The impact of wearable devices on consumer behavior: How fitness trackers and smartwatches influence habits and lifestyle choices

Guilherme Ferreira

Dissertation written under the supervision of professor Daniel Fernandes

Dissertation submitted in partial fulfilment of requirements for the MSc in Business, at the Universidade Católica Portuguesa, January 2026.

Abstract

Abstract: Wearable devices such as fitness trackers and smartwatches have become increasingly integrated into daily life, yet their actual impact on long-term behavioral change and habit formation remains incompletely understood. Therefore, this thesis explores how these technologies influence consumer motivation, behavioral patterns, and lifestyle choices, examining whether wearables drive genuine health transformation or merely facilitate short-term engagement. To address this aim, a two-phase approach was employed. First, a literature review of 50 sources established the theoretical foundation, examining behavior change frameworks including Self-Determination Theory, Feedback Loop Theory, the Technology Acceptance Model, and Commitment Device Theory. Second, a survey of 150 current wearable users gathered empirical data on usage patterns, motivations, and perceived behavioral impacts. The findings reveal that wearables facilitate gradual behavioral change primarily through heightened self-awareness rather than direct modification, with users maintaining engagement when devices support intrinsic motivations over extrinsic rewards. The study validates that wearables function as soft commitment devices, creating accountability without compromising autonomy. However, it also identifies critical misalignments: the industry's emphasis on gamification contradicts user needs, and practical barriers like battery life remain more significant obstacles than previously recognized. Finally, it is argued that effective wearable design must prioritize supporting user agency, provide actionable insights over data volume, and focus on refining core functionality to enable sustainable behavioral change across diverse populations.

Title: The impact of wearable devices on consumer behavior: how fitness trackers and smartwatches influence habits and lifestyle choices

Author: Guilherme Carvalho Ferreira

Keywords: Wearable devices, consumer behavior, habit formation, behavior change, commitment devices, fitness trackers, smartwatches.

Resumo

Resumo: Os dispositivos *wearables*, como *fitness trackers* e *smartwatches*, tornaram-se amplamente integrados na vida quotidiana. Contudo, o seu impacto na mudança comportamental a longo prazo permanece incompletamente compreendido. Neste contexto, esta tese analisa de que forma estas tecnologias influenciam a motivação dos consumidores, os comportamentos de saúde e as escolhas de estilo de vida, avaliando se promovem mudanças sustentadas ou apenas envolvimento de curto prazo.

Para responder a este objetivo, foi adotada uma abordagem em duas fases. Numa primeira fase, realizou-se uma revisão da literatura, composta por 50 fontes, que permitiu enquadrar teoricamente o estudo com base em modelos de mudança comportamental, incluindo a Teoria da Autodeterminação, a Teoria dos Ciclos de Feedback, o Modelo de Aceitação da Tecnologia e a Teoria dos Dispositivos de Compromisso. Numa segunda fase, foi aplicado um inquérito a 150 utilizadores de *wearables*, recolhendo os seus dados sobre padrões de utilização, motivações e impactos comportamentais.

Os resultados indicam que os *wearables* facilitam mudança comportamental gradual através do aumento da autoconsciência, sendo o envolvimento mais sustentado quando apoiam motivações intrínsecas. O estudo sugere ainda que funcionam como dispositivos de compromisso, promovendo responsabilização sem comprometer a autonomia. No entanto, identificam-se limitações, nomeadamente o desalinhamento entre a aposta da indústria na gamificação e as necessidades dos utilizadores, bem como barreiras práticas como a duração da bateria.

Conclui-se que o design eficaz de *wearables* deve priorizar o apoio à autonomia do utilizador e o fornecimento de *insights* acionáveis, de forma a promover mudança comportamental sustentável.

Título: O impacto dos dispositivos *wearables* no comportamento do consumidor: como os *fitness trackers* e *smartwatches* influenciam os hábitos e as escolhas de estilo de vida

Autor: Guilherme Carvalho Ferreira

Palavras-chave: Dispositivos *wearables*, comportamento do consumidor, formação de hábitos, mudança comportamental, dispositivos de compromisso, *fitness trackers*, *smartwatches*.

Acknowledgements

I would like to express my gratitude to my supervisor, Professor Daniel Fernandes, for his guidance, advice, and continued support throughout the development of this thesis. His insights and constructive feedback were fundamental in shaping this work and in ensuring clarity and consistency throughout the research process.

I am deeply grateful to my parents for their unconditional support and constant encouragement throughout my academic journey. Their trust and belief in me have been invaluable. I also wish to thank my younger sister, Maria, and my brother, João, who, even at a distance, have consistently offered guidance, advice, and support.

A special thank you goes to Bárbara for her patience, encouragement, and determination in motivating me during challenging moments and for never allowing me to give up on completing this thesis.

Finally, I would like to thank my closest friends for their understanding and support throughout this demanding period.

Table of Contents

Table of Figures

Table of Tables

List of Abbreviations

(In order of appearance)

IoT - Internet of Things

BCTs - Behavior Change Techniques

HBM - Health Belief Model

SDT - Self-Determination Theory

FLT - Feedback Loop Theory

TAM - Technology Acceptance Model

ECG - Electrocardiogram

GPS - Global Positioning System

TRA - Fishbein's Theory of Reasoned Action

AI - Artificial Intelligence

1 Introduction

1.1 Background and problem statement

In recent years, wearable technologies such as fitness trackers and smartwatches have gained considerable popularity for their ability to monitor health, improve daily routines, and promote healthier lifestyles (ÇiÇek 2015; Ometov et al. 2021). These devices now play a significant role not only in physical activity tracking but also in preventive health and behavioral regulation, supported by features like biometric sensors, real-time feedback, and data visualization (Cheng et al. 2021; Bello and Figetakis 2023). As wearables become increasingly embedded in everyday life, they offer a unique opportunity to influence user behavior through mechanisms like self-monitoring, gamification, and personalized goal-setting (Hydari et al. 2022).

Despite their growing adoption, the impact of wearable devices on long-term behavioral outcomes remains complex. While studies demonstrate that wearables can promote positive change, issues such as user abandonment, loss of motivation, privacy concerns, and technological limitations persist (Lazar et al. 2015; Fadhil 2019a; Cilliers 2020). Moreover, many commercial wearables rely heavily on external motivators, such as badges, streaks, and social comparisons, that may undermine intrinsic motivation over time (Kerner and Goodyear 2017). This raises concerns about whether these tools genuinely support habit formation and lasting lifestyle changes or merely trigger short-term engagement.

Existing research has explored the theoretical underpinnings of behavior change drawing from frameworks such as the Technology Acceptance Model, Health Belief Model, and the Self-Determination Theory (Davis 1987; Champion and Skinner 2008; Hagger et al. 2020). However, a gap remains in connecting these theories with real-world user experiences, particularly in the context of commercial wearables used outside clinical or research environments. In particular, while the literature highlights behavior change techniques (BCTs) embedded in these devices, less is known about how users perceive, engage with, and respond to these mechanisms in practice (Mercer et al. 2016; Lehrer et al. 2021).

1.2 Aim and Scope

The aim of this thesis is to explore the impact of wearable devices, specifically fitness trackers and smartwatches, on consumer behavior, with particular attention to how these technologies influence motivation, habit formation, and lifestyle choices.

As wearable adoption becomes increasingly common, it is essential to understand not only how these devices function technically, but also how users engage with them psychologically and behaviorally. To address this aim, the research is guided by the following questions:

Overarching Research Question: How do wearable devices influence consumer behavior in terms of motivation, habit formation, and lifestyle choices?

Sub-Research Questions:

- **RQ1:** What theoretical frameworks explain how wearable devices promote behavioral change, and what are the key mechanisms through which these devices influence user behavior?
- **RQ2:** What are the actual experiences and perceptions of wearable device users regarding behavioral change, motivation, and autonomy in health decision-making?

The scope of the research is twofold, corresponding to the two sub-research questions. First, a systematic literature review was conducted to map the theoretical landscape and identify key frameworks and behavior change techniques relevant to wearable use, including the Health Belief Model (HBM), Self-Determination Theory (SDT), Feedback Loop Theory (FLT), and the Technology Acceptance Model (TAM). This phase addresses RQ1 by establishing the theoretical foundation for understanding how wearables influence behavior.
Second, a user-centered empirical phase was implemented through a survey targeting individuals currently using wearable devices. This survey aimed to gather insights into users' experiences, motivations, and the perceived effects of wearables on their daily habits and health-related decisions, directly addressing RQ2 by capturing real-world user perspectives.
The study focuses primarily on commercial wearables used in non-clinical contexts, examining both the potential and limitations of these tools in fostering long-term behavioral change. It does not address the technical development of wearable hardware or regulatory frameworks, but rather concentrates on the intersection between device design, user engagement, and behavior change from a consumer behavior perspective.

1.3 Research methods

As previously mentioned, the present study investigates how fitness trackers and smartwatches influence consumer habits and lifestyle decisions through a two-phase approach. Phase one consisted of a literature review, in which 50 references were analyzed. These sources contributed to the theoretical foundation of the research and covered a range of categories, including academic papers focused on wearable technologies, their relationship with habit development, future applications of wearables, and broader frameworks related to behavior change. Phase two involved a survey, which gathered insights from 150 valid responses provided by current users of wearable devices (e.g., fitness trackers or smartwatches). The survey results were instrumental in shaping the empirical component of the study, offering a deeper understanding of user experiences, motivations, and perceived behavioral impacts associated with wearable use.

1.4 Relevance

By bridging academic frameworks with user-generated insights, this research contributes to a deeper understanding of how wearable technologies influence consumer behavior and what design elements enable or hinder sustained health-related habits. The findings provide theoretical value by connecting established behavior change models with real-world usage patterns, helping to refine our understanding of technology adoption, motivation, and lifestyle transformation. From a management perspective, the study offers practical implications for developers, marketers, and public health professionals seeking to better the design, engagement, and long-term value of wearable devices. As the wearable market continues to expand across health, fitness, and consumer sectors, the ability to promote consistent user engagement and meaningful behavioral outcomes will be critical to driving both impact and innovation. This research therefore supports not only academic inquiry but also the development of more inclusive, effective, and user-centered wearable devices.

2 Literature Review

2.1 Wearables

This section aims to provide an overview of wearable technologies, covering their evolution, key features, market trends, and integration into daily routines. Wearables are part of a broader ecosystem of connected devices that enhance daily life, leveraging advancements in sensors, connectivity, and data processing (ÇiÇek 2015). The growing integration of these devices into healthcare, fitness, and enterprise environments reflects their expanding role in both personal and professional contexts (Ometov et al. 2021). As their adoption continues to rise, understanding their development and impact is essential to assessing their future potential.

2.1.1 Definition and evolution of wearables

Wearable technologies, often called "wearables", can be understood as technological devices worn on the body that allow interaction and connectivity with digital systems (ÇiÇek 2015). While modern wearables are typically associated with electronic and connected functionalities, the concept can be traced back centuries. One of the earliest examples is the invention of spectacles by the English friar Roger Bacon in the 13th century, marking an early instance of body-worn assistive technology. In 1505, Peter Henlein created the first mechanical pocket watch, which later evolved into wristwatches in the 19th century, initially for military use. Over time, wearable devices expanded beyond timekeeping and vision correction, integrating into clothing and accessories worn on the head, wrist, and body. More recent innovations include applications in footwear and implantable sensors, as demonstrated in Figure 1. Milestones of the wearable devices' evolution (Ometov et al. 2021).

As this historical trajectory shows, wearables have progressively shifted from niche tools to mainstream technologies. Today, they have become part of everyday life, helping people track their health, fitness, and productivity (Xue 2019). Building on this trend, major tech companies have introduced smartwatches and other wearables that improve connectivity and health monitoring, making these devices more widely available.

