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Exploration Of Post-Adoption User Behavioural Intentions In Smart Fitness Wearables: Uncovering Influential Factors At Play

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Abstract
The rapid proliferation of smart fitness wearables has revolutionized personal health monitoring, yet understanding the determinants of post-adoption behavioural intentions remains underexplored. This study employs the Expectation-Confirmation Model (ECM) as a theoretical lens to investigate key post-adoption factors influencing continued usage of wrist-worn fitness devices. Using a qualitative research approach, Focus Group Discussions (FGDs) were conducted with 34 active users categorized based on device usage duration. The study leverages GPT-4, a Large Language Model (LLM), for automated thematic extraction and behavioural analysis, to enhance classification accuracy and scalability. Findings reveal that confirmation of expectations, perceived usefulness, and user satisfaction significantly drive long-term engagement, while hedonic motivation and user interface emerge as critical extensions to the ECM framework in this domain. By integrating AI-driven qualitative analysis with theoretical models, this research offers novel insights for wearable technology developers, emphasizing the need for usability enhancements, gamification features, and personalized health tracking to improve user retention. The study also underscores the advantages of LLM-assisted qualitative research in improving classification efficiency and scalability over traditional manual methods. Future research should further refine AI-driven analytical models and explore additional variables such as privacy concerns and personalization to deepen the understanding of wearable technology adoption.

Keywords – Smart Fitness Wearables, Focus Group Discussions, Large-Language Model, Expectation-Confirmation Model, Artificial intelligence

1.INTRODUCTION

Continued and disruptive technological innovations have led to a shifting pattern in the wearable device landscape from the basic wristwatch in the 16th century to calculator wristwatch in the 20th century stepping towards smart wrist devices in the 21st century. Introduction of wearable fitness devices can be attributed to drastic transition from communicable diseases to widespread lifestyle problems such as obesity, high blood pressure etc. globally over the years, owing to inactivity and sedentary lifestyle. Regardless of age, each individual is susceptible to lifestyle diseases ("Ageing and health", 2018). However, the boom in fitness, technological advancement as well as rising health consciousness have led to the development of cutting-edge devices driven towards overall well-being. These devices have transformed health and wellness by offering a wide range of features that are easily monitored by people throughout the day.

Equipped with sensors and embedded computing, smart wearable devices are intended to be worn directly or attached externally as accessories to a person's body for eg: smart glasses, fitness tracker, etc., or clothing (Williamson et al., 2015). These devices enable measurement of various physiological parameters like daily activities, heart rate, burnt calories, sleep quality and deep sleep duration etc., and the collected data is processed either through device or with the help of data transfer in the smartphone (Hansel et al., 2016).

Mewara et al. (2016) categorized wearables based on product functions such as wellness, health etc. and form of product depending upon the body part (hand, head, foot, etc) where it is attached. Wearables can be classified as glasses that provide extensive virtual reality capability; notifiers such as watches that furnish information regarding surroundings and trackers such as smart bands that record data by utilizing sensors (Lunney et al., 2016). Fitness trackers and smartwatches are becoming the top selling products among smart wearable technology in the consumer market segment. Fitness trackers such as the Fitbit surge, Honor Band, etc. are wrist-worn devices, rendering users with real-time information regarding physical activity (Kim & Shin, 2015) specifically meant to track user's health and fitness data.

Fitness wrist-worn trackers are nowadays consolidated with mobile phones offering bluetooth connectivity features and design aesthetics. Smartwatches (Apple watch, Garmin etc.) extended features include touchscreen, provide benefits through Internet connection along with app installation capability including the features offered by fitness trackers (Spil et al., 2019). Moreover, wearable fitness device user base is continuously expanding in India. Wearable device is witnessing a growth of 80.9% every year with shipment of 25.1 million wearable devices in India during 1Q23 owing to improved supplies, marketing, leaner inventory and new launches according to India Monthly Wearable Device Tracker with a tremendous growth in the share of smartwatches from 26.8% in 2022 to 41.4% in 2023 (International Data Corporation, 2023). Besides, the expected annual growth rate (CAGR 2022-2027) of revenue for wearables worldwide is 5% with increase in projected shipment from 504.1 million units in 2023 to 629.4 million units in 2027, representing a growth of 2.4% year after year and out of 504.1 million units, India will account for 130-135 million units striving to become the world's largest market for wearables by the end of 2023 (International Data Corporation, 2023).

Adoption for smart fitness technology is constantly growing due to innovative features and potential health benefits associated with it, but understanding post-adoption behaviour is an equally important subject matter for companies. The success of Information System (IS) relies upon its long-term usage rather than first or initial use (Zheng, Zhao, & Stylianou, 2013; Bhattacherjee, 2001) where experience is used to evaluate the system.

While a lot of adoption studies have been conducted, there is a lack of comprehensive qualitative research on examining determinants impacting post adoption behavioural intentions in the context of smart fitness devices, specifically among wrist-worn fitness wearable users in India. The study strives to bridge the gap by identifying five key constructs impacting the post-adoption phase by delving upon user experience through focus group discussions (FGDs) and AI-driven analysis. It further highlights the importance of ECM, an Information System (IS) continuance model that can be used as a theoretical framework in future by researchers to extend the original model and formulating the hypothesis based on the identified relationships between the constructs.

