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Research Article

Wearable from the Perspective of Healthcare Professionals

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Abstract—**Technology, also known as "wearable devices, technology or wearables" in the literature, refers to all electronic technological devices that can be easily worn on the body today. The concept of -smart-, which we have recently heard especially in cell phones, is also integrated with wearable technological devices. Thus, wearable technology can also be referred to as smart wearable devices. Keeping up with rapid technological change, society is more interested in wearable technology than standard technological products.**

The aim of this study is to identify the factors that influence healthcare professionals' intentions to use wearable technology and to evaluate these factors at both organizational and individual levels. Additionally, the study seeks to reveal the bibliographic evolution of the concept through bibliometric analysis. In line with this objective, the research investigates the intention to use wearable technology among healthcare professionals working in public and private hospitals in Istanbul, within the framework of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), developed by Venkatesh and colleagues. Furthermore, a total of 4,534 academic publications indexed in the Web of Science (WoS) between 1996 and 2025 were analyzed using VOSviewer software to map the conceptual development of wearable technology. In the empirical phase, surveys were administered to 730 healthcare workers, with 728 valid responses analyzed using the SPSS software. According to the results of factor analysis, regression, and ANOVA, the most influential predictors of intention to use wearable technology were performance expectancy (β = 0.618) and hedonic motivation (β = 0.513). Facilitating conditions, price/value perception, and habit showed moderate effects, while social influence and effort expectancy demonstrated only limited significance.

Index Terms— **Wearable Technology, Technology and Innovation Management, Organizational Behavior, Bibliometric Data Analysis.**

I. INTRODUCTION

THE rapid change in technology has significantly changed the daily lifestyles of both organizations and individuals, and this transformation has led to the widespread use of wearable technology, especially as mobile phones have become smarter and smarter. In the most general terms, wearable technology, which consists of electronic devices that people can carry on their bodies and can transfer instant data, has been used in a wide range of fields from health to education. Recent studies indicate that wearable health technologies have become increasingly widespread due to their ability to continuously monitor health data [1] and facilitate early diagnosis of conditions such as cardiac arrhythmias [2]. However, users encounter various barriers during the adaptation process. Concerns about data privacy and security [1][3], high costs [4], lack of digital health literacy among older adults [5], and the need for training among healthcare professionals to interpret data from these devices [6] have been identified as major deterrents to adoption. Although individuals with higher incomes show greater willingness to use wearable devices, the rate of health data sharing remains relatively low [7]. Moreover, the use of such technologies may further exacerbate healthcare delivery inequalities in developing countries, as access to these devices is closely tied to socioeconomic factors.

Health sector is an area where wearable technology is frequently used. It is expected that these systems, which have many ease of use such as patient tracking, monitoring, storing data about the patient, will be adopted by healthcare professionals and their usage rates will increase. In the conceptual framework part of the study, the numerous advantages of these devices for patients and their relatives were mentioned. However, is the benefit perceived by patients also perceived by healthcare professionals, i.e. those who apply these devices? When the literature is examined, it is observed that many technological innovations are met with resistance by healthcare professionals. The main reason for this is the employees' desire to change their habits and the need for technology knowledge. In this sense, it is important to know what factors affect the intention to use wearable technology products.

In the first part of this study, which consists of three parts, definitions related to wearable technology and the evolution of wearable technology are given. In the second part, Web of Science database was searched with the keyword "Wearable Technology" and 4534 publications written between 1996-2025 were analyzed with VOSviewer. In this section, publication years, publication types, publication fields, co-authorship analysis, citation analysis of authors, citation analysis of countries, keyword analysis, bibliographic match analysis of texts and bibliographic match analysis of authors were extracted respectively.

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II. CONCEPTUAL FRAMEWORK

A. *Wearable Technology Concept*

Wearable technology refers to mobile technology that can be attached to the body and worn. The said mobile device, which can be placed on the body, also provides the desired data transfer to the user [8]. One of the first known devices is known as the timing device mounted on the sole of the shoe. The purpose of the device, which was invented by Thorp in 1955 and started production with Shannon in 1961, was to cheat in games [9][10]. The 1980s was a period when there was a lot of development in wearable technology [11][12][13].

Again, one of the oldest known devices was invented by Mann. The device is a system that can be mounted on the back and has multimedia and video features. The system was developed over time and was named Lifelogging, with the ability to photograph and video the individual's entire time. Mann, who later produced a wireless wearable camera in 1994, became the architect of the first important products in the field of wearable technology with the Lifelogging system [14][15][16][17]. Other known examples of wearable technology from these dates are as follows:

- Although they were seen as calculators that replaced watches in the 1980s, the most specific example is actually the wearable glasses produced by Google in the 90s [18][19][20].
- The sociometer, which was developed in 2002 and is placed on the front to measure people's face-to-face communication 90s [21][22][23].
- A device that works with the help of a microphone and a sensor, produced by Wang in 2006 and aimed to identify people's movements by being placed on the arm [24].
- A device that is placed on the human body and works with kinetic sensors, aiming to prevent the falls caused by Giansanti in 2006 [25][26][27].

In 2015, Google Glass emerged with an ambitious innovative idea. Stating that they will produce a reality device, company claimed that this device, which will work by attaching to individuals' heads, will prevent people from lying. The idea received reaction from the public and production was stopped. However, he stated that he will continue to develop his ambitious innovative idea [28][29].

Wearable technology products are particularly important in the health sector and there are many tools developed in this field. Some of these electronic devices with different subheadings are products that monitor patients and help in diagnosis and treatment [30][31][13]. Nowadays, clinical devices that measure blood pressure and pulse rate and behavioral tools such as running and walking are quite common [11][30][8]. In addition to these, there are also medication reminders, diabetes devices that inject insulin periodically, reminders for Alzheimer's patients, and biochemical sensors [12][32][33][28][8].

Many of the above-mentioned sensor technologies enable the collection of data from the individual body [13][29]. Many systems have been developed to analyze the movements of the human heart, measuring oxygen levels and rhythm [30][34][35]. Lee and Patel examined the evolution of wearable technologies in the field of cardiovascular medicine and emphasized their significant impact on the early diagnosis and management of heart disease. The authors further noted that these devices are highly effective in applications such as remote monitoring, offer advantages for personalized treatment plans, and are increasingly being adopted in clinical practice [2]. Lee et al. [36] stated in their study that in the 2000s, health status could be monitored at any time thanks to a ring worn by the patient. It is also known that blood sugar and oxygen monitoring, including EEG measurements, can be performed in a separate system [37]. Wang et al. [38] stated in their study that a device attached to the earlobe can measure sugar 10% stronger than the sensitivity of finger measurement.

Smith and Doe (2023) conducted a detailed study on the effects of wearable health technologies on patient experience, reporting that while most patients had positive experiences, some found the devices complex and expressed concerns particularly regarding data security [7]. In a similar study conducted in the United States following the COVID-19 pandemic, Johnson and Nguyen (2024) explored patients' experiences with using wearable technologies and sharing their data [39]. The findings indicated that wearable technology usage rose to 33.36% in 2022, yet only 26.5% of users shared their health data with healthcare providers.

In another study examining the evolution of wearable health devices—from basic fitness trackers to sophisticated systems capable of real-time health monitoring and data collection—it was observed that the integration of artificial intelligence significantly contributed to the shift from reactive treatment to proactive, preventive care [40].