According to (Seneviratne et al. 2017), existing commercial wearable products can be categorized into three main groups: accessories, e-textiles, and e-patches. Accessories include wrist-worn devices such as smartwatches and wristbands, as well as head-mounted devices like smart eyewear and headsets or earbuds, and other forms such as smart jewelry and straps. E-textiles includes smart garments and foot- or hand-worn items.

E-patches refer to devices such as sensor patches and electronic tattoos or e-skins (Seneviratne et al. 2017). Beyond personal use, global challenges like an aging population and disease outbreaks have highlighted the importance of wearables in healthcare, driving innovation in the field (Cheng et al. 2021).

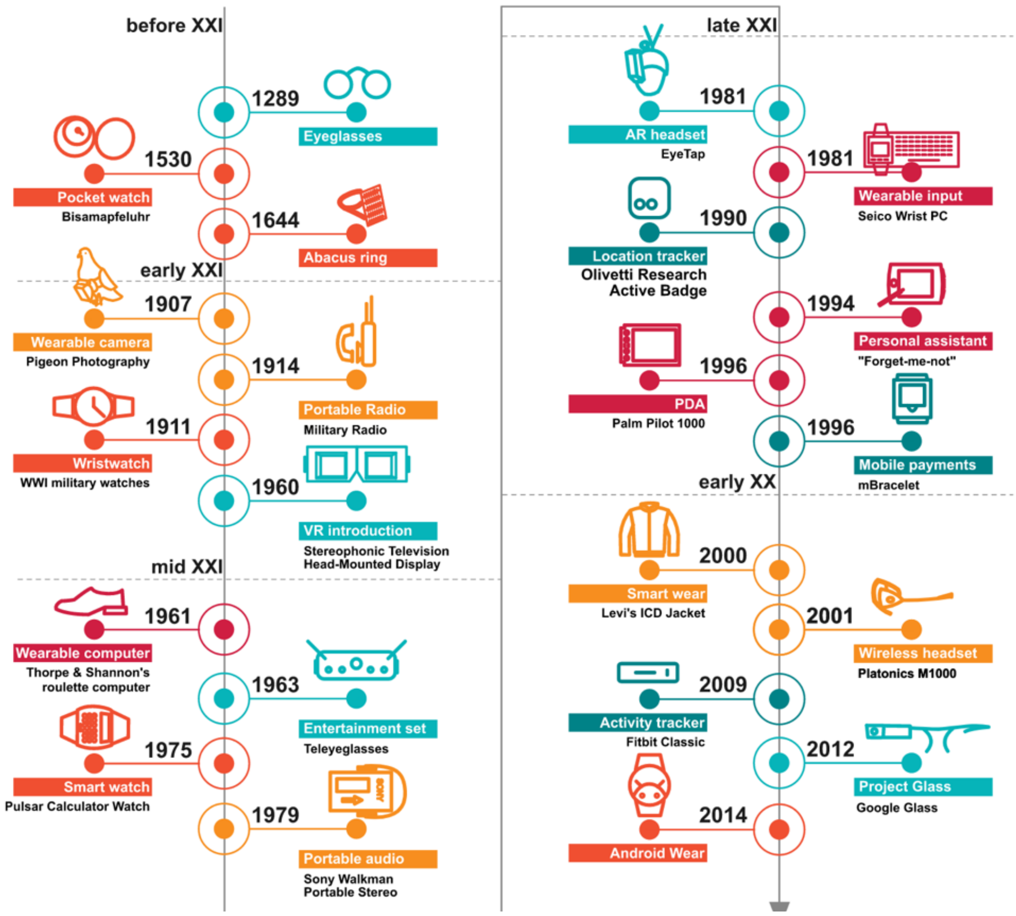

Figure 1. Milestones of the wearable devices' evolution

2.1.2 Wearables market overview

The wearable technology market has experienced significant growth, driven by health monitoring demand, Internet of Things (IoT) integration, and increasing consumer adoption. Over the past decade, sales have risen steadily, with projections indicating the market will exceed €150 billion by 2028 (Ometov et al. 2021). While initially driven by fitness and health applications, wearables are now expanding into enterprise and industrial use cases, reinforcing their role in personal settings, and becoming increasingly relevant in professional settings. Organizations are turning to these devices to support employee well-being, strengthen workplace safety, and improve productivity.

At the same time, their adoption is expanding to fields such as infotainment, smart cities, and transportation, where they contribute to ongoing processes of digital transformation (Ometov et al. 2021).

However, consumer interest in wearables remains strongest in the health and fitness sectors, where smartwatches and fitness trackers dominate the market. Fitness trackers primarily focus on activity monitoring, while smartwatches offer more advanced features, including heart rate tracking or internet connectivity (Seneviratne et al. 2017).

The wearable market can be segmented into two sub groups. First, devices for quantified self. This concept refers to “the process of collecting personalized data about one's own life and wellbeing using wearable devices and other advanced technology”. In this group are identified several types of devices, such as fitness trackers, smartwatches, and activity trackers. Fitness trackers, such as those from Fitbit and Xiaomi, emphasize step counting, calorie tracking, and basic health monitoring. Smartwatches, led by brands like Apple, Samsung, and Garmin, integrate advanced features such as Electrocardiogram (ECG) monitoring, Global Positioning System (GPS) tracking, and real-time health insights. Second, devices that are used in the healthcare environment to quantify disease progression. Meanwhile, medical and health wearables, including continuous glucose monitors, ECG patches, and wearable biosensors, are gaining regulatory approval for clinical applications, further expanding the industry’s reach (Vijayan et al. 2021).

Leading companies continue to shape the consumer market, with Apple dominating the smartwatch segment, selling over 16 million units in a single year (Amorim et al. 2020).

The enterprise market for wearables is expanding, with developments ranging from AR-based smart glasses to mixed-reality platforms and industrial-focused solutions, reflecting the growing diversity of applications in this field (Ometov et al. 2021). As the industry continues to evolve, innovations in smart textiles, implantable devices, and Artificial Intelligence (AI) powered health monitoring are shaping the future of wearables. These advancements are driving applications beyond traditional consumer electronics, enabling more sophisticated enterprise solutions and medical-grade technologies (Bello and Figetakis 2023).

2.1.3 Key features of wearables

The features of wearable devices may vary. The ones common to most are the battery and sensors, at the very least. Organizations have been increasingly incorporating advanced sensors, significantly improving users' ability to monitor their health and daily activities.

These devices rely on biosensors to measure key physiological indicators, including oxygen levels, heart rate, and movement. By continuously collecting and processing this data, wearables enable real-time tracking and remote monitoring, providing valuable insights into users' well-being (Cheng et al. 2021). The integration of these devices into the IoT further strengthen their functionality, allowing biometric data to be transmitted directly to cloud platforms for advanced analysis. This connectivity has strengthened their role in healthcare and fitness, facilitating improved patient monitoring and accelerating diagnoses (Bello and Figetakis 2023). The growing use of AI-powered wearables in medical applications has further improved real-time patient monitoring and rehabilitation. By continuously analyzing physiological data, these devices enrich medical outcomes, offering adaptive responses tailored to individual user needs (Vijayan et al. 2021).

At the same time, advancements in sensor technology are making wearables increasingly accurate and reliable. Modern devices incorporate multiple sensors to improve precision and minimize measurement errors, ensuring that users receive more consistent and actionable insights. These improvements are accompanied by innovations in miniaturization, which have led to the development of smart fabrics and embedded wearables. By integrating sensors directly into textiles or compact, flexible materials, wearables are becoming more comfortable, adaptable, and practical for everyday use (Amorim et al. 2020).

Beyond data collection, wearable technology incorporates various feedback mechanisms to improve communication, health monitoring, and user interaction. Haptic feedback, for instance, delivers non-visual alerts through vibrations or tactile sensations, allowing for hands-free interaction (Seneviratne et al. 2017).

Meanwhile, visual and auditory feedback are essential in wearable interfaces. For example, Google Glass provides real-time data visualization in medical environments, assisting surgeons with live sensor data. At the same time, some hearables offer auditory feedback on fitness metrics and enable hands-free control through head gestures (Seneviratne et al. 2017).

As wearable technology continues to evolve, the combination of advanced sensors, IoT connectivity, and interactive feedback systems are solidifying its role as a powerful tool for personal health management and professional medical applications.

2.1.4 The role of wearables in lifestyle and behavior

Wearable devices have become an integral part of daily life, passively tracking activities such as exercise, rest, and mood while providing real-time feedback that helps users adjust their behavior. Beyond simple tracking, they can shape behavior and promote forms of self-regulation within broader social and individual logics (Crawford et al. 2015).

Wearable computers were first designed to be less intrusive, allowing continuous data collection while users carry on with their routines and increasingly integrating into everyday life (Billinghurst and Starner 1999). To remain valuable in users' daily lives, wearables need to do more than gather data, offering functionalities that align with personal objectives.

(Adapa et al. 2018) identify fitness applications, design, and social influence as key drivers of adoption, linking these attributes to underlying values such as efficiency, image, and family. Despite their potential, continued adherence depends on practical factors that shape everyday usability. Although focused on healthcare systems, comfort, power consumption, and reliability are crucial for long-term use. When wearables integrate seamlessly into daily routines, require minimal effort, and deliver tangible benefits, they are more likely to become a lasting part of a user's lifestyle (Chan et al. 2012). However, biometric self-tracking can have unintended negative consequences. It can be beneficial, especially in medical contexts, where tracking leads to improved health outcomes, but when people use wearables or health apps compulsively, with an obsession for self-optimization, it can actually harm their mental health and quality of life. In such cases, self-tracking is no longer a choice but a compulsion, similar to an addiction. The term ″self-disimprovement″ is used to describe this paradox, when tools meant to improve health end up causing psychological strain or anxiety (Motyl 2020).

2.1.5 Wearables as Commitment Devices

Many healthy behaviors, such as exercising regularly, eating better, or quitting smoking, involve short-term costs in exchange for long-term benefits, which makes them easy to delay or avoid. In this sense, "health behaviors are plagued by commitment problems" because they require immediate effort or discomfort in pursuit of future gains (Derksen et al. 2024). To bridge the gap between intention and action, behavioral scientists advocate for precommitment strategies that help individuals follow through on the goals they set. A commitment device is any mechanism we voluntarily adopt in the present to restrict our future behavior and increase the likelihood of acting in line with our long-term interests (Holzwarth 2018).

As (Winter 2014) explains, “to precommit is to choose now to limit your options later, preventing yourself from making the wrong choice in the face of temptation.” For example, publicly declaring one’s goals is a common example of this approach.
Commitment devices differ from nudges, which subtly modify the choice environment to encourage better decisions while preserving freedom of choice. According to (Thaler and Sunstein 2008), a nudge is any feature of the choice architecture that predictably influences behavior without restricting options or significantly altering economic incentives. This type of intervention gently steers individuals toward better choices in a non-intrusive way, while remaining easy and inexpensive to avoid, thus guiding rather than coercing behavior.
Instead of changing the material costs and benefits associated with a decision, interventions of this kind typically restructure the decision-making context so as to psychologically bias individuals toward the option recommended by policymakers. Accordingly, nudges enroll interventions, such as reminders, cues highlighting social norms and values, and modifications to choice architecture (Cervantez and Milkman 2024).
A classic example of a simple nudge is placing fruit and healthy food at eye level in a cafeteria. It is intended to promote healthier choices, whereas banning junk food would not qualify because it entirely eliminates an option rather than subtly guiding behavior (Thaler and Sunstein 2008).
Another example is the "copy-paste prompt," a behavioral strategy developed by (Mehr et al. 2020), which encourages individuals to observe and adopt goal-achievement techniques from peers in their social network. Rather than relying on abstract or generalized advice, this approach encourages individuals to seek out specific, actionable strategies employed by those they know and trust.
In (Mehr et al. 2020) study on exercise habits, participants were asked to “pay attention to how people you know get themselves to [pursue the goal]” and to inquire about the motivational techniques their acquaintances used directly. For instance, they were instructed to identify “an effective hack or strategy that someone you know uses as motivation to exercise.” This method encourages personalized learning by encouraging individuals to adopt strategies that are not only tested but also socially and contextually relevant. By selecting and copying a peer’s strategy, participants gain a greater sense of autonomy, ownership, and confidence in their plan, which may enhance both motivation and follow-through.
In contrast, a commitment device typically introduces a concrete constraint or consequence that changes the stakes of inaction, such as financial penalties or enforced deadlines.