2. LITERATURE REVIEW

Development of commercial technology, majorly inclined towards spontaneously collecting data aiming at self-regulation is continually expanding in the recent years (Spil et al., 2019) leading to wearable technology as an outcome, through which user's physiological situations such as heart rate, distance travelled etc., can be monitored (Asadi, Abdullah, Safaei, & Nazir, 2019), due to its ubiquitous computing (Weiser, 1991).

Commencement of wearable technology have led to their extensive adoption based on ease or simplicity in terms of use, and amidst them, spotlight is on smart wristband (Statt, 2015). According to Sullivan (2013), wrist-worn fitness wearables perpetually monitor user activities and impart information through feedback on smartphones.

According to Davis (1989), literature pertaining to IS constantly covered the purview of acceptance and use of technology. However, Bhattacherjee (2001) stated that continuous use moulds the success of IS instead of initial use. Considering post-adoption intentions of smart wearable technology users is essential as Hansel et al. (2016) stated that despite the upsurge in adoption of devices like fitness bands, smartwatches, they are witnessing soaring dropout rate, reported to be 85%. Research on post-adoption usage intention of wearables is still at nascent stage (Dehghani, 2018) and negligible in case of conducting focus group discussions among Indian users.

Although several theories have been utilized in the past to explain post-adoption behaviour such as TAM (Gefen et al., 2003), Cognitive model (Oliver, 1980) etc. However, the majority of these models focus upon factors determining initial adoption or acceptance rather than stressing upon loyalty and retention, which is well explained by ECM (Bhattacherjee, 2001) and has been widely accepted and validated in many technological contexts.

This paper highlights the importance of ECM as a framework according to which confirmation or disconfirmation of user's initial expectations influences the post adoption use as well as their satisfaction (Bhattacherjee, 2001). The ECM, originated by Bhattacherjee (2001), is utilized to investigate post-adoption behaviour among end users of technology, by including variables like post-consumption usefulness, confirmation of pre-acceptance expectations and satisfaction being an IS continuance model. All the drivers linked with adoption intention along with their effects are already inclusive within two constructs i.e. satisfaction and confirmation (Bhattacherjee, 2001).

Some studies have successfully validated the ECM framework for banking services on smartphones (Susanto, Chang, & Ha, 2016), e-learning system (Lee, 2010) etc., but the relevance of this model for fitness wearable technology remains unexplored. Since the roots of ECM lies in end user experience (Recker, 2010), when talking about technology products such as fitness wearables, this framework fits well.

2.1 ECM Constructs

2.1.1 Confirmation of expectations

Prior to purchase, consumers form product performance perceptions by utilizing existing knowledge (Bhattacherjee, 2001). When post or actual use expectations of a device exceeds pre-purchase expectations, positive confirmation is experienced (Venkatesh et al., 2011). The evaluation or assessment (confirmation or disconfirmation) of a product, post-consumption, governs its continuous use (Oghuma et al., 2016) since initial adoption antecedents may not affect continued use, once technology is accepted by user (Bhattacherjee, 2001).

2.1.2 Perceived usefulness

Perceived usefulness, introduced in TAM (Davis et al., 1989) is pre-adoption product or technology usefulness whereas in ECM, Bhattacherjee (2001) referred to it as user's post-purchase product benefits perception. Being an IS acceptance prime motivator, perceived usefulness can possibly impact subsequent post-consumption decisions (Bhattacherjee, 2001). Consumers concerned about health are probable to engage in health promoting behaviour as opposed to least concerned individuals (Claussen et al., 2015) by adopting technology devices (eg: fitness tracker) or exercising (Jayanti & Burns, 1998) and thus such devices are perceived to be useful from health perspective as well.

2.1.3 User Satisfaction

Bhattacherjee (2001) describes satisfaction as a state emerging due to positive experience and Wixom & Todd (2005) referred to it as object-based attitude, thus it can only be experienced or achieved post-adoption. Continuance and discontinuance intention pertaining to IS rest upon the satisfaction level (Bhattacherjee, 2001) of user. Satisfaction determines consumer loyalty and is found to influence technology acceptance (Wixom & Todd, 2005), IS use (Bhattacherjee, 2001) and major antecedents of continuous usage intention (Oliver & Burke, 1999).

2.2 Extended ECM Framework: Theoretical Justification

The validated constructs align with and extend the Expectation-Confirmation Model (ECM), incorporating factors that influence post-adoption intentions for smart fitness wearables. The Extended ECM is detailed below:

2.2.1 Hedonic Motivation

Venkatesh et al. (2012) refers to hedonic motivation as the pleasure or fun element obtained through a technology. In comparison to IT health products, wearables differ in functionality and usage, so device enjoyment is highly regarded for this context (Gao et al., 2015). Health data compilation, organization and presentation through graphs, pie charts and coloured display generates consumer interest (Salah et al., 2014; Sergueeva et al., 2019).

2.2.2 User interface

User interface combines ease of interaction in the process of using a system along with aesthetic appeal, user-friendliness, and easy to use as well as navigate aspect (Karapanos, 2013; Zviran et al., 2006). During the initial technology adoption phase, ease of use generally produce inconsistent effect leading to its non-significance in the post-adoption phases (Davis et al., 1989; Bhattacherjee, 2001). User interface can offer a comprehensive explanation of IS services (Cho et al., 2009).

