing health: a cross sectional study using 2019 HINTS data. *Health and Technology*, 11(2): 331-339.

Yang H., Yu J., Zo H., & Choi M. (2016). User acceptance of wearable devices: An extended perspective of perceived value. *Telematics and Informatics*, 33(2): 256-269.

Yang Q., Al Mamun A., Wu M., & Naznen F. (2024). Strengthening health monitoring: Intention and adoption of Internet of Things-enabled wearable healthcare devices. *Digital Health*, 10, 20552076241279199.

Yang Q., Li P., Liu X., & Wei C. (2025). Exploring the functional quality attributes of smart home for older adults based on qualitative research and Kano model. *Frontiers in Public Health*, 13, 1541571.

Zhang Z., Xia E., & Huang J. (2022). Impact of the moderating effect of national culture on adoption intention in wearable health care devices: meta-analysis. *JMIR mHealth and uHealth*, 10(6), e30960.

Zhao Z., Haikel-Elsabeh M., Baudier P., Renard D., & Brem A. (2024). Functional, hedonic, and social motivated consumer innovativeness as a driver of word-of-mouth in smart object early adoptions: an empirical examination in two product categories. *International Journal of Technology Management*, 95(1-2): 226-252.

MECOSAN – ISSNe 2384-8804, 2025, 134 DOI: 10.3280/mesa2025-134oa22030