In practice, the distinction is not always clear, because many interventions might include both techniques. Booking a doctor's appointment, for instance, serves as a "soft commitment", it acts as both a nudge (via scheduling and reminders) and a plan that increases follow-through, even though there is no financial penalty for missing it (Derksen et al. 2024).
The effectiveness of commitment devices lies in their ability to harness prior motivation. By creating mechanisms that preserve this motivation when it inevitably declines, such devices increase consistency. Timely feedback and reinforcement are essential. If the consequences of failure are only felt long after the behavior, their influence may weaken. As (Rogers et al. 2014) note, dynamic and adaptive commitment tools, such as apps that provide weekly progress feedback or wearables that issue real-time reminders, are emerging to help individuals stay on track. These tools work best when they start with achievable goals that build confidence and gradually intensify, reinforcing engagement through both structure and responsiveness.
Additionally, research on the "Fresh Start Effect" by (Riis et al. 2014) highlights how strategically timed interventions can improve goal pursuit. The authors found that temporal landmarks, such as the start of a new week, month, or birthday, serve as psychological fresh starts that help individuals separate from their past failures and re-engage with their goals. This insight supports the idea that commitment devices and behavioral nudges can be even more effective when deployed around these fresh start moments, helping users feel renewed motivation and reinforcing their intention to stick to a plan or adopt new behaviors. Wearable devices can play a critical role in this context by providing real-time tracking, tailored reminders, and motivational prompts that align with these fresh start moments, reinforcing commitment and making goal pursuit more tangible and consistent.

2.2 Behavior Change Frameworks

Wearables are designed not only to collect data but to promote and support healthier routines through behavioral reinforcement. These devices come equipped with "built-in behavior change strategies that aim to actively trigger and motivate desired behaviors" (Lehrer et al. 2021). To understand their influence on daily habits and lifestyle choices, it is important to explore psychological mechanisms that explain how individuals adopt and sustain new behaviors. What follows is an overview of four theoretical behavior change models, a review of BCTs present in wearables, and its limitations, with attention to how theory and design intersect to shape real-world outcomes.

2.2.1 Theories of behavior change

This section focuses on four foundational frameworks: (1) the Health Belief Model (HBM), (2) the Feedback Loop Theory (FLT), (3) the Self-Determination Theory (SDT), and (4) the Technology Acceptance Model (TAM).

Key Theories of Change

Theory	Core Concept	Relevance to Wearables	Key References
Health Belief Model (HBM)	Health actions depend on perceived risk, belief in serious consequences, and perceived benefits outweighing barriers	Wearables can increase perceived health risk and benefits of activity by tracking health metrics	Champion & Skinner (2008)
Feedback Loop Theory (FLT)	Behavior is shaped through ongoing feedback cycles of measurement, comparison, & adjustment	Continuous, real-time feedback from wearables encourages habit formation by reinforcing actions	Rachmad (2024), DiClemente et al. (2001)
Self-Determination Theory (SDT)	Effective change depends on satisfying needs for autonomy, competence, & relatedness	Customization, goal setting, and social features in wearables support intrinsic motivation	Hagger et al. (2020) Kerner & Goodyear (2017)
Technology Acceptance Model (TAM)	Use depends on perceived usefulness & ease of use of the technology	Wearables gain adoption if perceived as easy to use and useful in daily life	Davis (1987), Marangunić & Granić (2015)

Figure 2. Key theories of change and their relevance to wearable devices (AI-generated illustration)

(1) *Health Belief Model:* The HBM suggests that individuals are more likely to engage in health-promoting behaviors when they perceive themselves to be at risk, believe the consequences are serious, and view the benefits of action as outweighing the barriers (Champion and Skinner 2008).

(2) *Feedback Loop Theory:* FLT highlights how behavior is shaped through continuous feedback cycles involving measurement, comparison, and adjustment. The core concept of this theory is that "feedback, when given consistently and timely, can create a continuous improvement cycle, allowing individuals and organizations to adapt and enhance their performance". Clear feedback based on accurate data is vital. Wearable devices master in this domain by delivering instant notifications and progress updates (Rachmad 2024). The effectiveness of such loops, however, depends on the personal relevance and timing of feedback.

When perceived as empowering, feedback can reinforce habits, but if experienced as controlling, it may reduce motivation (DiClemente et al. 2001).

(3) *Self-Determination Theory:* SDT emphasizes the importance of intrinsic motivation and the satisfaction of three psychological needs: autonomy, competence, and relatedness. The SDT model suggests that supporting autonomous self-regulation, rather than enforcing compliance, leads to more effective and ethical healthcare interventions. Health professionals can improve outcomes by promoting patients' psychological needs, helping them to become self-determined in managing their health (Hagger et al. 2020). It provides a useful lens to understand how wearable devices influence health-related behaviours. For example, wearable devices can support these needs by offering goal-setting flexibility, measurable progress, and social features like group challenges. However, wearables often rely on external motivators, such as: step goals and badges, streaks or reminders, or social comparison which might boost short-term engagement but may undermine long-term engagement (Kerner and Goodyear 2017).

(4) *Technology Acceptance Model:* The TAM has its roots in the social psychology of decision making, particularly Ajzen and Fishbein's Theory of Reasoned Action (TRA). Its strength lies in providing a simple yet powerful explanation: if users perceive a technology as useful and easy to use, they are likely to develop positive intentions and eventually use it. While ease of use matters (especially as a barrier to initial adoption), the ultimate driver is often whether the user believes the technology will improve performance or productivity (Davis 1987). Over time, TAM has been applied to an enormous variety of technologies and contexts. Originally developed for studying workplace information systems, TAM has since been used to examine user acceptance of e-learning platforms, healthcare systems (e.g., telemedicine, electronic health records), e-commerce and online banking services, mobile applications, social media, and even novel innovations like virtual reality. As society moves forward in the era of new technologies (AI, IoT, etc.), TAM and its descendant models continue to provide a "thesis-ready" theoretical grounding for understanding why people choose to adopt or resist new innovation (Marangunić and Granić 2015).

2.2.2 Behavior change techniques (BCTs) found in wearables

Wearable fitness devices have emerged as influential tools for promoting physical activity by incorporating BCTs grounded in behavioral science. Core techniques commonly embedded in commercial wearables include self-monitoring, goal setting, feedback on performance, prompts and cues, social comparison, and reward systems (Düking et al. 2020).

The same research conducted a content analysis of five high-end wrist-worn devices and found that the wearables Fitbit Versa and Garmin Vivoactive 3 included the largest number of effective BCTs, such as action planning, biofeedback, and social rewards, all linked to improved physical activity engagement.

However, the effectiveness of these techniques depends not only on their presence but also on how users interact with them. (Lehrer et al. 2021) identify four user engagement patterns, following, ignoring, combining, and self-leading, and argue that the most sustained behavior changes occurred when users combined the device's guidance with their own self-leadership strategies, such as setting personal goals and self-cueing. This interplay between IT-based leadership and user autonomy promotes internalized motivation, a key factor for long-term behavioral maintenance.

Additionally, recognizing which BCTs are especially effective in improving or regulating specific vital signs paves the way for more personalized and goal-oriented health interventions. This could improve health outcomes and support more efficient use of resources across healthcare and wellness initiatives (Del-Valle-Soto et al. 2024).

(Mercer et al. 2016) also emphasize that the presence of BCTs alone is insufficient, as their effectiveness depends on how users interact with them.

Users with lower digital or health literacy may not access all features, and those who are less intrinsically motivated may require more emotionally resonant interventions.

As such, the study recommends future collaboration between wearable developers and behavioral scientists to ensure that devices integrate a more comprehensive set of BCTs aligned with both user needs and evidence-based practice.

2.2.3 Limitations of behavior change techniques (BCTs) found in wearables

Wearable devices employ various BCTs to promote healthier habits, but research has identified several critical limitations that impede their long-term effectiveness. While wearable devices offer exciting opportunities to support healthier lifestyles, they also come with important limitations that can't be overlooked.

One growing concern is around data privacy and security. These devices collect a lot of personal and health information, and users are often unsure how their data is stored, used, or shared. Another major challenge is keeping people engaged over time. Many users start off motivated, but that interest often fades, leading to reduced use or complete abandonment of the device. Part of the problem is that the novelty wears off quickly, and many wearables aren't built to support long-term motivation or adapt to changing user needs (Del-Valle-Soto et al. 2024).

In addition, the devices themselves often have a short lifespan, whether due to battery issues, outdated software, or simply being replaced by newer models (Düking et al. 2020). Finally, while most wearables encourage physical activity, they don't always focus enough on reducing sedentary behavior, which is just as important for long-term health. To truly support lasting behavior change, wearables need to be more secure, more engaging, longer-lasting, and better aligned with how people live day to day (Düking et al. 2020).

2.3 Opportunities

Wearables have evolved from simple tracking tools to proactive systems that integrate deep learning and predictive analytics, shaping user habits over time (Karako 2024). Beyond individual health benefits, these devices also support social connections through gamification and collaborative challenges (Zhu et al. 2017). The following subsections examine how wearables contribute to well-being, personalized health interventions, and social engagement.

2.3.1 Health and fitness

Wearable technology can promote physical activity and support healthier behaviors when feedback is timely, clear, and action oriented (Hydari et al. 2022). Gamified features such as leaderboards and competition have been linked to higher motivation and sustained engagement. In a study of Fitbit users, adopting leaderboards increased daily steps by about 370 on average, with the largest gains among previously sedentary users (Hydari et al. 2022). Beyond promoting physical activity, wearables have also proven useful in detecting early signs of health conditions. By analysing physiological patterns, these devices can help identify potential indicators of arrhythmias, and even neurodegenerative diseases, allowing for timely interventions and personalized health management (Karako 2024).

Wearables have also been widely adopted in remote health monitoring, particularly for elderly individuals and those with chronic illnesses.

Their ability to collect and transmit health-related information in real time allows healthcare professionals and caregivers to track changes in a patient's condition, detect potential complications, and intervene when necessary (Lee et al. 2016).

2.3.2 Personalization and Data Analytics

Personalization in wearables relies on analytics that learn the individual baseline and its evolution over time. Wearables have progressively moved toward individualized services as device capabilities and data pipelines matured, which frames the current focus on tailoring outputs to the person rather than to population averages (Guk et al. 2019).
Rather than static insights, modern wearables adapt to changing routines and contexts, which requires a longer-term view of the user data lifecycle.
The convergence of wearable technologies and deep learning represents a transformative opportunity to advance health management and enable proactive disease prevention, delivering highly tailored health insights and interventions specific to each individual.
These advancements allow for improved accuracy in monitoring and diagnosis by analyzing unique patterns extracted from diverse sensor data, such as heart rate, activity levels, or sleep quality (Sabry et al. 2022). Also, linking wearable data with clinical records strengthens personalization by anchoring guidance in an individual clinical context over longer horizons (Karako 2024).
Technically, personalization depends on robust time series modeling and careful data stewardship. Deep learning can capture short and long range dependencies, but reliable personalization only emerges when signals are well calibrated, artifacts are controlled, and models are validated with rigor to avoid misleading interpretations. Privacy and security safeguards are also necessary given the sensitivity of continuous data streams and their tight link to smartphones and companion apps (Shajari et al. 2023). On this basis, it is increasingly imperative to establish robust privacy-preserving solutions and manage the trade-off between privacy and data utility, as machine learning-driven wearable technologies become deeply integrated in modern healthcare (Sabry et al. 2022).