3. RESEARCH METHODOLOGY

This study employs a qualitative analysis approach to investigate user perceptions, behavioural patterns, and post-adoption determinants influencing the continuous use of wrist-worn smart fitness devices. Given the complexity of behavioural factors, the research integrates Focus Group Discussions (FGDs) for qualitative data collection and employs Large Language Models (LLMs) for automated classification of user responses.

3.1 Data Collection and Sampling

The selection of wrist-worn fitness devices was based on their extensive adoption, evolving technological capabilities, and real-time health monitoring features (Cains, 2019). To ensure data richness and reliability, purposive sampling was utilized, focusing on active fitness wearable users. The participant selection process included the following eligibility criteria:

- Ownership of at least one wrist-worn fitness tracker for a minimum of three months.
- Active engagement with the device's health tracking features.

The recruitment process involved reaching out to 80 individuals, of whom 40 agreed to participate. After further screening for suitability, 34 participants were selected for the final study. These participants were categorized into four focus groups based on their usage experience:

- Group 1 (3-6 months) → 8 participants
- Group 2 (6-12 months) → 9 participants
- Group 3 (12-24 months) → 9 participants
- Group 4 (Above 24 months) → 8 participants

Each focus group discussion lasted 45-50 minutes and followed a semi-structured format. The open-ended questions were designed to explore themes in-depth, encouraging respondents to share their experiences, motivations, and expectations regarding their wearable devices. Some key discussion points included:

- *What factors motivated you to adopt a wrist-worn fitness tracker?*
- *Did your initial expectations align with your actual user experience?*
- *Which features influenced your decision to continue using the device?*

To maintain data reliability, two researchers independently transcribed the responses verbatim, while a mediator facilitated discussions to ensure the capture of unbiased and diverse insights. Few responses given by different participants are detailed in Appendix 2.

3.2 Data Analysis and Classification Using LLM

Traditional qualitative analysis methods, such as NVivo, rely on manual classification and inter-rater agreement, making them time-consuming. By leveraging GPT-4, this study achieves higher classification accuracy (99.2%), enhances thematic consistency, and reduces human bias, ensuring more reliable insights into post-adoption behaviour.

This research highlights the transformative role of AI in analysing qualitative data, providing actionable insights for developers and researchers seeking to enhance user retention in the rapidly evolving wearable technology landscape. To achieve systematic, scalable, and unbiased classification, this study leveraged GPT-4 (via ChatGPT Plus) as a Large Language Model (LLM) for automated response classification. This approach was selected due to its superior contextual comprehension and higher classification accuracy compared to conventional manual and rule-based methods.

3.2.1 Dataset Preparation

LLM-Based Thematic Extraction:

Step 1: Extracting Themes Without Predefined Categories

To demonstrate that an LLM autonomously generated behavioural constructs, we employed ChatGPT-4 for unsupervised thematic analysis. Unlike traditional methods, where predefined categories guide classification, this approach allowed the LLM to independently derive themes from raw user responses.

Input Prompt to ChatGPT-4: *"Analyse the following user responses and extract recurring themes that explain post-adoption behaviour of smart fitness devices. Do not classify into predefined categories; instead, identify the dominant themes emerging from user statements."*

Sample User Responses (Unlabelled Data):

- *"I love how my smartwatch tracks my heart rate and provides detailed insights on my workouts."*
- *"The device motivates me to stay active and push my limits, especially with the step challenges."*
- *"I enjoy changing my smartwatch faces to match my mood, and the colours are visually appealing."*
- *"The interface is easy to use, and I can navigate menus effortlessly, even when working out."*
- *"The smartwatch integrates well with my mobile phone, syncing data smoothly across apps."*
- *"I initially bought this watch expecting just step tracking, but the stress monitoring feature was an unexpected bonus."*
- *"The battery life is long-lasting, so I don't have to worry about frequent charging, which is very convenient."*
- *"I was sceptical about its accuracy at first, but after using it for a while, I see that it provides very reliable data."*
- *"I love the reminders to move; they help me stay on track even when I have a busy schedule."*

Key Findings and Implications

1. AI-Generated Responses Enhance Classification Accuracy: When ChatGPT first generates responses, classification accuracy reaches 99.2%, compared to 90.8% when only human-written responses are classified.
2. LLM Outperforms NVivo in Efficiency: NVivo relies on manual validation and inter-rater agreement, making it time-consuming. The LLM-based method is fully automated and highly scalable.
3. Semantic Consistency Reduces Errors: AI-generated responses are inherently aligned with AI classification logic, leading to higher precision and fewer misclassifications.

Step 2: ChatGPT-4 Extracts Themes Without Predefined Labels

When asked to extract themes, ChatGPT-4 produced the following emergent constructs based purely on semantic analysis:

1. Health Monitoring and Insights – Heart rate tracking, workout data, stress monitoring.
2. Motivation and Goal Tracking – Step challenges, activity reminders, fitness tracking.
3. Aesthetic and Customization Appeal – Watch face customization, colours, visual appeal.
4. Ease of Use and Navigation – Simple UI, intuitive menus, seamless interaction.
5. Device Integration and Connectivity – Syncing with mobile apps, data synchronization.
6. Expectation vs. Reality – Unexpected features, surpassing initial expectations.
7. Battery Life and Convenience – Extended battery, reduced charging needs.
8. Reliability and Trust in Data – Accuracy of health tracking, scepticism turning into trust.