The analysis of this study is based on the UTAUT2 model. In their study examining the determinants of wearable technology intention in the field of healthcare in Godoy and Lopez (2023) found that perceived usefulness, social influence, and hedonic motivation were influential predictors, particularly in the context of fitness-related wearables [41]. The authors also noted that perceived usefulness indirectly influenced health motivation. Another study that integrated the UTAUT2 model with the Technology Readiness Index (TRI) focused on older adults' intention to use wearable healthcare technologies. The findings revealed that, in addition to the determinants of the UTAUT2 model, digital health literacy was a significant factor influencing the intention to use wearable technologies among elderly individuals. Specifically, digital health literacy level was found to negatively affect performance expectancy, effort expectancy, and behavioral intention [42].

In 2003, Venkatesh and colleagues proposed the Unified Theory of Acceptance and Use of Technology (UTAUT), which measured behavioral intention to use technology based on four core constructs: facilitating conditions, social influence, effort expectancy, and performance expectancy. The study also examined how certain demographic variables moderated the effects of these determinants [43]. In a subsequent study in 2008, Venkatesh and Bala adopted a more comprehensive approach by integrating both cognitive and emotional factors to explain technology acceptance. They particularly emphasized external variables influencing perceived ease of use and perceived usefulness, thereby forming the third version of the Technology Acceptance Model (TAM3) [44]. Later, in 2012, Venkatesh, Thong, and Xu expanded the original UTAUT to account for individual-level behavior, developing UTAUT2. Their extended model introduced new constructs such as hedonic motivation and price/value perception, significantly improving the explanatory power regarding individuals' behavioral intention and actual usage of technology. UTAUT2 thus offered a more robust theoretical framework for understanding personal technology acceptance [45].

Recent studies have provided updated insights into the adoption of technologies in the healthcare sector. For example, Wang et al. (2022) demonstrated that digital competence, organizational support, and perceived individual benefit significantly influence the acceptance of mobile health applications [46]. Similarly, Alharbi and Drew (2023) emphasized that habit and hedonic motivation are critical determinants in the adoption of wearable devices. These findings reinforce the relevance and applicability of the UTAUT2 model in the context of contemporary healthcare technologies [47].

In the field of wearable technologies in healthcare, an analysis of clinical- and consumer-grade devices, their application areas, and regional distribution indicates that the health technology market is projected to grow from $78.6 billion in 2023 to $174.4 billion by 2030, with a compound annual growth rate (CAGR) of 14.4% [48].

In recent years, interest in wearable technologies in the field of healthcare has increased significantly; however, studies focusing on the adoption of these technologies remain rather limited. A bibliometric analysis of 4,534 studies published between 1996 and 2025 in the Web of Science database reveals that the concept has predominantly focused on advantages such as patient monitoring and data security. Notably, analyses based on technology acceptance models, particularly from the perspective of healthcare professionals, are found to be much more limited. In this context, the present study aims to address this gap by examining the acceptance process within the framework of the UTAUT2 model, specifically from the perspective of healthcare workers.

B. Wearable Technology Bibliometric Data Analysis

TABLE I
DISTRIBUTION OF PUBLICATIONS BY YEAR (2005–2025)

Year	*Number of Publications*	*Year*	*Number of Publications*
2025	90	2011	11
2024	814	2010	10
2023	506	2009	22
2022	508	2008	14
2021	515	2007	17
2020	404	2006	10
2019	409	2005	9

TABLE II
TYPES OF PUBLICATIONS

Types of Publications	*Number of Publications*	*Types of Publications*	*Number of Publications*
Article	2,626	Withdrawn Release	13
Article review	620	Correction	9
Meeting Summary	140	News Item	6
Early Access	96	Data Sheet	4
Editorial Material	86	Book	3
Book Chapters	50	Book Review	3
Letter	32	Proceedings Book	1,035

TABLE III
PUBLICATION AREAS

Publication Areas	*Number of Publications*
Engineering Electrical and Electronics	805
Materials Science Multidisciplinary	394
Computer Science Theory Methods	385
Engineering Biomedical	344
Computer Science Information Systems	340
Instrumentation	324
Interdisciplinary Applications in Computer Science	322
Computer Science Cybernetics	284
Health Sciences Services	262
Chemistry Analytical	258
Applied Physics	258
Sport Sciences	257
Telecommunications	256
Computer Science Artificial Intelligence	255
Medical Informatics	255
Nanoscience Nanotechnology	189
Clinical Neurology	162
Public Environment Occupational Health	151
Neurosciences	149
Chemistry Multidisciplinary	130
Rehabilitation	124
Chemistry Physical	119
Medicine General Internal	119
Engineering Multidisciplinary	111

In this part of the study, 4,534 studies were found in the Web of Science database on 09.01.2025 by selecting all fields with the keyword "*wearable technology*". When the years of the studies were analyzed, it was observed that they were conducted between 1996 and 2025. The year-based numbers of the studies are shown in Table 1.

As can be seen in the table, there has been an increase in the number of publications every year.

When the type of studies is analyzed, it is observed that the highest number of publications is 2,626 articles. The number of other types of publications is shown in Table 2.

When the studies are analyzed in terms of disciplines, it is observed that the highest number of 805 publications was made in the field of Engineering. Other disciplines and their numbers are shown in Table 3. (The table includes disciplines with a minimum of 100 publications).

1) *Co-authorship analysis*

Authors were examined with the criteria of at least one publication and at least one citation and the number of 312 authors was reached. Bonato Paolo, Jungil Choi, Roozbeh Ghaffari, John A. Rogers, Yiwen Gao, He Li, Bastian Bloem, Walter Maetzler and Natasha Shull have two publications each and other authors have one publication each. The analysis identified 35 items, 3 clusters, 397 links and 398 link strengths.

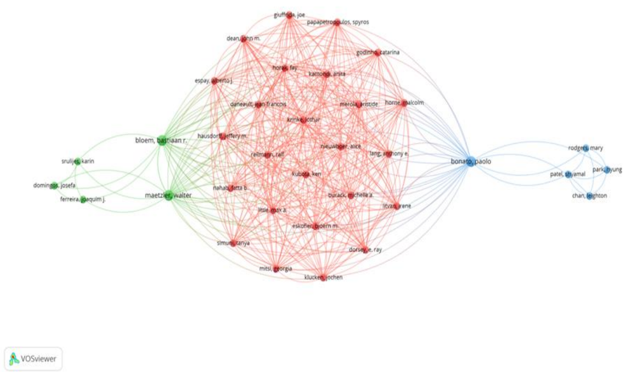

Fig.1. Co-authorship of Authors Indicating Collaboration Between Author

2) *Citation of authors analysis*

In order to identify citation networks, a citation map was created with at least one publication and one citation criterion. Through 53 interconnected units, 24 clusters, 262 links and 263 link strengths were identified. Most cited authors and number of citations: Patel et al. (2012) 1392 [12], Ray et al. (2019) 887 [20], Shi et al. (2021) 711 [8], Singh et al. (2017) 644 [31], Yang et al. (2017) 581 [10], Bandodkar et al. (2016) 576 [30], Salarian et al. 464 [11], Jayatilaka et al. (2019), 459 [49], Dwivedi et al. (2019), 426 [13] citations.

Fig.2. Co-authorship of Authors Indicating Collaboration Between Author.