2.3.3 Wearables and social connections

Wearable devices are transforming the way people engage with fitness by making social interaction a key motivator.

Features like social sharing and competition help users stay committed to their exercise routines, as they receive encouragement, support, and feedback from peers, reinforcing a sense of accountability and connection (Zhu et al. 2017). Beyond simply tracking steps or calories, these devices create opportunities for interaction, whether through face-to-face conversations, messaging apps, or social media. Leaderboards and real-time notifications further tap into the human drive for competition and achievement, making fitness a shared experience rather than a solitary effort (Kreitzberg et al. 2016).

Thus, a team of researchers applied the Theory of Planned Behavior to explore how social sharing and competition influence commitment to exercise (Zhu et al. 2017). Their research shows that these features do more than just track progress, they actively shape users intentions by encouraging positive attitudes toward physical activity, increasing social validation, and enhancing the sense of control over personal fitness goals.

For example, social influence plays a powerful role in structured environments like workplaces and family groups, where collective motivation can drive healthier behaviors. Recognizing this, many organisations have started integrating wearables into corporate wellness programs, using them to track employee activity and encourage participation in health initiatives (Zhu et al. 2017).

2.4 Challenges

The growing popularity of wearable devices has brought about substantial changes in health monitoring and consumer behavior. However, their widespread adoption and long-term effectiveness are accompanied by several important challenges that can limit their impact. Factors such as device abandonment, concerns around data privacy, technological limitations, and unequal access across populations all play a role in shaping user experience and outcomes. Understanding these barriers is essential for improving wearable design, ensuring ethical data practices, and promoting more inclusive health interventions. The following section explores these key challenges in greater detail, highlighting the need for thoughtful, user-centered solutions.

2.4.1 Wearable abandonment

Wearable abandonment is shaped by behavioral and psychological dynamics that influence how users interact with these technologies (Fadhil 2019a).

While initial enthusiasm is common, users frequently struggle to maintain long-term use, particularly when the effort involved in using the device outweighs the value it offers. Despite their initial appeal, maintaining user engagement with wearable health trackers remains a significant challenge. Although adoption rates are initially high, approximately 30% of users stop using their devices within the first six months. A key reason for this decline is the failure of wearables to meet user expectations, especially when the data provided are not perceived as useful, actionable or too generic (Fadhil 2019a). When a device does not align with an individual's personal goals or expected benefits fail to materialize, disappointment often arises, leading to disengagement over time (Lazar et al. 2015). In addition to motivational and perceptual barriers, abandonment is also driven by physical and functional limitations. Some users noted that the burden of keeping the device charged and operational undermined its perceived usefulness. Others found the data difficult to interpret, preferring clear and actionable summaries instead of raw information. A great number also mentioned that instead of keeping track of their historical data, they would prefer that these devices had more "personalized suggestions" and tailored to their routines and behaviors. This disconnection between what users need and what devices provide contributes significantly to the decision to abandon wearable technology (Lazar et al. 2015).

2.4.2 Data privacy and security

One of the key challenges brought by the rapid spread of wearable technologies is how they affect the privacy and security of personal data. As these devices become part of people's daily routines and health practices, the way they collect, store, and manage sensitive information needs careful attention.

As shown before, wearables gather health data continuously, often without users fully understanding what is being collected or what happens to that information. Many manufacturers include terms in their policies that give them the right to keep and use user data (Paul and Irvine 2014). In some cases, this includes the commercial use of health information or the retention of data even after the user leaves the service. These practices are often hidden in complex and unclear documents. At the same time, many users are not aware of the risks. It was found that a large part of users do not realise the importance of protecting their health data or the possibility of it being accessed without their knowledge. This lack of awareness puts them at greater risk of data breaches and misuse (Cilliers 2020). The way companies communicate their policies also affects user trust.

Privacy policies are often written in ways that are too general or too complex, making it difficult for users to understand what they are agreeing to. As a result, users may feel they are giving up control over their data rather than making informed choices (Banerjee et al. 2018). There are also technical problems. Several wearable systems still lack strong security features such as proper encryption or clear standards for protecting information. This leaves the systems open to cyberattacks and increases the risk that personal data may be exposed (Vijayan et al. 2021).

2.4.3 Technological barriers

Although wearable devices offer promising capabilities for health tracking and lifestyle management, their effectiveness is often hindered by technological limitations. One of the primary concerns is the reliability of sensor data, especially in uncontrolled environments. When users notice that their device is under- or over-counting steps, or giving implausible calorie burn estimates, they may lose confidence in the intervention. In addition, technical glitches, battery life constraints, and lack of integration with other systems all pose barriers (Del-Valle-Soto et al. 2024). These frequent device malfunctions and performance inconsistencies discourage long-term engagement.

Additionally, issues such as short battery life, poor interoperability with other digital platforms, and limited storage capacity pose significant usability challenges (Xue 2019). These challenges are further complicated by usability problems, including unintuitive interfaces and the need for frequent maintenance (Loncar-Turukalo et al. 2019).

When users lose confidence in a system, often due to challenges with proper device usage, their willingness to tolerate and continue using the technology tends to decline. It’s important that organizations create prototypes and assess them in authentic, daily environments. The development of intuitive and discreet wearable technologies was seen as key to promoting wider acceptance and integration into people's everyday routines (Chan et al. 2012).

2.4.4 Equity and accessibility

Equity and accessibility are critical factors yet often overlooked dimensions in the discourse surrounding wearable technologies. Studies have noted that factors like technological literacy, age, and socioeconomic background influence how well individuals adopt and respond to wearable interventions.

For example, older adults or underserved populations may find wearable interfaces confusing or may lack the smartphones and connectivity required, leading to lower engagement.

These literacy and usability issues contribute to disparities in outcomes. For example, if an intervention is too complex or intimidating, users may abandon it regardless of its potential benefits. To overcome this limitation, researchers stress the importance of inclusive design and education: interventions should be simple, accessible, and accompanied by guidance so that a broad range of users can understand and act on the feedback provided (Chan et al. 2012; Del-Valle-Soto et al. 2024).

It was also found that cost remains a primary barrier, limiting access for underserved populations (De Sario Velasquez et al. 2024). Furthermore, (Baumgart and Wiewiorra 2016) indicated that individuals with lower self-control or digital literacy are less likely to sustain wearable use, suggesting a cognitive component to accessibility. Moreover, most wearables are not tailored to accommodate a broad range of health needs or physical abilities, as highlighted by (Loncar-Turukalo et al. 2019). Bridging these gaps requires inclusive design, targeted education, and policy interventions that promote equitable access to wearable health technologies.

3 Methodology

3.1 Research Design Introduction

This section outlines the methodological framework adopted to address the research questions guiding this study. The overarching research question, "How do wearable devices influence consumer behavior in terms of motivation, habit formation, and lifestyle choices?", is addressed through two complementary approaches that correspond to two sub-research questions. To answer these questions, a two-phase research design was implemented. The approach was reflective and exploratory in nature, combining both qualitative insights and quantitative data to develop a comprehensive understanding of user behavior.

Phase One involved a literature review aimed at addressing RQ1: What theoretical frameworks explain how wearable devices promote behavioral change, and what are the key mechanisms through which these devices influence user behavior? This phase included the selection, collection, and thematic analysis of academic publications to identify key theoretical frameworks, behavior change models, and empirical findings related to wearable technology and its influence on consumer behavior.

Phase Two consisted of a survey targeting current users of wearable devices, designed to address RQ2: What are the actual experiences and perceptions of wearable device users regarding behavioral change, motivation, and autonomy in health decision-making? The goal was to gather direct insights into user experiences, motivations, and lifestyle changes influenced by the use of wearable devices. This phase covered a participant outreach approach and the descriptive and statistical analysis of collected responses.

Together, these two phases offer both theoretical and empirical foundations to address the central research question and support a well-rounded discussion in later chapters.

3.2 Phase One - Literature Review

The literature review served as the foundational step to address RQ1, establishing how wearable devices, particularly fitness trackers and smartwatches, interact with consumer behavior, with an emphasis on habit formation, motivation, and lifestyle change. To conduct this review, Google Scholar was used as the primary search engine. Given the rapidly evolving nature of the topic, particular attention was paid to the publication year and citation count of each source, ensuring both relevance and scholarly impact.

Several search queries were developed to align with the requirements of the academic databases used. The initial queries were broad, for example, "wearable devices," "wearables habit formation," or "behavior change frameworks." These were later refined into more targeted terms such as "wearables machine learning," "commitment devices," or "fresh start effect," to capture more specific themes relevant to the research objectives.

A total of 58 sources were initially collected. Following a more detailed evaluation, based on abstract relevance, citation count, and publication date, 10 were excluded. In particular, for studies related to wearable technologies, recent publications were prioritized due to the rapid evolution of these devices over the past decade. However, foundational theoretical works, such as (Davis 1987), were retained given their continued relevance as peer-reviewed conceptual frameworks. Additionally, upon the recommendation of the thesis advisor, particular attention was given to the work of Katy Milkman, Professor at The Wharton School of the University of Pennsylvania, whose research on behavior change significantly informed this study. The final selection consisted of 50 references, comprising academic articles and books or book chapters.

3.3 Phase Two - Wearable User Experience Survey

The primary objective of the survey was to address RQ2 by gathering empirical data on how users actually experience wearable technologies in their daily lives. While the literature review provided theoretical frameworks and evidence from prior studies, it was essential to collect first-hand insights to better understand how fitness trackers and smartwatches influence motivation, habit formation, and lifestyle choices among current users.

The design of the survey included both closed and open-ended questions, as well as ranking and rating exercises, allowing for a multi-dimensional view of user experience. Specifically, two of the survey questions were adapted directly from reviewed academic sources. Question 9 was inspired by (Peng et al. 2021), who investigated habit formation in wearable activity tracker use among older adults. Similarly, the answer scale for Question 14 was adapted from (Fadhil 2019b), whose research examined the various stages of wearable health tracking adoption and abandonment.

The remaining survey items were developed with the aim of capturing participants' subjective experiences with wearable devices and assessing whether these tools were contributing to the formation of healthier habits and lifestyle choices. The survey was distributed through multiple channels, including social media platforms, email outreach, and personal networks.

To specifically reach active wearable users, outreach efforts also included running and fitness communities on Instagram and Facebook. Particularly, two running-focused Instagram communities shared the survey with their audiences, contributing to the overall reach.

In total, 235 responses were collected. However, only 150 were considered valid for analysis, as Question 4 served as a screening question to ensure that participants were current users of wearable devices (e.g., fitness trackers or smartwatches). For a comprehensive view of the survey design and question structure, readers are referred to Appendix A, which contains the complete survey.