While the LLM autonomously clustered themes, a secondary manual verification was conducted to ensure theoretical consistency. Researchers manually reviewed ChatGPT-4's construct mapping to validate:

1. Theoretical relevance – Whether AI-generated constructs align with ECM and TAM.
2. Construct validity – Whether user responses within a construct shared semantic and contextual coherence.
3. Manual reclassification – If ambiguity existed, responses were reassigned based on expert judgment.

To ensure alignment with theoretical models, ChatGPT-4 was then explicitly guided to classify the identified themes based on established behavioural models, including:

- Expectation-Confirmation Model (ECM) (Bhattacherjee, 2001)
- Technology Acceptance Model (TAM) (Davis, 1989)
- Post-Adoption Behavioural Frameworks (Venkatesh et al., 2012)

The final constructs retained for analysis were those most frequently observed in user discussions and theoretically supported by prior literature. This hybrid validation process allowed for AI-driven scalability while maintaining academic rigor. The identified themes were then mapped to constructs derived from ECM, TAM, and related frameworks.

ChatGPT-4 was explicitly prompted: *"Group the following themes into higher-order behavioural constructs based on theoretical frameworks like ECM and TAM. If a theme does not fit, classify it based on contextual similarity."*
As a result, the following constructs were finalized:

LLM-Generated Themes	**Final Construct Mapping (Hybrid Validation)**
Health Monitoring & Data Insights	Perceived Usefulness (ECM, TAM)
Motivation & Goal Attainment	Hedonic Motivation (Venkatesh et al., 2012)
Aesthetic Appeal & Customization	User Interface (Zviran et al., 2006)
Expectation vs. Reality	Confirmation of Expectation (ECM)
Overall User Experience	Satisfaction (ECM, Customer Satisfaction)

To further validate the AI-generated constructs, a thematic frequency analysis was performed. The LLM-derived constructs were ranked based on their frequency of occurrence across all 34 participants' responses.

Final Construct	**Induction Rate (%)**	**Validated By**
Perceived Usefulness	85%	AI & Manual
Hedonic Motivation	71%	AI & Manual
User Interface	80%	AI & Manual
Confirmation of Expectation	77%	AI & Manual
Satisfaction	89%	AI & Manual

While three additional constructs—Comfort, Price Sensitivity, and Social Influence—were identified by ChatGPT-4, these themes had lower induction rates (<50%) and were excluded. Table 1 (See Appendix 1) presents some snippets from the focus group discussion. The LLM successfully identified constructs aligned with ECM and TAM, and manual validation confirmed their relevance with >95% classification accuracy.

Final Dataset Construction

The dataset comprised qualitative responses collected from 34 participants. Each response was categorized into one of the five predefined constructs. Responses from focus group discussions (FGDs) were transcribed and formatted for AI processing. Minimal pre-processing was performed to retain natural sentence structures and ensure context preservation. Two different experimental setups were implemented:

1. LLM Classification on Human-Generated Responses
   - ChatGPT-4 was used to classify raw focus group responses, ensuring objective analysis.
2. LLM Classification on AI-Generated Responses
   - The model was first prompted to generate 240 unique responses per construct, forming a large-scale labelled dataset.
   - The generated responses were then reclassified by GPT-4, aligning the dataset with the model's classification logic.

3.2.2 LLM-Based Classification Process

The LLM was prompted with a standardized classification instruction: *"Classify the following response into one of these categories: 'Perceived Usefulness', 'Hedonic Motivation', 'User Interface', 'Confirmation of Expectation', 'Satisfaction'."*

The model returned a predicted category for each response. After classification, minor misclassifications were reviewed, particularly cases where semantic ambiguity resulted in overlap between categories. Final refinements ensured that themes aligned well with the original focus group discussions

3.2.3 Performance Evaluation: Accuracy Metrics

To quantitatively evaluate classification performance, the Precision, Recall, F1-Score, and Overall Accuracy were computed:

Mathematical Formulation

1. Precision (P): Measures the fraction of correctly classified responses among all responses assigned to a given construct.

P = TP / (TP + FP)

where TP (True Positives) are correctly classified responses, and FP (False Positives) are misclassified responses.

2. Recall (R): Measures the fraction of correct classifications relative to all responses that actually belong to a given construct.

R = TP / (TP + FN)

where FN (False Negatives) are actual responses misclassified into another category.

3. F1-Score (F1): The harmonic mean of precision and recall, providing a balanced performance metric.

F1 = (2 × P × R) / (P + R)

4. Overall Accuracy (A): Measures the total proportion of correctly classified responses across all constructs.

A = TP_total / (TP_total + FP_total + FN_total)

4. Results

4.1 LLM-Based Classification Without AI-Generated Responses

In the first phase, ChatGPT-4 was used only as a classifier, without prior exposure to AI-generated responses. The model was provided with human-written responses and prompted to classify them into the five constructs. To validate the accuracy, a subset of randomly selected responses was manually cross-verified.

The classification performance was as follows:

Category	**Precision (P)**	**Recall (R)**	**F1-Score (F1)**
Perceived Usefulness	0.91	0.89	0.90
Hedonic Motivation	0.88	0.87	0.87
User Interface	0.90	0.91	0.90
Confirmation of Expectation	0.86	0.85	0.85
Satisfaction	0.92	0.91	0.92
Overall Accuracy (A)	**90.8%**	—	—

The primary source of misclassification was semantic ambiguity, where some responses overlapped between constructs (e.g., Hedonic Motivation and User Interface when responses referred to aesthetic appeal).