3) *Citation of countries*

In order to examine the country analysis of the publications, 15 units, 4 clusters, 38 links and 54 link strengths were formed in the analysis made with at least one work and one citation criteria. The most cited countries are USA (10950) with 27 publications, China (5113) with 15 publications, Australia (2032) with 5 publications, Germany (1306) and Singapore (1174) with 3 publications each, Netherlands (1123), and Italy (1107) with 4 publications each and Taiwan (1048) with 3 publications.

Fig. 3.. Citation of Countries.

4) *Keyword analysis*

According to the results of the analysis of the most frequently used keywords of the concept in publications, "wearable technology" ranks first with 17 repetitions. The other most frequently used keywords are as follows: Parkinson's disease, wearable devices and wearable sensors 4 times each, digital health, internet of things, healthcare, wearable electronics, wearable 3 times each. In the analysis, 140 units, 17 clusters, 483 connections and 500 connection strengths were observed.

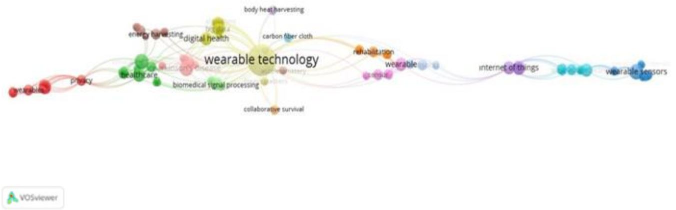

Fig. 4. Most Frequently Used Keyword Links.

5) *Bibliographic match analysis of texts*

In the bibliographic matching analysis of the texts, 7 clusters, 184 links and 1049 link strengths were observed in 36 units in the analysis with the criterion of at least 1 publication and at least 1 citation. The publications with the highest number of bibliographic matches were Patel et al. (2012) with 1392 citations [12], Ray (2019) with 887 citations [20], Shi (2021) with 711 citations [8], Yanh (2017) with 581 citations [10]. In the total connection power ranking, the top three were Ray (2019) with 438 connection power [20], Lou (2020) with 263 connection [50] power and Yang (2017) with 220 connection [10] power.

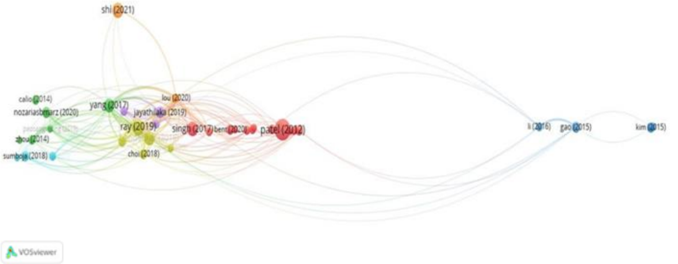

Fig. 5. Bibliographic Match Links of the Works.

6) Bibliographic match analysis of authors

In the bibliographic matching analysis of the authors, at least one publication and one citation criteria were determined. 13 clusters, 9601 links and 272058 link strength were identified in 230 units. The authors with the highest number of matches were Alia Sad [51] with 216 citations, Choi with 1226 links [52], and bandodkar with 887 links [30].

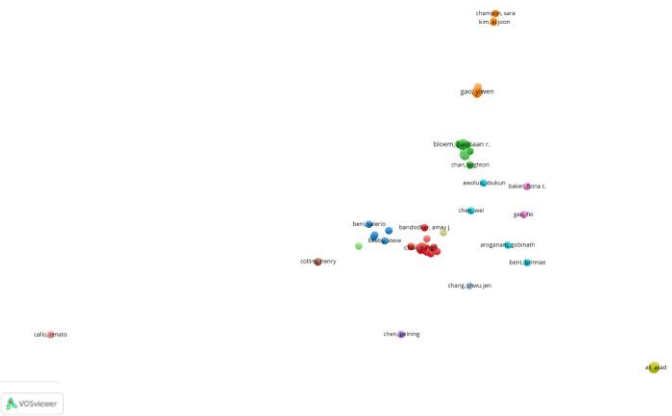

Fig. 6. bibliographic matching links of authors.

III. RESEARCH METHOD

Technology Acceptance Model was used in the study. The model was developed by Vankatesh et al. in 2003 and took its final form in 2012 [44][45][53]. According to the model found by Vankatesh et al. in 2003 and finalized with the additions made in 2012, the consumer's intention to use wearable technology depends on the following factors [44][45]:

- Price-value comparison
- Pleasant motivating power
- Performance expectation
- Being a facilitator
- Social impact
- Effort expectation
- Habit

The study on the contribution of the variable added to the model during the development of the model, which did not have an independent variable Price/Value Perception in the first model used, was conducted by Xu et al. [54]. All variables of the model have been studied frequently in the literature. Performance Expectation; It is determined by the advantages it offers, ease of use and business compatibility [53]. Effort expectation; Ease of use and its positive and negative effects on intention to use have been examined many times in the literature [55][56]. Social Impact; It was examined for the advice and opinions that individuals care about [57]. Pleasurable Motivation; The variable, first studied by Rodríguez et al., was examined at the level of happiness that use gives the person. Facilitation; It is interpreted as a kind of belief in supporting the use of technology [57][58] Habits; It has been supported in the literature by studies on network games and mobile internet [54].

A. Model

The model of the study is shown in Figure 7. In line with the model, the hypotheses are as follows:

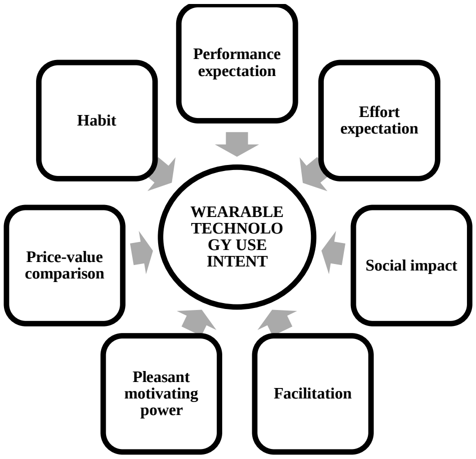

Fig. 7. Working Model

H1: The independent variable, Effort Expectancy (EE), affects the dependent variable, Wearable Technology Usage Intention, at a statistically significant level.

H2: The independent variable, Social Impact (SI), affects the dependent variable, Wearable Technology Usage Intention, at a statistically significant level.

H3: The independent variable, Facilitation (FA), affects the dependent variable, Wearable Technology Usage Intention, at a statistically significant level.

H4: The independent variable, Pleasure Motivation (PMP), affects the dependent variable, Wearable Technology Usage Intention, at a statistically significant level.

Wearable technology positively affects the intention to use.

H5: The independent variable, Price - Value Perception (PV), affects the dependent variable, Wearable Technology Usage Intention, at a statistically significant level.

H6: The independent variable, Habit (HA), affects the dependent variable, Wearable Technology Usage Intention, at a statistically significant level.

H7: The independent variable, Performance Expectation (PE), affects the dependent variable, Wearable Technology Usage Intention, at a statistically significant level.

B. Sample

Data were collected by survey method from 728 healthcare personnel working in public and private hospitals in Istanbul. The sample size was determined based on the Sample Size Table for α = 0.05 presented by Yazıcıoğlu and Erdoğan (2024). According to the table, reaching 600 participants is sufficient for a 95% confidence level and a 4% margin of error [59]. The hospitals and personnel to be surveyed in Istanbul were determined by convenience sampling method. The surveys were distributed one-on-one in envelopes and collected after 5 days. Out of 730 surveys, 2 surveys were invalid, and data was generated from a total of 728 surveys. The first part of the scale survey included demographic questions. In the second part, a 24-question wearable technology usage intention scale was used. Answers were rated on a 5-point Likert scale. SPSS23.0 Statistics Program was used for analysis. Frequency analysis for demographic characteristics, factor analysis for the distribution of data, validity and reliability analysis, and anova and regression correlation analysis were performed to measure the effects of variables. In addition, in the conceptual framework part of the study, all fields were searched in the WebofScience database with the keyword "*wearable technology*". The data obtained was analyzed with the VOSviewer program.