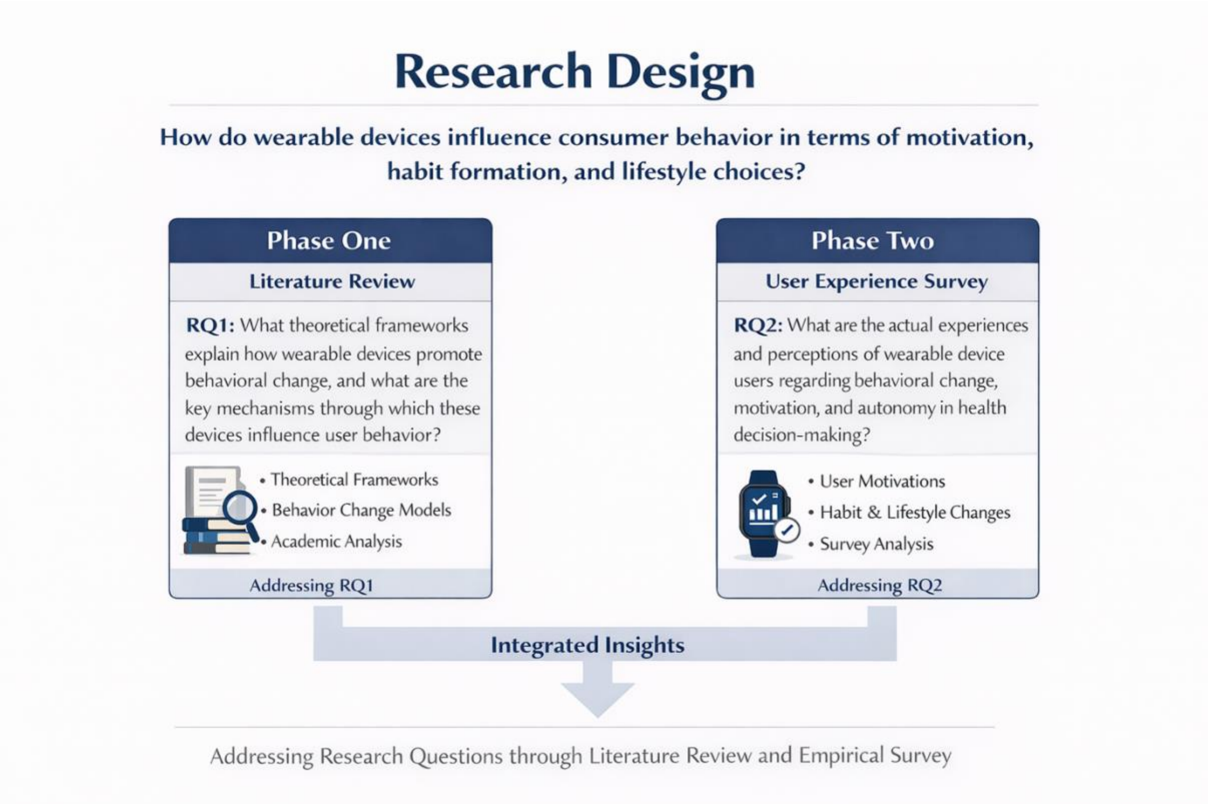

Figure 3. Research design and study phases (AI-generated illustration)

4 Analysis and Discussion

4.1 Introduction

This chapter presents the analysis and interpretation of findings from both phases of the study: the systematic literature review and the empirical survey conducted with wearable device users. The first three sections outline key insights related to wearable user experience, drawing from both academic sources and the survey responses. This is followed by a discussion section, which seeks to connect the survey results with the behavior change frameworks introduced earlier.
By integrating theoretical and empirical perspectives, this chapter aims to critically assess how wearable technologies influence consumer behavior, habit formation, and lifestyle choices within the surveyed sample.

4.2 Literature Review Analysis

Given the interdisciplinary nature of the topic, the review aimed to map key theoretical frameworks, alongside recent empirical studies on wearable adoption, BCTs, and digital health engagement. By curating both recent developments and enduring conceptual models, this review ensured the research was grounded in established behavioral science while remaining responsive to the rapid innovation of wearable technologies.
The reviewed literature spanned diverse yet interconnected domains: from user motivation and self-regulation (Mercer et al. 2016; Kerner and Goodyear 2017) to the physiological and technical capabilities of modern wearables (Cheng et al. 2021; Bello and Figetakis 2023). Studies on behavior change models provided a conceptual foundation for understanding how wearables can support habit formation and long-term health engagement (Lehrer et al. 2021; Del-Valle-Soto et al. 2024). Furthermore, the integration of nudges (Thaler and Sunstein 2008), commitment devices (Rogers et al. 2014; Derksen et al. 2024), and motivational boosts (Riis et al. 2014) demonstrated the variety of behavioral tools now embedded in digital self-tracking platforms.
At the same time, the review illuminated critical challenges. User abandonment, privacy concerns, and technical barriers remain recurring limitations (Fadhil 2019b; Xue 2019; Cilliers 2020), pointing to a need for more user-centered and adaptive designs.
The literature also pointed to disparities in digital access and engagement based on age, socioeconomic status, and digital literacy, raising questions about inclusivity and long-term impact (Chan et al. 2012; De Sario Velasquez et al. 2024).

Altogether, the literature review established both the promise and limitations of wearable technologies, informing the structure of the survey that followed and helping shape the conceptual lens through which the empirical findings are analyzed in this chapter.

4.3 Survey Analysis

The survey allowed for the exploration of users perceived benefits, patterns of engagement, behavioral shifts, and possible barriers to sustained use. By designing questions that reflected both theoretical constructs and real-world scenarios, the instrument was intended to bridge the gap between academic theory and user experience. This approach also enabled the researcher to identify whether the behavioral mechanisms highlighted in the literature such as goal reinforcement, self-monitoring, and commitment were reflected in the actual experiences of participants. The demographic distribution of the sample was relatively balanced, with the majority falling within the 25–34 age range and an even split between genders. Most participants identified as working professionals and reported long-term use of their devices (over one year), suggesting a degree of technological familiarity and routine integration. The dataset captured not only self-reported changes in health behaviors, such as increased exercise, goal tracking, and sleep monitoring, but also nuanced user sentiments about motivation, ease of use, and device effectiveness. Importantly, the survey also explored barriers to engagement, the emotional relationship with the device, and whether wearables are perceived as commitment tools or behavior enforcers.

Together, these insights lay the foundation for the next section, which presents more detailed findings on wearable user experience, including selected survey tables that are most relevant to the key results, and interprets these findings considering the behavioral theories reviewed earlier.

4.3.1 Findings on Wearable User Experience

Participant Demographics and Wearable Usage

As previously mentioned, the survey received a total of 235 responses. However, only 150 were considered valid for analysis, as they were completed by individuals who identified as current users of wearable devices (e.g., fitness trackers or smartwatches).

Among these 150 participants, three age groups were most prominent, particularly those between 18 and 44 years old. The largest segment by far was the 25–34 age group, comprising 62 participants and representing 41.3% of the sample.

Gender distribution was relatively balanced: 81 participants identified as male (54%), 68 as female (45.3%), and one participant identified as non-binary. In terms of occupation, most participants were working professionals, accounting for 125 participants (83.3%), which aligns with the age distribution observed earlier.

This alignment between the age distribution and occupational status suggests that wearables have found their primary market among individuals who are established in their careers and likely possess both the disposable income and the health awareness that accompanies professional life.

Table 1. Descriptive characteristics of survey participants (n = 150).

Variable	***n***	**%**
Age Groups (years)		
Under 18	1	0.7
18 – 24	28	18.7
25 – 34	62	41.3
35 – 44	31	20.7
45 – 54	14	9.3
55 – 64	11	7.3
65 +	3	2.0
Sex		
Male	81	54.0
Female	68	45.3
Non-binary	1	0.7

Occupation		
Working Professional	125	83.3
Student	20	13.3
Retired	3	2.0
Unemployed	1	0.7
Pre-Retired	1	0.7

Regarding the type of wearable devices in use, the most commonly reported was the Apple Watch, used by 62 participants (41.3%). Garmin followed as the second most popular brand, with 35 participants (23.3%). Among the remaining responses, no other device brand emerged as significantly represented. This distribution reflects broader consumer electronics trends while also hinting at different user priorities. Apple Watch users may prioritize integration with existing ecosystems and lifestyle features, while Garmin users may lean toward specialized fitness and athletic performance tracking.

Table 2. Types of wearable devices used by survey participants (n = 150).

Device type	***n***	**%**
Apple Watch	62	41.3
Garmin	35	23.3
Other	24	16.0
Xiaomi Mi Band	15	10.0
Samsung Galaxy Watch	9	6.0
Fitbit	5	3.3

Note. "Other" includes less frequently reported wearable devices.

In terms of duration of use, 100 out of the 150 participants (66.7%) indicated that they had been using their wearable device for more than one year, suggesting a strong prevalence of long-term engagement among the sample.

Regarding feature utilization, workout tracking emerged as the most prioritized function (104 participants), followed closely by heart rate monitoring (91), step counting (80), notifications (79), and sleep tracking (78).

This hierarchy reveals that participants primarily engage with health and fitness metrics rather than smart features, positioning wearables more as health tools than general-purpose computing devices worn on the wrist.

Table 3. Wearable features most frequently used by survey participants.

Wearable features	***n***	**%**
Workout tracking	104	69.3
Heart Rate Monitoring	91	60.7
Step counting	80	53.3
Notifications	79	52.7
Sleep Tracking	78	52.0
Calorie Tracking	43	28.7
GPS/location tracking	30	20.0
Stress or mindfulness features	22	14.7
Other	3	2

Note. Participants could select multiple features. Percentages are calculated based on the total number of participants (n = 150) and therefore do not sum to 100%.

Behavioral Impact of Wearables

The data indicate that behavioral change associated with wearable use is gradual rather than transformational. Nearly half of participants (49.3%) reported "some small changes" in their habits, while 26.7% observed "significant changes," and 22.7% noted no major differences. This distribution suggests that wearables serve more effectively its users for incremental lifestyle adjustments rather than for initiating radical shifts.

The most frequently reported behavioral change was increased awareness of daily routines (68 participants), positioning self-awareness as a key psychological outcome.

This was followed by tangible changes in behavior: 66 participants reported exercising more regularly, 58 became more attentive to sleep, 54 increased their daily walking, and 52 tracked personal goals more consistently.

Specifically, these behavior shifts align closely with the most-used features, suggesting a clear link between device engagement and health-related action.

Primary motivations for wearable use included improving physical activity (83 participants), tracking specific health metrics (78), and curiosity or technological interest (68). Additionally, 43 participants highlighted motivation or accountability as key reasons for continued use.

Motivation and Engagement

The motivational profile suggests that wearables successfully promote positive reinforcement patterns. Half of all participants reported feeling "somewhat motivated," and 28.7% felt "very motivated." Only 20% indicated neutral feelings, suggesting that most users experience at least moderate motivational benefits.

When ranking motivators, "track progress" emerged as the top reason, followed by "feel healthier," "compete with others," "avoid feeling guilty," and "earn rewards/badges." This hierarchy underscores those intrinsic motivations such as self-improvement and well-being, outweigh extrinsic elements like gamification.

Emotionally, 42% of participants reported feeling "more motivated," while 32.7% felt "more confident" about their health. Fewer than one in five reported no emotional change. Device influence was further reinforced by strong ratings: "My wearable helps me set achievable goals" received a 4.18/5 average, while "I feel more aware of my health behaviors" rated highest at 4.25/5. However, responses to "I have developed healthier habits due to my device" (3.64/5) and "I would maintain these behaviors even without the device" (3.63/5) point to lingering uncertainty around habit autonomy.

On the question of sustained use, 67.3% of participants had never stopped using their device, while 32% reported temporary pauses, typically due to vacations, charging issues, or accessory changes. Most of those who discontinued ultimately resumed usage, suggesting a strong underlying motivation.

Wearables as Commitment Devices

The concept of wearables functioning as commitment devices was affirmed by a large proportion of participants.

When asked directly, 38.7% said "yes, definitely," and 42.7% responded “to some extent”, a combined 81.4% acknowledging at least partial commitment-related influence. Only 18.7% rejected this characterization.

Table 4. Perception of wearable devices as commitment tools (n = 150).