Correctly Classified Examples:

- *"I love the customizable watch faces and themes. It's fun to change the look of my smartwatch."* → Hedonic Motivation
- *"I appreciate how clear and readable the display is, even in bright sunlight."* → User Interface
- *"I get to know when to drink water, which keeps me hydrated throughout the day."* → Perceived Usefulness

Misclassifications Observed:

The model occasionally misclassified Hedonic Motivation as User Interface, especially when responses mentioned visual appeal.

- Some generalized responses (e.g., *"I like my smartwatch"*) were categorized ambiguously.

4.2 LLM-Based Classification With AI-Generated Responses

In the second phase, ChatGPT-4 was first prompted to generate a dataset of 240 unique responses per construct (total 1200 responses) after providing it with few (2-3) examples per construct. Subsequently, the same model was used to classify the actual responses based on these AI-generated responses. To validate the accuracy, a subset of randomly selected responses was manually cross-verified.

The classification performance significantly improved:

Category	**Precision (P)**	**Recall (R)**	**F1-Score (F1)**
Perceived Usefulness	0.99	0.99	0.99
Hedonic Motivation	0.98	0.98	0.98
User Interface	0.99	0.99	0.99

Confirmation of Expectation	0.97	0.98	0.97
Satisfaction	0.99	0.99	0.99
Overall Accuracy (A)	**99.2%**	—	—

The significant improvement in classification accuracy (from 90.8% to 99.2%) can be attributed to:

1. Elimination of Ambiguity: AI-generated responses were structured in a way that minimized overlaps between constructs.
2. Higher Semantic Alignment: The LLM could better recognize and classify new responses looking at its own generated dataset.

5. CONCLUSIONS AND FUTURE WORK

This study highlights the growing adoption of smart fitness wearables and the need to understand the factors influencing post-adoption behavioural intentions. By leveraging GPT-4 for automated classification, the study significantly improved efficiency, accuracy, and scalability in analysing qualitative data. While manual classification remains valuable for validation, LLM-based classification offers a faster, more objective, and scalable approach. The findings confirm that confirmation of expectation, perceived usefulness, and satisfaction are key drivers of continued wearable use, alongside hedonic motivation and user interface, thereby extending the traditional ECM framework. The results underscore the importance of usability, motivation, and productivity in shaping user satisfaction and long-term engagement. A seamless user interface, ease of navigation, and engaging features can enhance retention, while gamification elements foster sustained interest. Given the evolving nature of wearable technology, this study provides insights that can help developers refine user-centric features and improve the overall user experience. By integrating AI-driven qualitative analysis with theoretical models, this research not only advances methodological approaches but also offers actionable insights for developers aiming to enhance user experience and long-term adoption.

The study does not directly test the ECM's hypothesis so future research can build upon these findings and explore additional factors in designing a research framework to explicitly test the model's hypothesis and validate it in the specific domain of smart fitness technology. Future research should focus on fine-tuning LLMs with domain-specific data and developing hybrid models that combine AI efficiency with human oversight. Expanding this framework to explore additional factors, such as privacy concerns and personalization, could provide deeper insights into user behaviour. As the market for wearable technology evolves, AI-assisted qualitative analysis offers a promising avenue for enhancing research efficiency and advancing user-centered design strategies.

REFERENCES

1. Agarwal, R., & Prasad, J. (1997). The role of innovation characteristics and perceived voluntariness in the acceptance of Information Technologies. *Decision Sciences*, *28*(3), 557–582. https://doi.org/10.1111/j.1540-5915.1997.tb01322.x
2. Ageing and health. (2018). Retrieved January 16, 2020, from https://www.who.int/news-room/fact-sheets/detail/ageing-and-health
3. Asadi, S., Abdullah, R., Safaei, M., & Nazir, S. (2019). An Integrated SEM-Neural Network Approach for Predicting Determinants of Adoption of Wearable Healthcare Devices. *Mobile Information Systems*, *2019*, 1–9. doi: 10.1155/2019/8026042
4. Baker-Eveleth, L., & Stone, R. W. (2015). Usability, expectation, confirmation, and continuance intentions to use electronic textbooks. *Behaviour & Information Technology*, *34*(10), 992–1004. doi: 10.1080/0144929x.2015.1039061
5. Bhattacherjee, A. (2001). Understanding Information Systems Continuance: An Expectation-Confirmation Model. *MIS Quarterly*, *25*(3), 351. doi: 10.2307/3250921
6. Bhattacherjee, A., & Premkumar, G. (2004). Understanding Changes in Belief and Attitude toward Information Technology Usage: A Theoretical Model and Longitudinal Test. *MIS Quarterly*, *28*(2), 229-254. doi: 10.2307/25148634
7. Cains, J. T. (2019). What Is Wearable Fitness Technology and How Can It Help You? https://www.dummies.com/health/exercise/what-is-wearable-fitness-technology-and-how-can-it-help-you/ (2019). Accessed 10 January 2020
8. Canhoto, A. I., & Arp, S. (2016). Exploring the factors that support adoption and sustained use of health and fitness wearables. *Journal of Marketing Management*, *33*(1-2), 32–60. doi: 10.1080/0267257x.2016.1234505
9. Chen, S.-C., Yen, D. C., & Hwang, M. I. (2012). Factors influencing the continuance intention to the usage of Web 2.0: An empirical study. *Computers in Human Behavior*, *28*(3), 933–941. doi: 10.1016/j.chb.2011. 12.014
10. Cho, V., Cheng, T. E., & Lai, W. J. (2009). The role of perceived user-interface design in continued usage intention of self-paced e-learning tools. *Computers & Education*, *53*(2), 216–227. doi: 10.1016/j.compedu.2009. 01.014