In previous studies using the UTAUT2 model, methods such as internal consistency coefficient (Cronbach's Alpha) and Exploratory Factor Analysis (EFA) have been commonly applied to ensure the validity and reliability of the scales. Godoy and Lopez (2023) reported achieving reliability values above $\alpha > 0{,}70$ for all sub-dimensions in their study [41], while Ryu, Lee, and Choi (2024) confirmed the validity of the UTAUT2 and digital health literacy scales through KMO and Bartlett's tests, obtaining reliable findings [42].

C. Analysis

The Cronbach-Alpha coefficient of the independent variables was between 0.882 and 0.996 and the p value was within the confidence interval. Therefore, all independent variables were accepted as valid and reliable for the study.

The frequency and percentage distributions of the demographic characteristics of the participants are shown in Table 4:

TABLE IV
DEMOGRAPHIC DISTRIBUTION OF PARTICIPANTS

Variable	*Frequency*	*Percentage*
Distribution of Participants by Gender		
Woman	379	51,1
Male	349	47,9
Distribution of Participants by Age		
Between 20-30Years	235	32,3
Between 31-40 Years	275	37,8
Between 41-50 Years	188	25,8
51+ Age Above	30	4,1
Participants' Task		
Health Officer	308	42,3
Nurse	253	34,8
Technician	111	15,2
Doctor	56	7,7
Total	728	100

As seen in Table 4, 51.1% of the participants are female and 47,9% are male. There is very little difference in the gender distribution of female participants. When the age groups are analyzed, it is observed that the highest number of participants (37,8%) is between the ages of 31-40 and the lowest number (4,1%) is over the age of 51. The number of participants between the ages of 20-30 (32,3%) is also significant. Therefore, it can be stated that the participants are predominantly in the middle age group. When the distribution of the duties of the participating health personnel is analyzed, it is seen that most of them are health officers (42,3%) and nurses (34,8%). The lowest number of participants were doctors (7,7%).

In the study, the relationship between all independent variables in the model and the dependent variable was examined. Regression analyses were performed separately for each independent variable and the overall fit of the model was evaluated.

Since the regression analysis included 728 valid participant data, the degrees of freedom of the model were calculated as follows:

Regression degrees of freedom (df_regression)= 7 (7 independent variables) Residual error degrees of freedom (df_hata)= 720

Total Degrees of freedom (df_total)= 727

In this context, ANOVA, regression and model fit statistics were analyzed for each independent variable.

In the regression analysis conducted to examine the effect of effort expectancy on the intention to use wearable technology, the model was found to be statistically insignificant ($p > 0{,}05$) as shown in Table 5. According to the regression coefficients (Table 6), the beta value of effort expectancy is 0,095, indicating a weak and non-significant effect ($p = 0{,}198$). Furthermore, the model fit statistics (Table 7) reveal a very low explanatory power ($R = 0{,}115$, $R^2 = 0{,}013$). However, the absence of effect size measures and confidence intervals limits the interpretability and robustness of the statistical findings. Future studies should consider reporting effect size metrics (e.g., Cohen's f^2) and 95% confidence intervals to better assess the strength and reliability of the model.

TABLE V
EFFECT OF EFFORT EXPECTANCY ON INTENTION TO USE WEARABLE TECHNOLOGY ANOVA TABLE

EE	Sum of Squares	Degrees of Freedom	Mean of Squares	*F*	*p*
1 Regression	10,642	7	1,52	1,557	0.139
Residual (error)	702,329	720	,976		
Total	712,971	727			

TABLE VI
EFFECT OF EFFORT EXPECTANCY ON INTENTION TO USE WEARABLE TECHNOLOGY REGRESSION COEFFICIENTS

EE	B	Standard error	Beta	***t***	***p***
(Fixed)	0,632	0,046	-	13,587	<0.001
Effort Expectation	0,087	0,078	0,095	1,224	0,198

TABLE VII
EFFORT EXPECTANCY MODEL FIT STATISTICS

R	R2	Adjusted R^2	Standard Error
0,115	0,013	0,009	0,998

The regression analysis evaluating the impact of social influence on the intention to use wearable technology revealed that the model is statistically insignificant ($p = 0{,}198$) as shown in Table 8. Table 9 presents the regression coefficients, where the beta coefficient for social influence is 0,082 with a p-value of 0,198, indicating a weak and non-significant relationship. Model fit statistics (Table 10) further demonstrate low explanatory power ($R = 0{,}103$, $R^2 = 0{,}011$, Adjusted $R^2 = 0{,}008$). Similar to the previous model, this analysis also lacks effect size and confidence intervals, which are critical for interpreting the robustness and reliability of the findings. It is recommended that future studies report these statistics to enhance the analytical depth and generalizability of the model results.

TABLE VIII
EFFECT OF SOCIAL INFLUENCE ON INTENTION TO USE WEARABLE TECHNOLOGY ANOVA TABLE

SI	Sum of Squares	Degrees of Freedom	Mean of Squares	*F*	*p*
1 Regression Residual (error) Total	8,431	7	1,204	1,231	0,198
	704,54	720	,978		
	712,971	727			

TABLE IX
EFFECT OF SOCIAL INFLUENCE ON INTENTION TO USE WEARABLE TECHNOLOGY REGRESSION COEFFICIENTS

SI	B	Standard error	Beta	***t***	***p***
(Fixed)	0,619	0,047	-	13,234	<0.001
Social Impact	0,075	0,079	0,082	1,109	0,198

TABLE X
SOCIAL IMPACT MODEL FIT STATISTICS

R	R2	Adjusted R^2	Standard Error
0,103	0,011	0,008	0,982

The regression analysis evaluating the effect of facilitating conditions on the intention to use wearable technology yielded statistically significant results ($p < 0,001$), as shown in Table 11. Table 12 indicates that the facilitating conditions variable has a moderate and positive influence on behavioral intention, with a beta coefficient of 0.386 and a statistically significant t-value (5,392, $p < 0,001$). Model fit statistics in Table 13 also support the robustness of the model ($R = 0,621$, $R^2 = 0,386$, Adjusted $R^2 = 0,382$), indicating that approximately 38.2% of the variance in behavioral intention can be explained by facilitating conditions. These results suggest that technological infrastructure, support, and access to necessary resources play an important role in users' intention to adopt wearable technologies.