Level of agreement	***n***	**%**
To some extent	64	42.7
Yes, definitely	58	38.7
Not really	28	18.7
Not sure what that means	0	0.0

Responses regarding pressure to meet goals further validate this pattern. While 40.7% reported feeling such pressure “occasionally,” 24.7% said “rarely,” 20.7% “often,” and 14% “never.” The average agreement with the statement “I feel pressure to meet my wearable’s targets” was 3.06/5. Nearly half (48.7%) acknowledged having changed their behavior (e.g., walking more, skipping rest) to meet a device-generated goal, an important indicator of behavioral influence. Importantly, most participants (51.3%) said they do not find wearable tracking to be “too controlling or compulsive,” although 46.7% expressed interest in features supporting rest or time away from tracking. This balance suggests that users value accountability but recognize the importance of flexibility.

Table 5. Perceived value of wearables in supporting balance and recovery (n = 150).

Level of agreement	***n***	**%**
Yes, that would help	70	46.7
Maybe	46	30.7
No, I like it	34	22.7

A majority (72.7%) stated their intention to continue long-term use because "it helps me stay committed," with another 20% remaining open to continuation. Just 2% deemed the devices not useful, indicating a strong retention base.

Table 6. Participants' intention to continue wearable device use (n = 150).

Intended use	***n***	**%**
Yes, it helps me stay committed	109	72.7
Maybe, if I can stay motivated	30	20.0
Not sure yet	8	5.3
No, I don't find it useful	3	2.0

User Experience & Data Utility

Usability proved excellent: 74.7% found their device "extremely easy" to use and 20% said "somewhat easy", meaning 94.7% found wearables accessible and user-friendly. Data utility was similarly high: 50% rated it "very helpful" and 46% "somewhat helpful" (96% total). Feature ranking by usefulness matched usage patterns: workout logging, step counting, heart rate monitoring, sleep tracking, and notifications. This consistency reinforces that users primarily value wearables as health tools.

However, improvement areas emerged in four themes: battery life, data accuracy, bulky design, and AI integration. Battery life was the most common complaint. As one Apple Watch user stated: "Battery life should be better. For example, I don't have any data on my sleep because I need to leave it charging overnight."

Participants also expressed interest in advanced features: automated workout advice, nutritional guidance ("calories that I need to consume"), and additional metrics like glucose monitoring. These requests suggest readiness for wearables to evolve from passive data collectors to proactive health coaches.

Autonomy and Control in Health Decision-Making

The survey examined whether devices empower users or assume control. Results show hybrid agency: 50.7% selected "a mix of both," 32% "mostly self-guided," and only 6.7% "mostly guided by the device."

This suggests wearables function as decision-support tools rather than decision-making authorities. Checking behaviors varied: 42.7% checked at regular times, 41.3% randomly, and 16% had no routine. These results suggest that many users engage habitually, integrating wearables into their daily health routines.

A subtle tension is evident: although most participants do not report feeling controlled, 48.7% acknowledged modifying behavior to meet device goals.

This suggests participants distinguish between being "guided by" (passive) and "motivated by" (active choice with prompting) their device. The moderate rating (3.63/5) for "I would maintain these behaviors even without the device" suggests ambivalence. Participants aren't confident changes are fully autonomous but don't believe they're entirely dependent either.

While 15.3% reported tracking has become "too controlling or compulsive," the strong intention to continue (72.7% plan long-term use) suggests participants view the device's influence as beneficial rather than restrictive. Participants feel supported and accountable rather than surveilled and constrained.

The data shows that participants are not fully controlled by their devices, nor are they completely independent. Instead, most people find a practical balance, using wearables to stay motivated and aware of their habits, while still feeling free to ignore the device when they choose.

4.3.2 Spearman Correlation Analysis and Results

To examine relationships between key variables beyond descriptive patterns, Spearman's rank correlation tests were conducted. This non-parametric test was selected as appropriate for ordinal data and does not require normal distribution assumptions. Three correlations were analyzed to test theoretical propositions regarding wearable device usage and behavioral outcomes, providing insights into how wearables may influence behavior over time. For the analysis of perceived autonomy and behavioral internalization, participants who selected “not sure” regarding their sense of control ($n = 16$) were excluded, resulting in a sample of 134. Similarly, for the motivation and intention to continue analysis, “not sure yet” responses ($n = 8$) were excluded, yielding a sample of 142. The behavioral internalization variable, originally measured on a 5-point Likert scale, was condensed into three categories (disagree, neutral, agree) to facilitate correlation analysis. Statistical significance was evaluated at $p < .05$.

Table 7. Correlation coefficients and p-values for the three tested relationships.

Variables	***n***	**rs**	**p-value**
Duration of use × Habit change magnitude	150	0.01	0.919
Motivation level × Intention to continue	142	0.21	0.014
Perceived autonomy × Behavioral	134	0.17	0.044

Note. $p < .05$.
Correlation strength interpretation: 0.10-0.30 (weak), 0.30-0.50 (moderate), ≥ 0.50 (strong).

Duration of Use and Habit Change Magnitude

The analysis revealed no significant relationship between duration of device use and the magnitude of reported habit changes ($rs = 0.01$, $p = 0.919$). This finding indicates that wearing a device for a longer period does not correlate with experiencing more significant behavioral modifications. Participants who have worn their devices for less than six months report similar levels of habit change as those who have used them for over a year. This challenges the assumption that longer exposure to wearable feedback automatically leads to progressively larger behavioral transformations. Instead, the data suggest that the incremental changes participants experience tend to stabilize rather than compound over time.

Motivation Level and Intention to Continue

A weak but statistically significant positive correlation was found between motivation level and intention to continue long-term use ($rs = 0.21$, $p = 0.014$). Participants who reported feeling more motivated by their wearable device were more likely to express commitment to continued usage. This relationship, while modest in strength, provides empirical support for the importance of intrinsic motivation in sustaining device engagement. Participants who feel "very motivated" show stronger intention to maintain their wearable use compared to those who feel only "somewhat motivated" or "neither motivated nor unmotivated." This finding validates Self-Determination Theory's proposition that genuine motivation, rather than external pressure or obligation, drives sustained behavior change efforts.

Perceived Autonomy and Behavioral Internalization

A weak positive correlation emerged between perceived autonomy in health decisions and behavioral internalization ($rs = 0.17$, $p = 0.044$).

Participants who reported feeling more self-guided in their health decisions showed greater confidence that they would maintain their healthy behaviors even without the device. Consequently, those who felt more guided by the device expressed less certainty about behavioral independence. While the correlation is modest and the p-value approaches the significance threshold, this relationship suggests that preserving user agency may contribute to more autonomous habit formation. Participants who experience their wearable as a supportive tool rather than a directive authority appear more likely to internalize the behaviors they have developed.

4.4 Discussion

This section connects the empirical findings from the survey with the theoretical frameworks reviewed in Chapter 2, focusing on how user experiences align with or diverge from established behavior change models.

4.4.1 Behavioral Change: From Theory to Practice

The survey findings reveal that wearable devices primarily facilitate gradual rather than transformational behavioral change. This pattern aligns with behavior change literature suggesting that sustained habit formation occurs through incremental adjustments (Lehrer et al. 2021).

The most commonly reported change was increased awareness of daily routines, which supports Feedback Loop Theory's emphasis on continuous cycles of measurement, comparison, and adjustment (DiClemente et al. 2001). Wearables exceed at making invisible behaviors visible through instant notifications and progress updates.

The alignment between most-used features (workout tracking, heart rate monitoring, step counting) and reported behavioral changes (exercising more, walking more, tracking goals) demonstrates the clear pathway from feature engagement to action described by (Mercer et al. 2016).

4.4.2 Motivation: Intrinsic Over Extrinsic

The survey revealed that intrinsic motivations significantly outweigh extrinsic motivators. "Track progress" and "feel healthier" ranked as top motivators, while "compete with others" and "earn rewards/badges" scored lower.

This finding directly supports Self-Determination Theory, which emphasizes that autonomous self-regulation leads to more effective and sustainable behavior change (Hagger et al. 2020).
The relatively low ranking of gamification elements validates concerns raised by (Kerner and Goodyear 2017) that external motivators like badges and social comparisons may undermine intrinsic motivation. Participants appear more interested in genuine health outcomes than artificial rewards, indicating a potential misalignment between some design features and user needs.
The high average ratings for "My wearable helps me set achievable goals" and "I feel more aware of my health behaviors" indicate that wearables successfully support perceived competence, one of the three psychological needs identified in Self-Determination Theory. However, moderate average ratings for "I have developed healthier habits due to my device" and "I would maintain these behaviors even without the device" reveal uncertainty about whether behaviors have been fully internalized. This suggests wearables may be effective at initiating behaviors but less successful at cultivating true habit autonomy.

4.4.3 Wearables as Commitment Devices

The finding that 81.4% of participants recognize at least some commitment function provides strong empirical validation for the theoretical proposition that wearables help users follow through on their intentions (Rogers et al. 2014; Derksen et al. 2024). Nearly half of participants admitted to changing behavior specifically to meet device goals, demonstrating tangible influence on daily decision-making.
However, an important distinction emerges, while commitment devices typically involve concrete constraints like financial penalties, wearables operate through softer mechanisms like visual feedback and notifications. The moderate pressure rating (3.06/5) and the fact that 51.3% do not find tracking "too controlling" suggest wearables function as "soft commitment devices" that increase follow-through without harsh penalties.
The user desire for features promoting rest and recovery highlights a limitation in current design. Most behavior change techniques in wearables focus on activity promotion rather than balance (Düking et al. 2020), suggesting an opportunity to incorporate more holistic health support.

4.4.4 Technology Acceptance and Usability

The exceptionally high usability and data utility ratings strongly support the Technology Acceptance Model, which posits that perceived usefulness and ease of use drive adoption and continued use (Davis 1987; Marangunić and Granić 2015). The high retention rate and strong continuation intention further validate these predictions.

However, the four primary improvement themes, battery life, data accuracy, bulky design, and AI integration, align with technological barriers identified in the literature (Xue 2019; Del-Valle-Soto et al. 2024).

The numerous remarks from participants illustrate how practical limitations directly undermine core use cases, consistent with (Lazar et al. 2015) findings on abandonment factors.

User interest in advanced features like automated workout advice and nutritional guidance reflects readiness for wearables to evolve from passive data collectors to proactive health coaches, aligning with recent literature on personalization and AI integration (Sabry et al. 2022; Karako 2024).

4.4.5 Autonomy and User Agency

The finding that half of the participants experience "a mix of both" self-guidance and device guidance, with only 6.7% feeling "mostly guided by the device," suggests wearables function primarily as decision-support tools rather than decision-making authorities. This provides empirical grounding for Self-Determination Theory's emphasis on autonomous self-regulation (Hagger et al. 2020).

The apparent contradiction, where 48.7% change behavior to meet device goals yet most don't report feeling controlled, suggests participants distinguish between being "guided by" (passive) and "motivated by" (active choice with prompting) their device. This aligns with (Lehrer et al. 2021) finding that sustained changes occur through combining device guidance with user self-leadership.

The moderate rating (3.63/5) for maintaining behaviors without the device reflects realistic uncertainty about behavioral internalization. This may not be problematic, as behaviors often require ongoing environmental support, and wearables may function as part of the extended self rather than external controllers (Crawford et al. 2015).

4.4.6 Key Divergences from Literature

Several important gaps emerge between survey findings and literature expectations. First, social features matter less than some studies suggest (Zhu et al. 2017; Hydari et al. 2022). Social comparison ranked lower than intrinsic motivators, possibly because everyday consumer use differs from structured research interventions where social features are actively promoted. Second, privacy concerns, extensively discussed in literature (Banerjee et al. 2018; Cilliers 2020), did not emerge prominently in user feedback. This may indicate that current participants represent a self-selected group less concerned about privacy, or that concerns remain latent until breaches occur. This gap highlights the need for better communication about data practices. Third, the survey's demographic homogeneity (working professionals aged 25-44) underscores accessibility concerns raised in literature about equity and digital literacy barriers (Chan et al. 2012; Del-Valle-Soto et al. 2024). The sample captures "successes" but says little about those who cannot access or choose not to adopt these technologies.