11. Claussen, J., Essling, C., & Kretschmer, T. (2015). When less can be more – Setting technology levels in complementary goods markets. *Research Policy*, *44*(2), 328–339. doi: 10.1016/j.respol.2014.10.005
12. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319. doi: 10.2307/249008
13. Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, *35*(8), 982–1003. doi: 10.1287/mnsc.35.8.982
14. Dehghani, M. (2018). Exploring the motivational factors on continuous usage intention of smartwatches among actual users. *Behaviour & Information Technology*, *37*(2), 145–158. doi: 10.1080/0144929x.2018.1424246
15. Dehghani, M., Kim, K. J., & Dangelico, R. M. (2018). Will smartwatches last? factors contributing to intention to keep using smart wearable technology. *Telematics and Informatics*, *35*(2), 480–490. doi: 10.1016/j.tele.2018.01.007
16. Gao, Y., Li, H., & Luo, Y. (2015). An empirical study of wearable technology acceptance in healthcare. *Industrial Management & Data Systems*, *115*(9), 1704–1723. doi: 10.1108/imds-03-2015-0087
17. Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in Online Shopping: An Integrated Model. *MIS Quarterly*, *27*(1), 51-90. doi: 10.2307/30036519
18. Gordon, K. (2019). Topic: Fitness & activity tracker. Retrieved from https://www.statista.com/topics /4393/fitness-and-activity-tracker/
19. Hänsel, K., Wilde, N., Haddadi, H., & Alomainy, A. (2016). Wearable Computing for Health and Fitness: Exploring the Relationship between Data and Human Behaviour. https://doi.org/10.48550/arXiv.1509.05238.
20. Hong, J., Lee, O. K., & Suh, W. (2013). A study of the continuous usage intention of social software in the context of instant messaging. *Online Information Review*, *37*(5), 692–710. doi: 10.1108/oir-08-2011-0144
21. Hsiao, C.-H., Chang, J.-J., & Tang, K.-Y. (2016). Exploring the influential factors in continuance usage of mobile social Apps: Satisfaction, habit, and customer value perspectives. *Telematics and Informatics*, *33*(2), 342–355. doi: 10.1016/j.tele.2015.08.014
22. Hsiao, K.-L. (2017). What drives smartwatch adoption intention? Comparing Apple and non-Apple watches. *Library Hi Tech*, *35*(1), 186–206. doi: 10.1108/lht-09-2016-0105
23. India Wearable Market Ships 25.1mn Units in 1Q23, Growing by 80.9% YoY, Says IDC India. International Data Corporation (IDC). https://www.idc.com/getdoc.jsp?containerId=prAP50657923 (2023). Accessed 31 July 2023
24. Jayanti, R. K., & Burns, A. C. (1998). The Antecedents of Preventive Health Care Behavior: An Empirical Study. *Journal of the Academy of Marketing Science*, *26*(1), 6–15. doi: 10.1177/0092070398261002
25. Kaewkannate, K., & Kim, S. (2018). The Comparison of Wearable Fitness Devices. *Wearable Technologies*. doi: 10.5772/intechopen.76967
26. Karapanos, E. (2013). Modeling Users Experiences with Interactive Systems. *Studies in Computational Intelligence*. doi: 10.1007/978-3-642-31000-3
27. Kassarjian, H. (1977). Content Analysis in Consumer Research, *Journal of Consumer Research*, *4*(1), 8–18, doi: 10.1086/208674
28. Kalantari, M. (2017). Consumers adoption of wearable technologies: literature review, synthesis, and future research agenda. *International Journal of Technology Marketing*, *12*(1), 1. doi: 10.1504/ijtmkt.2017.10008634
29. Kim, B. (2010). An empirical investigation of mobile data service continuance: Incorporating the theory of planned behavior into the expectation–confirmation model. *Expert Systems with Applications*, *37*(10), 7033–7039. doi: 10.1016/j.eswa.2010.03.015
30. Kim, H.-W., Chan, H. C., & Gupta, S. (2007). Value-based Adoption of Mobile Internet: An empirical investigation. *Decision Support Systems*, *43*(1), 111–126. doi: 10.1016/j.dss.2005.05.009
31. Kim, K., Hwang, J., Zo, H., & Lee, H. (2014). Understanding users' continuance intention toward smartphone augmented reality applications. *Information Development*, *32*(2), 161–174. doi: 10.1177/0266666914535119
32. Kim, K. J., & Shin, D.-H. (2015). An acceptance model for smart watches. *Internet Research*, *25*(4), 527–541. doi: 10.1108/intr-05-2014-0126
33. Kim, Y. H., Kim, D. J., & Wachter, K. (2013). A study of mobile user engagement (MoEN): Engagement motivations, perceived value, satisfaction, and continued engagement intention. *Decision Support Systems*, *56*, 361–370. doi: 10.1016/j.dss.2013.07.002
34. Lee, H., Choi, S. Y., & Kang, Y. S. (2009). Formation of e-satisfaction and repurchase intention: Moderating roles of computer self-efficacy and computer anxiety. *Expert Systems with Applications*, *36*(4), 7848–7859. doi: 10.1016/j.eswa.2008.11.005
35. Lin, X., Featherman, M., & Sarker, S. (2017). Understanding factors affecting users' social networking site continuance: A gender difference perspective. *Information & Management*, *54*(3), 383–395. doi: 10.1016/j.im.2016.09.004
36. Lunney, A., Cunningham, N. R., & Eastin, M. S. (2016). Wearable fitness technology: A structural investigation into acceptance and perceived fitness outcomes. *Computers in Human Behavior*, *65*, 114–120. doi: 10.1016/j.chb.2016.08.007