TABLE XI
EFFECT OF FACILITATION ON INTENTION TO USE WEARABLE TECHNOLOGY ANOVA TABLE

FA	Sum of Squares	Degrees of Freedom	Mean of Squares	*F*	*p*
1 Regression Residual (error) Total	265,282	7	37,912	62,545	<0.001
	436,329	720	0,606		
	701,711	727			

TABLE XII
EFFECT OF FACILITATION ON INTENTION TO USE WEARABLE TECHNOLOGY REGRESSION COEFFICIENTS

FA	B	Standard error	Beta	***t***	***p***
(Fixed)	0,695	0,047	-	21,214	<0.001
Facilitation	0,716	0,148	0,386	5,392	<0.001

TABLE XIII
FACILITATION MODEL FIT STATISTICS

R	R2	Adjusted R^2	Standard Error
0,621	0,386	0,382	0,778

The regression analysis examining the effect of hedonic motivation on the intention to use wearable technology reveals highly significant results ($p < 0,001$), as shown in Table 14. Table 15 demonstrates that hedonic motivation has a strong and positive influence on behavioral intention, with a beta coefficient of 0,513 and a high t-value (12,824, $p < 0,001$). The model fit indices in Table 16 ($R = 0,716$, $R^2 = 0,513$, Adjusted $R^2 = 0,509$) indicate that hedonic motivation alone explains over 50% of the variance in intention to use wearable technology. This underscores the critical role of enjoyment and personal satisfaction in motivating healthcare professionals to adopt wearable devices.

TABLE XIV
EFFECT OF PLEASURABLE MOTIVATION ON INTENTION TO USE WEARABLE TECHNOLOGY ANOVA TABLE

PMP	Sum of Squares	Degrees of Freedom	Mean of Squares	*F*	*p*
1 Regression Residual (error) Total	203,815	7	29,116	38,613	<0.001
	542,638	720	0,754		
	746,453	727			

TABLE XV
REGRESSION COEFFICIENTS OF THE EFFECT OF HEDONIC MOTIVATION ON INTENTION TO USE WEARABLE TECHNOLOGY

PMP	B	Standard error	Beta	***t***	***p***
(Fixed)	0,523	0,032	-	14,935	<0.001
Pleasurable Motivation	1,512	0,131	0,513	12,824	<0.001

TABLE XVI
PLEASURABLE MOTIVATION MODEL FIT STATISTICS

R	R2	Adjusted R^2	Standard Error
0,716	0,513	0,509	0,868

The regression analysis indicates that price/value perception significantly predicts the intention to use wearable technology ($p < 0,001$), as illustrated in Table 17. Table 18 shows that the variable has a notable positive impact with a beta coefficient of 0,391 and a strong t-value of 6,235 ($p < 0,001$). According to Table 19, the model fit statistics ($R = 0,625$, $R^2 = 0,391$, Adjusted $R^2 = 0,387$) reveal that nearly 39% of the variance in usage intention is explained by individuals' evaluation of the balance between cost and benefit. This suggests that cost-effectiveness is a key motivator in wearable technology adoption among healthcare professionals.

TABLE XVII
EFFECT OF PRICE/VALUE PERCEPTION ON INTENTION TO USE WEARABLE TECHNOLOGY ANOVA TABLE

PV	Sum of Squares	Degrees of Freedom	Mean of Squares	*F*	*p*
1 Regression Residual (error) Total	211,815	7	30,259	43,476	<0.001
	501,156	720	0,696		
	712,971	727			

TABLE XVIII
REGRESSION COEFFICIENTS OF THE EFFECT OF PRICE/VALUE PERCEPTION ON INTENTION TO USE WEARABLE TECHNOLOGY

PV	B	Standard error	Beta	***t***	***p***
(Fixed)	0,693	0,025	-	12,455	<0.001
Price value perception	0,576	0,178	0,391	6,235	<0.001

TABLE XVIX
PRICE/VALUE PERCEPTION MODEL FIT STATISTICS

R	R2	Adjusted R^2	Standard Error
0,625	0,391	0,387	0,834

The regression results demonstrate that habit is a statistically significant predictor of wearable technology usage intention ($p < 0,001$), as indicated in Table 20. Table 21 highlights a strong standardized beta coefficient of 0,413, with a t-value of 5,856 ($p < 0,001$), confirming its meaningful contribution to the model. The model fit indices in Table 22 ($R = 0,643$, $R^2 = 0,413$, Adjusted $R^2 = 0,409$) show that habitual behavior explains over 41% of the variance in intention. This suggests that fostering routine use is critical in increasing adoption rates among healthcare workers.

TABLE XX
EFFECT OF HABITS ON INTENTION ON INTENTION TO USE WEARABLE TECHNOLOGY ANOVA TABLE

HA	Sum of Squares	Degrees of Freedom	Mean of Squares	*F*	*p*
1 Regression Residual (error) Total	276,632	7	39,519	64,344	<0.001
	442,111	720	0,614		
	718,743	727			

TABLE XXI
REGRESSION COEFFICIENTS OF THE EFFECT OF HABITS ON INTENTION TO USE WEARABLE TECHNOLOGY

HA	B	Standard error	Beta	***t***	***p***
(Fixed)	0,767	0,038	-	19,423	<0.001
Habits	0,817	0,151	0,413	5,856	<0.001

TABLE XXII
HABITS MODEL FIT STATISTICS

R	R2	Adjusted R^2	Standard Error
0,643	0,413	0,409	0,785

As shown in Table 23, performance expectancy significantly influences the intention to use wearable technology ($F = 102,461$, $p < 0,001$). Table 24 further confirms this with a standardized beta coefficient of 0,618 and a high t-value of 8,031 ($p < 0,001$), suggesting that perceived usefulness is a strong motivator. The model fit in Table 25 reveals an R^2 of 0,499 and an adjusted R^2 of 0,495, indicating that nearly 50% of the variance in usage intention can be explained by performance expectancy alone. These findings highlight the crucial role of demonstrating practical benefits in promoting technology adoption among healthcare professionals.

TABLE XXIII
EFFECT OF PERFORMANCE EXPECTATION ON INTENTION TO USE WEARABLE TECHNOLOGY ANOVA TABLE

PB	Sum of Squares	Degrees of Freedom	Mean of Squares	*F*	*p*
1 Regression Residual (error) Total	325,753	7	46,536	102,461	<0.001
	326,725	720	,454		
	652,478	727			

TABLE XXIV
REGRESSION COEFFICIENTS OF THE EFFECT OF PERFORMANCE EXPECTATION ON INTENTION TO USE WEARABLE TECHNOLOGY

PB	B	Standard error	Beta	***t***	***p***
(Fixed)	0,746	0,035	-	22,852	<0.001
Performance Expectation	0,955	0,129	0,618	8,031	<0.001

TABLE XXV
PERFORMANCE EXPECTATION MODEL FIT STATISTICS

R	R2	Adjusted R^2	Standard Error
0,705	0,499	0,495	0,454

According to the results of the regression analyses, performance expectancy and hedonic motivation emerged as the most influential variables on healthcare professionals' intention to use wearable technology. These variables stand out with both high beta coefficients and statistically significant levels. While habit, facilitating conditions, and price/value perception were found to have a moderate effect, effort expectancy and social influence were determined to have no statistically significant impact on usage intention. An examination of the model fit statistics revealed that the models associated with performance expectancy and hedonic motivation have high explanatory power, whereas those related to the other variables demonstrated relatively lower fit levels. These findings indicate that individual benefit perception and intrinsic motivation play a decisive role in the technology adoption process, whereas external social influences appear to play a comparatively weaker role.

Convenience sampling was chosen due to practical constraints related to institutional access and time limitations. Permissions and ethical approvals were obtained from various hospitals in Istanbul, and participants were recruited based on accessibility. Nonetheless, we acknowledge that this sampling strategy may limit generalizability. Future studies are recommended to adopt stratified sampling techniques based on hospital type, medical specialty, and demographic characteristics to achieve broader representativeness and comparative insights.