5 Conclusion

5.1 Conclusion

This thesis provides both theoretical grounding and practical insights into the evolving relationship between users and their wearables.

The literature review highlighted several key theoretical frameworks relevant to understanding wearable use and BCTs. Wearables were shown to act as behavior change facilitators by offering goal setting, self-monitoring, and immediate feedback, thereby reinforcing positive habits. Theories of commitment devices and feedback loops further emphasized wearables' potential to increase accountability and sustain user engagement, while also revealing the risks of over-reliance or behavioral rigidity.

The user survey supported and extended these findings. While most users reported only gradual behavioral shifts rather than dramatic lifestyle changes, the cumulative evidence indicated meaningful improvements in health awareness, physical activity, and goal tracking. Wearables were found to be particularly effective in promoting motivation through personalized feedback, goal achievement visualization, and daily engagement prompts. The majority of participants perceived their devices as useful and easy to use, affirming TAM's core propositions.

Importantly, the survey also revealed that participants navigate a balance between autonomy and external influence. Most participants felt empowered by their devices, using them as tools for reflection and action rather than feeling overly controlled. However, some reported experiences of pressure, anxiety, or compulsive behaviors, highlighting the need for design strategies that support user autonomy and emotional well-being.

Perhaps one of the most significant findings is the widespread perception of wearables as informal commitment devices. By acting as persistent reminders of personal goals, they help users stay accountable and reinforce identity-related behaviors. This insight confirms the utility of viewing wearables not only as data collectors or health monitors, but as behavioral frameworks that support self-regulation and long-term habit development.

In sum, this thesis concludes that while wearables are not magic solutions for behavior change, they offer meaningful support structures that, when aligned with users' psychological needs and preferences, can facilitate healthier lifestyles. The challenge moving forward lies in maximizing their potential for sustained impact, while minimizing risks of dependence or disengagement. Wearables must be designed not simply to prompt more activity, but to boost motivation, autonomy, and ultimately, behavioral resilience.

5.2 Limitations

This study has important limitations related to both the literature review and empirical research. The literature review, while comprehensive in scope with 50 sources, relied primarily on Google Scholar as the search engine and may have missed relevant studies in specialized databases. The rapidly evolving nature of wearable technology means that some sources, particularly technical specifications and market data, may have become outdated during the research period. Additionally, the interdisciplinary nature of the topic meant that certain areas, such as clinical applications of wearables or detailed hardware engineering, received less attention in favor of consumer behavior and psychological frameworks.

Regarding the empirical research, the sample was demographically homogeneous, primarily working professionals aged 25-44, limiting generalizability to other age groups and socioeconomic backgrounds.

As a self-selected group of successful adopters, the sample cannot address experiences of those who abandoned devices or never adopted them, particularly regarding equity and accessibility barriers.

The cross-sectional design captures a single moment rather than tracking how user-device relationships evolve over time. Questions about habit internalization and long-term behavioral sustainability require longitudinal investigation. Additionally, while open-ended questions provided some qualitative insights, in-depth interviews or ethnographic observation could reveal richer understanding of daily practices and social contexts shaping wearable use.

5.3 Future research

Future research should prioritize these directions. First, diverse populations must be studied, particularly underrepresented groups facing technological or economic barriers. Second, longitudinal studies should examine whether gradual changes accumulate into meaningful long-term health outcomes or plateau over time. Third, as wearables incorporate AI and predictive analytics, research must investigate how these advancements affect user trust, autonomy, and the boundary between helpful guidance and algorithmic control.

Understanding how to design wearable technologies that are simultaneously sophisticated, supportive, practical, and accessible across diverse populations remains the critical challenge for researchers, designers, and policymakers working to realize the full potential of these devices in promoting healthier lifestyles.

References

Adapa, Apurva, Fiona Fui-Hoon Nah, Richard H. Hall, Keng Siau, and Samuel N. Smith. 2018. "Factors Influencing the Adoption of Smart Wearable Devices." *International Journal of Human–Computer Interaction* 34 (5): 399–409. https://doi.org/10.1080/10447318.2017.1357902.

Amorim, Vicente J. P., Ricardo A. O. Oliveira, and Mauricio Jose da Silva. 2020. "Recent Trends in Wearable Computing Research: A Systematic Review." arXiv:2011.13801. Preprint, arXiv, November 27. https://doi.org/10.48550/arXiv.2011.13801.

Banerjee, Syagnik (Sy), Thomas Hemphill, and Phil Longstreet. 2018. "Wearable Devices and Healthcare: Data Sharing and Privacy." *The Information Society* 34 (1): 49–57. https://doi.org/10.1080/01972243.2017.1391912.

Baumgart, Ruth, and Lukas Wiewiorra. 2016. *The Role of Self-Control in Self-Tracking*.

Bello, Yahuza, and Emanuel Figetakis. 2023. "IoT-Based Wearables: A Comprehensive Survey." arXiv:2304.09861. Preprint, arXiv, April 12. https://doi.org/10.48550/arXiv.2304.09861.

Billinghurst, Mark, and Thad Starner. 1999. *Wearable Devices: New Ways to Manage Information*.

Cervantez, Jose A., and Katherine L. Milkman. 2024. "Can Nudges Be Leveraged to Enhance Diversity in Organizations? A Systematic Review." *Current Opinion in Psychology* 60 (December): 101874. https://doi.org/10.1016/j.copsyc.2024.101874.

Champion, Victoria L., and Celette Skinner. 2008. "The Health Belief Model." In *Health Behavior and Health Education: Theory, Research, and Practice*, 4th ed. Jossey-Bass.

Chan, Marie, Daniel Estève, Jean-Yves Fourniols, Christophe Escriba, and Eric Campo. 2012. "Smart Wearable Systems: Current Status and Future Challenges." *Artificial Intelligence in Medicine* 56 (3): 137–56. https://doi.org/10.1016/j.artmed.2012.09.003.

Cheng, Yuemeng, Kan Wang, Hao Xu, Tangan Li, Qinghui Jin, and Daxiang Cui. 2021. "Recent Developments in Sensors for Wearable Device Applications." *Analytical and Bioanalytical Chemistry* 413 (24): 6037–57. https://doi.org/10.1007/s00216-021-03602-2.

ÇiÇek, Mesut. 2015. *WEARABLE TECHNOLOGIES AND ITS FUTURE APPLICATIONS*. 3 (4).

Cilliers, Liezel. 2020. "Wearable Devices in Healthcare: Privacy and Information Security Issues." *Health Information Management Journal* 49 (2–3): 150–56. https://doi.org/10.1177/1833358319851684.

Crawford, Kate, Jessa Lingel, and Tero Karppi. 2015. "Our Metrics, Ourselves: A Hundred Years of Self-Tracking from the Weight Scale to the Wrist Wearable Device." *European Journal of Cultural Studies* 18 (4–5): 479–96. https://doi.org/10.1177/1367549415584857.

Davis, Fred. 1987. *User Acceptance of Information Systems. The Technology Acceptance Model (TAM)*. No. 529. University of Michigan School of Business Administration.

De Sario Velasquez, Gioacchino D., Sahar Borna, Michael J. Maniaci, et al. 2024. "Economic Perspective of the Use of Wearables in Health Care: A Systematic Review." *Mayo Clinic Proceedings: Digital Health* 2 (3): 299–317. https://doi.org/10.1016/j.mcpdig.2024.05.003.

Del-Valle-Soto, Carolina, Juan Carlos López-Pimentel, Javier Vázquez-Castillo, et al. 2024. "A Comprehensive Review of Behavior Change Techniques in Wearables and IoT: Implications for Health and Well-Being." *Sensors* 24 (8): 2429. https://doi.org/10.3390/s24082429.

Derksen, Laura, Jason T Kerwin, Natalia Ordaz Reynoso, and Olivier Sterck. 2024. "Healthcare Appointments as Commitment Devices." *The Economic Journal* 135 (665): 81–118. https://doi.org/10.1093/ej/ueae077.

DiClemente, Carlo C., Angela S. Marinilli, Manu Singh, and Lori E. Bellino. 2001. "The Role of Feedback in the Process of Health Behavior Change." *American Journal of Health Behavior* 25 (3): 217–27. https://doi.org/10.5993/AJHB.25.3.8.

Düking, Peter, Marie Tafler, Birgit Wallmann-Sperlich, Billy Sperlich, and Sonja Kleih. 2020. "Behavior Change Techniques in Wrist-Worn Wearables to Promote Physical Activity: Content Analysis." *JMIR mHealth and uHealth* 8 (11): e20820. https://doi.org/10.2196/20820.

Fadhil, Ahmed. 2019a. *Beyond Technical Motives: Perceived User Behavior in Abandoning Wearable Health & Wellness Trackers*.

Fadhil, Ahmed. 2019b. *Different Stages of Wearable Health Tracking Adoption & Abandonment: A Survey Study and Analysis*.

Guk, Kyeonghye, Gaon Han, Jaewoo Lim, et al. 2019. "Evolution of Wearable Devices with Real-Time Disease Monitoring for Personalized Healthcare." *Nanomaterials* 9 (6): 813. https://doi.org/10.3390/nano9060813.

Hagger, Martin S., Nelli Hankonen, Nikos L. D. Chatzisarantis, and Richard M. Ryan. 2020. "Changing Behavior Using Self-Determination Theory." In *The Handbook of Behavior Change*, 1st ed., edited by Martin S. Hagger, Linda D. Cameron, Kyra Hamilton, Nelli Hankonen, and Taru Lintunen. Cambridge University Press. https://doi.org/10.1017/9781108677318.008.

Holzwarth, Aline. 2018. "The Power of Precommitment." *Center for Advanced Hindsight — Blog*, October 10. https://advanced-hindsight.com/blog/the-power-of-precommitment/.

Hydari, Muhammad Zia, Idris Adjerid, and Aaron D. Striegel. 2022. "Health Wearables, Gamification, and Healthful Activity." *Management Science* 69 (7): 3920–38. https://doi.org/10.1287/mnsc.2022.4581.

Karako, Kenji. 2024. "Integration of Wearable Devices and Deep Learning: New Possibilities for Health Management and Disease Prevention." *BioScience Trends* 18 (3): 201–5. https://doi.org/10.5582/bst.2024.01170.

Kerner, Charlotte, and Victoria A. Goodyear. 2017. “The Motivational Impact of Wearable Healthy Lifestyle Technologies: A Self-Determination Perspective on Fitbits With Adolescents.” *American Journal of Health Education* 48 (5): 287–97. https://doi.org/10.1080/19325037.2017.1343161.

Kreitzberg, Daniel St. Clair, Stephanie L. Dailey, Teresa M. Vogt, Donald Robinson, and Yaguang Zhu. 2016. “What Is Your Fitness Tracker Communicating?: Exploring Messages and Effects of Wearable Fitness Devices.” *Qualitative Research Reports in Communication* 17 (1): 93–101. https://doi.org/10.1080/17459435.2016.1220418.

Lazar, Amanda, Christian Koehler, Theresa Jean Tanenbaum, and David H. Nguyen. 2015. “Why We Use and Abandon Smart Devices.” *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, September 7, 635–46. https://doi.org/10.1145/2750858.2804288.

Lee, Jaewoon, Dongho Kim, Han-Young Ryoo, and Byeong-Seok Shin. 2016. “Sustainable Wearables: Wearable Technology for Enhancing the Quality of Human Life.” *Sustainability* 8 (5): 466. https://doi.org/10.3390/su8050466.

Lehrer, Christiane, U. Yeliz Eseryel, Annamina Rieder, and Reinhard Jung. 2021. “Behavior Change through Wearables: The Interplay between Self-Leadership and IT-Based Leadership.” *Electronic Markets* 31 (4): 747–64. https://doi.org/10.1007/s12525-021-00474-3.