37. Mewara, D., Purohit, P., & Rathore, B. P. S. (2016). Wearable devices applications & its future. *International Journal of Technology Research in Engineering*, 59-64.
38. Miltgen, C. L., Popovič, A., & Oliveira, T. (2013). Determinants of end-user acceptance of biometrics: Integrating the "Big 3" of technology acceptance with privacy context. *Decision Support Systems*, *56*, 103–114. doi: 10.1016/j.dss.2013.05.010
39. Oghuma, A. P., Libaque-Saenz, C. F., Wong, S. F., & Chang, Y. (2016). An expectation-confirmation model of continuance intention to use mobile instant messaging. *Telematics and Informatics*, *33*(1), 34–47. doi: 10.1016/j.tele.2015.05.006
40. Oliveira, T., Thomas, M., Baptista, G., & Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Computers in Human Behavior*, *61*, 404–414. doi: 10.1016/j.chb.2016.03.030
41. Oliver, R. L. (1980). A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions. *Journal of Marketing Research*, *17*(4), 460–469. doi: 10.1177/002224378001700405
42. Oliver, R. L., & Burke, R. R. (1999). Expectation Processes in Satisfaction Formation. *Journal of Service Research*, *1*(3), 196–214. doi: 10.1177/109467059913002
43. Rashotte, L. (2007), "Social influence", in Ritzer, G. (Ed.), The Blackwell Encyclopedia of Sociology
44. Recker, J. (2010). Continued use of process modeling grammars: the impact of individual difference factors. *European Journal of Information Systems*, *19*(1), 76–92. doi: 10.1057/ejis.2010.5
45. Salah, H., MacIntosh, E., & Rajakulendran, N. (2014). Transforming Health: Decentralized and connected. Retrieved from https://www.marsdd.com /news/transforming-health-decentralized-connected-care/
46. Spil, T. A. M., Kijl, B., & Romijnders, V. (2019). The Adoption and Diffusion of Wearables. *IFIP Advances in Information and Communication Technology ICT Unbounded, Social Impact of Bright ICT Adoption*, 31–47. doi: 10.1007/978-3-030-20671-0_4
47. Statt, N. (2015). The rise and fall of fitness trackers in 2015. Retrieved from https://www.cnet.com /news/fitness-trackers-rise-and-fall/.
48. Sullivan, D. (2013). My life with the Fitbit Flex activity tracker. Retrieved from https://www.cnet.com/news/my-life-with-the-fitbit-flex-activity-tracker/.
49. Susanto, A., Chang, Y., & Ha, Y. (2016). Determinants of continuance intention to use the smartphone banking services. *Industrial Management & Data Systems*, *116*(3), 508–525. doi: 10.1108/imds-05-2015-0195
50. Talukder, M. S., Chiong, R., Bao, Y., & Malik, B. H. (2019). Acceptance and use predictors of fitness wearable technology and intention to recommend. *Industrial Management & Data Systems*, *119*(1), 170–188. doi: 10.1108/imds-01-2018-0009
51. Veeramootoo, N., Nunkoo, R., & Dwivedi, Y. K. (2018). What determines success of an e-government service? Validation of an integrative model of e-filing continuance usage. *Government Information Quarterly*, *35*(2), 161–174. doi: 10.1016/j.giq.2018.03.004
52. Venkatesh, V., Thong, J. Y. L., Chan, F. K. Y., Hu, P. J.-H., & Brown, S. A. (2011). Extending the two-stage information systems continuance model: incorporating UTAUT predictors and the role of context. *Information Systems Journal*, *21*(6), 527–555. doi: 10.1111/j.1365-2575.2011.00373.x
53. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*(1), 157. doi: 10.2307/41410412
54. Weiser, M. (1991). The Computer for the 21st Century. *Scientific American*, *265*(3), 94–104. doi: 10.1038/scientificamerican0991-94
55. Williamson, J., Liu, Q., Lu, F., Mohrman, W., Li, K., Dick, R., & Shang, L. (2015). Data sensing and analysis: Challenges for wearables. *The 20th Asia and South Pacific Design Automation Conference.* doi: 10.1109/aspdac.2015.7058994
56. Wixom, B. H., & Todd, P. A. (2005). A Theoretical Integration of User Satisfaction and Technology Acceptance. *Information Systems Research*, *16*(1), 85–102. doi: 10.1287/isre.1050.0042
57. Worldwide Wearables Market Is Forecast to Rebound in 2023 with Continued Growth Thereafter, According to IDC. International Data Corporation (IDC). https://www.idc.com/getdoc.jsp?containerId=prUS50984723 (2023). Accessed 31 July 2023
58. 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. doi: 10.1016/j.tele.2015.08.007
59. Zhang, M., Luo, M., Nie, R., & Zhang, Y. (2017). Technical attributes, health attribute, consumer attributes and their roles in adoption intention of healthcare wearable technology. *International Journal of Medical Informatics*, *108*, 97–109. doi: 10.1016/j.ijmedinf.2017.09.016
60. Zheng, Y., Zhao, K., & Stylianou, A. (2013). The impacts of information quality and system quality on users continuance intention in information-exchange virtual communities: An empirical investigation. *Decision Support Systems*, 56, 513–524. doi: 10.1016/j.dss.2012.11.008
61. Zviran, M., Glezer, C., & Avni, I. (2006). User satisfaction from commercial web sites: The effect of design and use. *Information & Management*, *43*(2), 157–178. doi: 10.1016/j.im.2005.04.002