IV. CONCLUSION

This study contributes to the literature by examining the intention to use wearable technologies within an organizational context. The findings reveal that performance expectancy, habit, and price-value perception are key predictors of usage intention. Habit emerged as a prominent factor, potentially reflecting individuals' increasing dependence on technology. In contrast, effort expectancy and social influence were not found to be statistically significant. This suggests that decisions regarding wearable technologies in the healthcare sector are primarily driven by personal benefits rather than social factors. However, elements such as organizational support, managerial attitude, and professional training may play a moderating role in shaping these intentions.

In this study, the behavioral intentions of healthcare professionals regarding the use of wearable technology were examined within the framework of the UTAUT2 model. It was found that perceived usefulness, hedonic motivation, and performance expectancy had a strong influence on behavioral intention. These results support the core constructs of the UTAUT2 model developed by Venkatesh et al. (2012) and demonstrate that the model can also be effectively applied in the healthcare context [45]. While prior studies in the literature have largely focused on individual and patient usage, this study, which involves healthcare workers within the sector, revealed that the effects of the model's constructs are similar to those observed in patient usage.

The findings are largely consistent with the results of the study by Godoy and Lopez (2023), who emphasized the importance of hedonic motivation and performance expectancy, particularly in the context of fitness applications. This suggests that the intention to use wearable technology in healthcare is not solely driven by functionality but is also shaped by motivational and emotional factors [41].

The limited influence of the social influence construct observed in this study stands out as a notable finding. In contrast, Gao, Li, and Lou (2015) reported that social influence was a significantly strong factor. This divergence may be attributed to differences in the sample group and professions, particularly demographic factors such as age or variations in technology-related cultural norms. The relatively low impact of social influence may also be explained by healthcare professionals' capacity for autonomous decision-making [18].

The price/value perception construct was found to have lower significance among participants working in public institutions. This suggests that in settings where wearable technologies are provided by the institution, individual cost perception may become less relevant. This result aligns with the findings of Ryu, Lee, and Choi (2024), which showed greater price sensitivity among elderly individuals [42].

Furthermore, the limited effect of the effort expectancy variable indicates a high level of digital literacy and technological competency among healthcare professionals. This can be interpreted as a result of the growing integration of digital transformation processes into institutional workflows in today’s technology-driven environment. Similarly, studies employing scales such as the Technology Readiness Index have reported that such user profiles tend to adapt more rapidly to new technologies [60].

The insignificant effects of effort expectancy and social influence may be attributed to the autonomous decision-making tendencies prevalent among healthcare professionals. Additionally, the high level of digital literacy among participants may have minimized the impact of effort expectancy. Similarly, in contexts where personal utility outweighs institutional motivation, the influence of social factors tends to be limited.

The organizational adoption of technology entails both individual and collective dynamics. In the healthcare sector, employees’ attitudes toward technology are closely linked to organizational culture and managerial support. Organizational learning and increased technological competence positively influence the intention to use wearable technologies [61]. As a result, this study, which tested the UTAUT2 model in the context of the healthcare sector, revealed findings that are largely consistent with those in the existing literature, while also highlighting certain differences. The findings offer valuable insights not only into the adoption of health technologies but also for policymakers, institutions, the academic literature, and healthcare administrators in shaping future strategies.

The VOSviewer analyses in the study showed in which disciplines high-quality academic publications in the field of wearable technology are focused, which concepts stand out alongside wearable technology, and which features stand out in highly cited publications. In particular, it was observed that patient monitoring systems, data security and usage advantages came to the forefront in studies conducted in the field of health. Bibliometric analysis helped us to understand the research trend in the field, the evolution of the concept and the important dynamics for the concept.

Healthcare managers can develop strategies to enhance factors such as hedonic motivation and performance expectancy, which have been found to significantly influence employees’ intention to use technology. In public institutions where the price/value perception is low, training programs emphasizing the cost-benefit balance of technologies may be implemented. Given the importance of habit, regular training sessions on technology use can help reinforce existing habits. The limited effect of the social influence variable may indicate a need to strengthen internal organizational communication and motivation. Accordingly, organizational support, technical infrastructure improvement, and increasing digital literacy levels should be considered in institutional budgeting and planning processes.

Technological innovation and rapid development bring with them conveniences but also some problems. Cyber attacks are at the forefront of these problems. Especially in the field of healthcare, this type of attack could risk the lives of many people. The security of technology used in every field is important. In wearable technology, data transfer is made mobile, but there is a hardware shortage that can store and quickly process large data groups transferred. As wearable technology increases, the size of the data transferred will also increase, and both its security and storage and processing will bring bigger problems. Knowing how to use technology safely is a challenge, and this affects the intention to use it. Despite all these obstacles, the life facilitating aspect of wearable technology and the rapid development in technology do not prevent the production of new devices and the widespread use of existing devices.

In this study, first of all, the fact that the data were selected on 728 people and by convenience sampling method can be considered as a limitation in terms of generalization. Increasing the number of samples and including different health institutions will provide more comprehensive results. In addition, since the survey method used is based on the perception of the participants, understanding and interpreting the questions correctly may also be among the limitations. Apart from these, another limitation of the study is that the VOSviewer analysis was conducted only in the WebofScience database and no data was obtained from other databases.

When the distribution of demographic characteristics is examined in general, it is seen that women, young and middle-aged groups, health officers and nurses are more common. the low number of personnel over the age of 51 and doctors participating in the study may suggest that the groups provide limited data on their intentions to use technology. These findings should be taken into consideration for other researchers who want to study in this field. If it is desired to take the opinion of the older age group and especially doctors on the subject, the sample balance should be reconsidered and expanded.

The exclusive use of quantitative research methods in this study limits the ability to explore the underlying reasons behind participants' behavioural intentions. Therefore, incorporating qualitative approaches—such as in-depth interviews or focus group discussions—in future research may offer more comprehensive and nuanced insights into the subject matter. The fact that the data were collected solely from Istanbul using a convenience sampling method limits the generalizability of the findings to the broader Turkish population or international context. Therefore, future studies would benefit from employing random sampling across multiple regions.

To further validate the proposed UTAUT2 model, it is recommended to test and compare alternative model configurations using model fit indices such as AIC, BIC, and RMSEA. Future studies may explore competing frameworks to derive stronger theoretical conclusions.

While this study highlights the key individual-level predictors of adoption, several practical limitations relevant to healthcare settings should be acknowledged. Concerns about data privacy and the reluctance to share personal health information may hinder widespread adoption. Moreover, factors such as organizational infrastructure, scalability, and long-term maintenance costs can influence the institutional integration of wearable technologies. Future research should explore these aspects through in-depth case studies or multi-level frameworks to provide actionable recommendations for overcoming such practical barriers.

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REFERENCES

[1] Deloitte Insights. (2023, October 10). *Tech companies have a trust gap to overcome—especially with women*. WSJ Custom Content from Deloitte. https://deloitte.wsj.com/sustainable-business/tech-companies-have-a-trust-gap-to-overcomeespecially-with-women-2e50a5cc

[2] Lee, M., & Patel, R. (2023). A comprehensive review on advancements in wearable technologies for cardiovascular medicine. *Cardiology Today*, 18(4), 200–215. https://doi.org/10.1016/j.cardtoday.2023.04.005

[3] TechTarget. (2023, November 15). *Challenges of using healthcare wearable technology*. TechTarget Virtual Healthcare. https://www.techtarget.com/virtualhealthcare/feature/Challenges-of-using-healthcare-wearable-technology

[4] Park, M. J., & Singh, A. (2024). Economic barriers to wearable health technology in low-income populations. *Journal of Global Health Reports*, 8(e2024013).