Appendix 1: Interview for the users of smart fitness wearables

- Have you ever had an experience with smart fitness wearables in your life? If yes, what type of smart fitness wearable device do you possess? Also mention the usage experience (in months).

(Based on the usage experience, participants were categorized into 4 groups for questioning purpose)

1. What motivated you to adopt a wrist-worn fitness device in the first place?
2. Were your initial expectations in alignment with actual experience of using these wearables?
3. Did you encounter any challenges while using fitness wearables? If yes, kindly elaborate on the issue.
4. What aspects do you consider valuable while using smart wearables? (Probes: Usefulness, Enjoyment, interface, compatibility, social influence or any other aspect?)
5. Are you satisfied with the overall experience of using smart fitness wearable?
6. Would you like to continue the use of smart fitness wearables? If yes, would you recommend these devices to your family and friends?

Appendix 2: Induction analysis results

Categories	Snippets from the focus group discussion
Perceived usefulness (85%)	Participant 2.2: The fitness tracker has become an essential part of my daily routine. It helps me monitor my sleep patterns, which has been very useful in improving my overall health and productivity. Participant 3.3: The calorie tracking feature of my smartwatch is very useful for maintaining my diet. It gives me a clear picture of my daily intake and expenditure, which has helped me manage my weight effectively. Participant 4.1: I find the reminders to move very useful, especially when I'm at work. It keeps me active throughout the day and helps me achieve my fitness goals even with a busy schedule. Participant 1.8: I find the continuous heart rate monitoring feature very useful, especially during intense workouts. It ensures that I'm training in the right heart rate zone for maximum efficiency.
Hedonic Motivation (71%)	.Participant 1.4: Tracking my workouts with my fitness tracker is enjoyable because it provides detailed feedback and insights. Seeing my progress in graphs and charts makes the whole fitness journey more engaging. Participant 4.8: I love the customizable watch faces and themes. It's fun to change the look of my smartwatch to match my mood or outfit, which makes me want to wear it all the time Participant 3.9: I enjoy the variety of workouts and activities available on my fitness tracker. From yoga to high-intensity interval training, the range of options keeps me excited and looking forward to my workouts. Participant 2.4: I find the virtual fitness challenges and leaderboards very exciting.
User Interface (80%)	Participant 2.6: I appreciate how clear and readable the display is, even in bright sunlight. The icons are well-designed and the layout is simple, making it easy to access the information I need quickly. Participant 3.8: The touch screen responsiveness is excellent. I love how smoothly I can swipe between screens and access different functions. Participant 4.4: The quick access to different fitness modes and health tracking features without navigating through complex menus is a huge plus. Participant 1.2: The voice command functionality makes it easy to control the device without having to use my hands, especially during workouts.
Confirmation of Expectation (77%)	Participant 3.7: I expected my smartwatch to help me stay active, but it has also improved my sleep quality. The sleep tracking and personalized tips have been more beneficial than I anticipated. Participant 1.3: My expectations were high because of the positive reviews, and my smartwatch did not disappoint. The seamless integration with my smartphone and the comprehensive health monitoring features are fantastic. Participant 4.6: I bought the smartwatch expecting basic fitness tracking, but it offers so much more. The stress tracking and mindfulness features have been a pleasant surprise and very helpful. Participant 2.1: I expected good durability, and my fitness tracker has proven to be robust. It withstands my active lifestyle, including outdoor runs and swimming, which is exactly what I needed.
Satisfaction (89%)	Participant 3.6: I am extremely satisfied with my smartwatch. It has become an essential part of my daily routine, helping me stay on top of my fitness goals and overall health.

	Participant 2.9: I am very pleased with the variety of features my fitness tracker offers. From sleep tracking to workout analytics, it covers all my needs comprehensively. Participant 4.6: I'm very happy with my fitness tracker. It provides all the data I need in an easy-to-understand format. Participant 1.1: My smartwatch keeps me motivated and accountable, and I couldn't be happier with its performance.
Categories with low induction rate **Price Sensitivity** **Social influence** **Comfort**	Participant 1.6: The fitness tracker offers excellent value for money. The benefits I get in terms of health insights outweigh the cost. Participant 4.2: Considering the advanced features and reliable performance, the price was quite reasonable. Participant 3.6: It's great to share my fitness achievements with friends and family. Participant 2.4: The social challenges and group workouts organized through my fitness tracker adds a fun element to staying active. Participant 4.7: I can comfortably wear a smartwatch all day. The band is soft and adjustable. Participant 3.7: The comfort of my fitness tracker is a big plus. The material is skin-friendly, and it doesn't cause any irritation, making it easy to wear all the time.