[5] Tran, N. K., & Wang, Y. (2024). Digital health literacy and adoption of wearable health technologies among older adults: A systematic review. *Frontiers in Public Health*, 12, 1449594. https://doi.org/10.3389/fpubh.2024.1449594

[6] TIME. (2024, January 8). *Health care leaders must be trained to manage AI and wearable data*. TIME Health Leadership Forum. https://time.com/7094012/health-leadership-forum-shell-3/

[7] Smith, J., & Doe, A. (2023). A scoping review of the patient experience with wearable technology. *Journal of Medical Devices*, 15(2), 123–135. https://doi.org/10.1016/j.jmd.2023.02.001

[8] Shi, X., Zuo, Y., Zhai, P., Shen, J., Yang, Y., Gao, Z., ... & Peng, H. (2021). Large-area display textiles integrated with functional systems. *Nature*, 591(7849), 240-245.

[9] Beloff, L. (2009). *The Hybronaut and other unexpected approaches to wearable technology*. In Re: Live, Media Art History Conference.

[10] Yang, T., Xie, D., Li, Z., & Zhu, H. (2017). Recent advances in wearable tactile sensors: Materials, sensing mechanisms, and device performance. *Materials Science and Engineering*: R: Reports, 115, 1-37 https://doi.org/10.1016/j.mser.2017.02.001

[11] Salarian, A., Russmann, H., Vingerhoets, F. J., Dehollain, C., Blanc, Y., Burkhard, P. R., & Aminian, K. (2004). Gait assessment in Parkinson's disease: toward an ambulatory system for long-term monitoring. *IEEE transactions on biomedical engineering*, 51(8), 1434-1443. https://doi.org/10.1109/TBME.2004.827933

[12] Patel, S., Park, H., Bonato, P., Chan, L., & Rodgers, M. (2012). A review of wearable sensors and systems with application in rehabilitation. *Journal of neuroengineering and rehabilitation*, 9, 1-17. https://doi.org/10.1186/1743-0003-9-21

[13] Dwivedi, A. D., Srivastava, G., Dhar, S., & Singh, R. (2019). A decentralized privacy-preserving healthcare blockchain for IoT. *Sensors*, 19(2), 326. https://doi.org/10.3390/s19020326

[14] Mann, S. (2003). Existential Technology: Wearable Computing Is Not the Real Issue!. *Leonardo*, 36(1), 19-25. https://doi.org/10.1162/002409403321611289

[15] Mann, S. (1997a). Smart clothing: The wearable computer and wearcam. Personal Technologies, 1, 21-27. https://doi.org/10.1007/BF01317885

[16] Mann, S. (1996). Smart clothing: The shift to wearable computing. *Communications of the ACM*, 39(8), 23-24. https://doi.org/10.1145/232014.232021

[17] Mann, S. (1997b). Wearable computing: A first step toward personal imaging. *Computer*, 30(2), 25-32. https://doi.org/10.1109/2.566147

[18] Gao, Y., Li, H., & Luo, Y. (2015). An empirical study of wearable technology acceptance in healthcare. *Industrial Management & Data Systems*, 115(9), 1704-1723 https://doi.org/10.1108/IMDS-03-2015-0087

[19] Sempionatto, J. R., Nakagawa, T., Pavinatto, A., Mensah, S. T., Imani, S., Mercier, P., & Wang, J. (2017). Eyeglasses based wireless electrolyte and metabolite sensor platform. *Lab on a Chip*, 17(10), 1834-1842. https://doi.org/10.1039/C7LC00192D

[20] Ray, T. R., Choi, J., Bandodkar, A. J., Krishnan, S., Gutruf, P., Tian, L., ... & Rogers, J. A. (2019). Bio-integrated wearable systems: a comprehensive review. *Chemical reviews*, 119(8), 5461-5533. https://doi.org/10.1021/acs.chemrev.8b00573

[21] Yu, D., Blocker, R. C., Susan Hallbeck, M., Patel, A., & Pasupathy, K. S. (2015a). Wearable sociometers in chaotic simulated environments. *Journal of Medical Devices*, 9(2), 020946. https://doi.org/10.1115/1.4030150

[22] Yu, D., Blocker, R., Hallbeck, S., Sir, M., Hellmich, T., & Pasupathy, K. (2015b, September). *Application of sociometer badges in simulated health environments: Can wearable devices quantify individual's workload*?. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (Vol. 59, No. 1, pp. 538-542). Sage CA: Los Angeles, CA: SAGE Publications. https://doi.org/10.1177/1541931215591117

[23] Ito-Masui, A., Kawamoto, E., Esumi, R., Imai, H., & Shimaoka, M. (2021). Sociometric wearable devices for studying human behavior in corporate and healthcare workplaces. *BioTechniques*, 71(1), 392-399. https://doi.org/10.2144/btn-2020-0160

[24] Ward, J. A., Lukowicz, P., Troster, G., & Starner, T. E. (2006). *Activity recognition of assembly tasks using body-worn microphones and accelerometers*. IEEE transactions on pattern analysis and machine intelligence, 28(10), 1553-1567. DOI: 10.1109/TPAMI.2006.197

[25] Giansanti, D. (2006a). Investigation of fall-risk using a wearable device with accelerometers and rate gyroscopes. *Physiological measurement*, 27(11), 1081. DOI 10.1088/0967-3334/27/11/003

[26] Giansanti, D., Maccioni, G., & Morelli, S. (2008). An experience of health technology assessment in new models of care for subjects with Parkinson's disease by means of a new wearable device. *Telemedicine And E-Health*, 14(5), 467-472. https://doi.org/10.1089/tmj.2007.0078

[27] Giansanti, D. (2006b). Investigation of fall-risk using a wearable device with accelerometers and rate gyroscopes. *Physiological measurement*, 27(11), 1081. https://doi.org/10.1088/0967-3334/27/11/003

[28] Rehman, U., & Cao, S. (2015, October). Augmented reality-based indoor navigation using google glass as a wearable head-mounted display. In 2015 IEEE International Conference on Systems, *Man, and Cybernetics* (pp. 1452-1457). IEEE. DOI: 10.1109/SMC.2015.257

[29] Baashar, Y., Alkawsi, G., Wan Ahmad, W. N., Alomari, M. A., Alhussian, H., & Tiong, S. K. (2023). Towards wearable augmented reality in healthcare: a comparative survey and analysis of head-mounted displays. *International journal of environmental research and public health*, 20(5), 3940. https://doi.org/10.3390/ijerph20053940

[30] Bandodkar, A. J., Jeerapan, I., & Wang, J. (2016). Wearable chemical sensors: present challenges and future prospects. *Acs Sensors*, 1(5), 464-482. https://doi.org/10.1021/acssensors.6b00250

[31] Singh, E., Meyyappan, M., & Nalwa, H. S. (2017). Flexible graphene-based wearable gas and chemical sensors. *ACS applied materials & interfaces*, 9(40), 34544-34586. https://doi.org/10.1021/acsami.7b07063

[32] Bergenstal, R. M., Tamborlane, W. V., Ahmann, A., Buse, J. B., Dailey, G., Davis, S. N., ... & Willi, S. M. (2010). Effectiveness of sensor-augmented insulin-pump therapy in type 1 diabetes. *New England Journal of Medicine*, 363(4), 311-320. DOI: 10.1056/NEJMoa1002853

[33] Wiederhold, B. K. (2013). Time to port augmented reality health apps to smart glasses?. Cyberpsychology, *Behavior, and Social Networking*, 16(3), 157-158. DOI: 10.1089/cyber.2013.1503

[34] Dias, D., & Paulo Silva Cunha, J. (2018). Wearable health devices—vital sign monitoring, systems and technologies. *Sensors*, 18(8), 2414. https://doi.org/10.3390/s18082414

[35] Prieto-Avalos, G., Cruz-Ramos, N. A., Alor-Hernandez, G., Sánchez-Cervantes, J. L., Rodriguez-Mazahua, L., & Guarneros-Nolasco, L. R. (2022). Wearable devices for physical monitoring of heart: a review. *Biosensors*, 12(5), 292. https://doi.org/10.3390/bios12050292

[36] Lee, J. M., Rhee, T. M., Chang, H., Ahn, C., Park, T. K., Yang, J. H.. & Hahn, J. Y. (2017). Deferred versus conventional stent implantation in patients with acute ST-segment elevation myocardial infarction: An updated meta-analysis of 10 studies. *International journal of cardiology*, 230, 509-517. https://doi.org/10.1016/j.ijcard.2016.12.071

[37] Patel, S., Lorincz, K., Hughes, R., Huggins, N., Growdon, J., Standaert, D., ... & Bonato, P. (2009). *Monitoring motor fluctuations in patients with Parkinson's disease using wearable sensors*. IEEE transactions on information technology in biomedicine, 13(6), 864-873 https://doi.org/10.1109/TITB.2009.2033471

[38] Wang, Z., Yang, Z., & Dong, T. (2017). A review of wearable technologies for elderly care that can accurately track indoor position, recognize physical activities and monitor vital signs in real time. *Sensors*, 17(2), 341. https://doi.org/10.3390/s17020341

[39] Johnson, L., & Nguyen, T. (2024). Usage trends and data sharing practices of healthcare wearable devices. *Journal of Medical Internet Research*, 26(1), e63879. https://doi.org/10.2196/63879

[40] Garcia, E., & Thompson, H. (2025). The future of wearable health technology: From monitoring to preventive healthcare. *HealthTech Innovations*, 22(1), 45–60. https://doi.org/10.1016/j.hti.2025.01.003

[41] Godoy, D., & López, A. (2023). Investigating the drivers of wearable technology adoption for healthcare in South America. *Information Technology & People*, 36(4), 1250–1274. https://doi.org/10.1108/ITP-01-2021-0049

[42] Ryu, B., Lee, J., & Choi, J. (2024). Investigating older adults' willingness to adopt wearable devices: An integration of UTAUT2 and TRI models. *Frontiers in Public Health*, 12, 1449594. https://doi.org/10.3389/fpubh.2024.1449594

[43] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. https://doi.org/10.2307/30036540

[44-36] Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision sciences*, 39(2), 273-315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

[45-37] Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, 157-178. https://doi.org/10.2307/41410412

[46] Wang, C., Wu, G., Zhou, X., & Lv, Y. (2022). An empirical study of the factors influencing user behavior of fitness software in college students based on UTAUT. *Sustainability*, 14(15), 9720. https://doi.org/10.3390/su14159720

[47] Alharbi, S., & Drew, S. (2023). Exploring the determinants of wearable health technology adoption: An application of the UTAUT2 model. International *Journal of Medical Informatics*, 175, 105071. https://doi.org/10.1016/j.ijmedinf.2023.105071

[48] Forinsights Consultancy. (2024). Wearable health technology market research & trends, 2024–2030. https://www.forinsightsconsultancy.com/reports/wearable-health-technology-market?utm_source=chatgpt.com (E.T. 01.06.2025)

[49] Jayathilaka, W. A. D. M., Qi, K., Qin, Y., Chinnappan, A., Serrano-García, W., Baskar, C., ... & Ramakrishna, S. (2019). Significance of nanomaterials in wearables: a review on wearable actuators and sensors. *Advanced Materials*, 31(7), 1805921 https://doi.org/10.1002/adma.201805921

[50] Lou, Z., Wang, L., Jiang, K., Wei, Z., & Shen, G. (2020). Reviews of wearable healthcare systems: Materials, devices and system integration. *Materials Science and Engineering*: R: Reports, 140, 100523. https://doi.org/10.1016/j.mser.2019.100523

[51] Alia, S. S., & Lago, P. (2024, May). *Daily routine recognition from longitudinal, real-life wearable sensor data for the elderly*. In 2024 International Conference on Activity and Behavior Computing (ABC) (pp. 1-9). IEEE. https://doi.org/10.1109/ABC61795.2024.10651644

[52] Choi, A., Chung, K., Chung, S. P., Lee, K., Hyun, H., & Kim, J. H. (2022). Advantage of vital sign monitoring using a wireless wearable device for predicting septic shock in febrile patients in the emergency department: a machine learning-based analysis. *Sensors*, 22(18), 7054. https://doi.org/10.3390/s22187054

[53] Yu, C. S. (2012). Factors affecting individuals to adopt mobile banking: Empirical evidence from the UTAUT model. *Journal of Electronic Commerce Research*, 13(2): 104.

[54] Xu, C., Peak, D., & Prybutok, V. (2014). A customer value, satisfaction, and loyalty perspective of mobile application recommendations. *Decision Support Systems*, 79, 171-183. https://doi.org/10.1016/j.dss.2015.08.008

[55] Martins, C., Oliveira, T., and Popovič, A. (2014). Understanding the Internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. *International Journal of Information Management*, 34(1), 1-13. https://doi.org/10.1016/j.ijinfomgt.2013.06.002

[56] Lewis, C.C. Fretwell, C.E., Ryan, J. and Parham, J.B. (2013). Faculty Use of Established and Emerging Technologies in Higher Education: A Unified Theory of Acceptance and Use of Technology Perspective. International *Journal of Higher Education*, 2(2): 22-34. http://dx.doi.org/10.5430/ijhe.v2n2p22

[57] Oechslein, O., Fleischmann, M., & Hess, T. (2014). An application of UTAUT2 on social recommender systems: Incorporating social information for performance expectancy. *In System Sciences* (HICSS), 2014 47th Hawaii International Conference on, 3297-3306.

[58] Rodriguez-Trujillo, R., Ajine, M. A., Orzan, A., Mar, M. D., Larsen, F., Clausen, C. H., & Svendsen, W. E. (2014). Label-free protein detection using a microfluidic Coulter-counter device. *Sensors and Actuators B: Chemical*, 190, 922-927. https://doi.org/10.1016/j.snb.2013.09.038

[59] Erdoğan, S. ve Yazıcıoğlu, Y., (2004). Spss uygulamalı bilimsel araştırma yöntemleri. Ankara: Detay Yayıncılık

[60] Godoe, P., & Johansen, T. S. (2012). Understanding adoption of new technologies: Technology readiness and technology acceptance as an integrated concept. *Journal of European Psychology Students*, 3(1), 38–52. https://doi.org/10.5334/jeps.aq

[61] Ruslaini, H., Supratikno, H., & Hariandja, E. S. (2025). Current challenges of organizational learning and cloud adoption technology toward SMEs' performance. *International Journal of Innovative Research and Scientific Studies*, 8(3), 1486–1496. https://doi.org/10.53894/ijirss.v8i3.6825

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