Loncar-Turukalo, Tatjana, Eftim Zdravevski, José Machado Da Silva, Ioanna Chouvarda, and Vladimir Trajkovik. 2019. “Literature on Wearable Technology for Connected Health: Scoping Review of Research Trends, Advances, and Barriers.” *Journal of Medical Internet Research* 21 (9): e14017. https://doi.org/10.2196/14017.

Marangunić, Nikola, and Andrina Granić. 2015. “Technology Acceptance Model: A Literature Review from 1986 to 2013.” *Universal Access in the Information Society* 14 (1): 81–95. https://doi.org/10.1007/s10209-014-0348-1.

Mehr, Katie S., Amanda E. Geiser, Katherine L. Milkman, and Angela L. Duckworth. 2020. “Copy-Paste Prompts: A New Nudge to Promote Goal Achievement.” *Journal of the Association for Consumer Research* 5 (3): 329–34. https://doi.org/10.1086/708880.

Mercer, Kathryn, Melissa Li, Lora Giangregorio, Catherine Burns, and Kelly Grindrod. 2016. “Behavior Change Techniques Present in Wearable Activity Trackers: A Critical Analysis.” *JMIR mHealth and uHealth* 4 (2): e40. https://doi.org/10.2196/mhealth.4461.

Motyl, Katharina. 2020. *Compulsive Self-Tracking: When Quantifying the Body Becomes an Addiction*.

Ometov, Aleksandr, Viktoriia Shubina, Lucie Klus, et al. 2021. “A Survey on Wearable Technology: History, State-of-the-Art and Current Challenges.” *Computer Networks* 193 (July): 108074. https://doi.org/10.1016/j.comnet.2021.108074.

Paul, Greig, and James Irvine. 2014. “Privacy Implications of Wearable Health Devices.” *Proceedings of the 7th International Conference on Security of Information and Networks*, September 9, 117–21. https://doi.org/10.1145/2659651.2659683.

Peng, Wei, Lin Li, Anastasia Kononova, Shelia Cotten, Kendra Kamp, and Marie Bowen. 2021. “Habit Formation in Wearable Activity Tracker Use Among Older Adults: Qualitative Study.” *JMIR mHealth and uHealth* 9 (1): e22488. https://doi.org/10.2196/22488.

Rachmad, Yoesoep. 2024. *Feedback Loop Theory*. https://doi.org/10.17605/OSF.IO/FSRDE.

Riis, Jason, Hengchen Dai, and Katy Milkman. 2014. “The Fresh Start Effect: Motivational Boosts Beyond New Year’s Resolutions.” *Management Science*.

Rogers, Todd, Katherine L. Milkman, and Kevin G. Volpp. 2014. *Commitment Devices: Using Initiatives to Change Behavior*.

Sabry, Farida, Tamer Eltaras, Wadha Labda, Khawla Alzoubi, and Qutaibah Malluhi. 2022. “Machine Learning for Healthcare Wearable Devices: The Big Picture.” *Journal of Healthcare Engineering* 2022 (April): 1–25. https://doi.org/10.1155/2022/4653923.

Seneviratne, Suranga, Yining Hu, Tham Nguyen, et al. 2017. “A Survey of Wearable Devices and Challenges.” *IEEE Communications Surveys & Tutorials* 19 (4): 2573–620. https://doi.org/10.1109/COMST.2017.2731979.

Shajari, Shaghayegh, Kirankumar Kuruvinashetti, Amin Komeili, and Uttandaraman Sundararaj. 2023. “The Emergence of AI-Based Wearable Sensors for Digital Health Technology: A Review.” *Sensors* 23 (23): 9498. https://doi.org/10.3390/s23239498.

Thaler, Richard H., and Cass R. Sunstein. 2008. *Nudge: Improving Decisions about Health, Wealth, and Happiness*. Yale university press.

Vijayan, Vini, James P. Connolly, Joan Condell, Nigel McKelvey, and Philip Gardiner. 2021. “Review of Wearable Devices and Data Collection Considerations for Connected Health.” *Sensors* 21 (16): 5589. https://doi.org/10.3390/s21165589.

Winter, Nick. 2014. *The Motivation Hacker*.

Xue, Yukang. 2019. “A Review on Intelligent Wearables: Uses and Risks.” *Human Behavior and Emerging Technologies* 1 (4): 287–94. https://doi.org/10.1002/hbe2.173.

Zhu, Yaguang, Stephanie L Dailey, Daniel Kreitzberg, and Jay Bernhardt. 2017. “‘Social Networkout’: Connecting Social Features of Wearable Fitness Trackers with Physical Exercise.” *Journal of Health Communication* 22 (12): 974–80. https://doi.org/10.1080/10810730.2017.1382617.

Appendix A. Survey on Wearable Devices and Lifestyle Habits

The following survey was designed to gather empirical data on wearable device usage patterns, user motivations, and perceived behavioral impacts. It was divided in nine sections:

- General Information
- Use of Wearables
- Motivation and Behavior Change
- User Experience
- Motivation and Psychology
- Habit Formation & Routine
- Feature Evaluation
- Behavior Change Impact
- Final Reflections and Commitment

Distributed through social media platforms, email outreach, and fitness communities, the survey collected 235 total responses, of which 150 were considered valid for analysis (completed by current wearable device users).

The instrument combined closed-ended questions, Likert scale ratings, ranking exercises, and open-ended questions to capture both quantitative patterns and qualitative user experiences. Questions 9 and 14 were adapted from (Peng et al. 2021) and (Fadhil 2019b), respectively, while remaining items were developed specifically for this research.

The full survey instrument is presented below. Responses shown are for illustrative purposes only and do not represent actual participant data.

General Information

1. **What is your age?** *

- Under 18
- 18–24
- 25–34
- 35–44
- 45–54
- 55–64
- 65+

2. **What is your gender?** *

- Woman
- Man
- Non-binary
- Prefer not to say

3. **What is your current occupation?** *

- Student
- Working Professional
- Retired
- Outro

Use of Wearables

4. **Do you currently use a wearable device (e.g., fitness tracker, smartwatch)?** *

- (●) Yes
- ( ) No

5. **Which device(s) do you use?** *

- (●) Fitbit
- ( ) Apple Watch
- ( ) Samsung Galaxy Watch
- ( ) Garmin
- ( ) Xiaomi Mi Band
- ( ) Outro

6. **How long have you been using wearable devices?** *

- (•) Less than 1 month
- ( ) 1–3 months
- ( ) 3–6 months
- ( ) 6–12 months
- ( ) More than 1 year

7. **How often do you wear your device?** *

- ( ) Daily
- ( ) A few times per week
- (•) Occasionally
- ( ) Rarely

8. **What features do you use most?** *

- [ ] Step counting
- [ ] Heart rate monitoring
- [ ] Sleep tracking
- [ ] Workout tracking (e.g., runs, gym sessions)
- [ ] Calorie tracking
- [ ] Notifications (calls, messages)
- [ ] GPS/location tracking
- [ ] Stress or mindfulness features
- [ ] Outro

Motivation and Behavior Change

9. **Why did you start using a wearable device?** *

- [ ] To improve physical activity
- [ ] To track specific health metrics
- [ ] Doctor's recommendation
- [ ] Curiosity / tech interest
- [ ] Motivation or accountability
- [ ] Social or peer influence
- [ ] Outro

10. **Since using your device, have you noticed any changes in your habits or routines?** *

- (●) Yes, significant changes
- ( ) Some small changes
- ( ) Not really
- ( ) Not sure

11. **Which behaviors have changed since you started using the device?** *

- [ ] I walk more
- [ ] I exercise more regularly
- [ ] I pay more attention to sleep
- [ ] I track my goals more consistently
- [ ] I feel more aware of my daily routines
- [ ] No noticeable change
- [ ] Outro

12. **How motivated do you feel to stay active or healthy thanks to your wearable?** *

- (x) Very motivated
- ( ) Somewhat motivated
- ( ) Neither motivated nor unmotivated
- ( ) Somewhat unmotivated
- ( ) Very unmotivated

13. **Have you ever stopped using your device for more than a week?** *

- ( ) Yes
- (x) No
- ( ) Prefer not to say

14. **If yes, what was the reason?** *

- [ ] Accessories Change
- [ ] Upgrading Model
- [ ] User Preferences
- [ ] Perceived Usefulness
- [ ] Wrong Purchase
- [ ] Priority Change
- [ ] Battery Life Efficiency
- [ ] Gift
- [ ] Size Issues
- [ ] Compatibility Issues
- [ ] Perceived Complexity
- [ ] Outro

User Experience

15. **How easy is it to use your wearable device?** *

- Extremely easy
- Somewhat easy
- Neutral
- Somewhat not easy
- Extremely not easy

16. **How helpful do you find the data your wearable provides?** *

- Very helpful
- Somewhat helpful
- Neither helpful nor unhelpful
- Somewhat unhelpful
- Very unhelpful

17. In your opinion, what could be improved in your device to better support your health or habits? *

...

Motivation & Psychology

18. **What motivates you most to use your wearable device?** *

1 To feel healthier

2 To compete with others

3 To track progress

4 To avoid feeling guilty

5 To earn rewards or badges

19. **How does using your device make you feel about your health?** *

- (●) More confident
- ( ) More anxious
- ( ) More motivated
- ( ) No change
- ( ) Outro

20. **Do you feel in control of your health decisions, or mostly guided by the device?** *

- ( ) Mostly self-guided
- (●) A mix of both
- ( ) Mostly guided by the device
- ( ) Not sure

Habit Formation & Routine

21. **Do you check your wearable at a specific time each day?** *

- ● Yes, at regular times (e.g., morning, after walks)
- ○ Randomly, when I remember
- ○ No routine at all
- ○ Outro

Feature Evaluation

22. **How useful are the following features in helping you maintain healthy habits?** *

	Useless	Somewhat useless	Neither useful nor useless	Somewhat useful	Very useful
Social competition	●	○	○	○	○
Sleep tracking	○	●	○	○	○
Heart rate monitoring	●	○	○	○	○
Workout logging	○	○	●	○	○
Step counting	○	○	○	●	○
Notifications	●	○	○	○	○
Rewards/streaks	○	○	○	●	○
Stress/mindfulness tools	○	○	●	○	○

Behavior Change Impact

Please indicate how much you agree with the following statements (Strongly Agree (5 Stars) → Strongly Disagree (1 star))

23. **My wearable helps me set achievable goals.** *

★ ★ ★ ★ ☆

24. **I feel more aware of my health behaviors since using a wearable.** *

★ ★ ★ ★ ☆

25. **I have developed healthier habits due to my device.** *

★ ★ ★ ★ ☆

26. **I would maintain these behaviors even without the device.** *

★ ★ ★ ★ ☆

27. **I feel pressure to meet my wearable's targets.** *

★ ★ ★ ★ ☆

Final Reflections and Commitment

28. **Do you see your wearable device as a commitment tool, something that helps you stay accountable to your health or fitness goals?** *

- ○ Yes, definitely
- ○ To some extent
- ◉ Not really
- ○ Not sure what that means

29. **Do you think using a wearable has led to any long-term changes in your behavior, mindset, or lifestyle?** *

- ○ Yes
- ◉ No
- ○ Maybe

30. **Have you ever felt pressure to meet the daily or weekly goals set by your wearable (e.g., steps, calories, activity rings)?** *

- ○ Yes, often
- ○ Occasionally
- ◉ Rarely
- ○ Never

31. **Do you ever feel that tracking your activity or health has become too controlling or compulsive?** *

- ◉ Yes
- ○ Maybe
- ○ No
- ○ I haven't thought about it

32. **Have you ever changed your behavior—such as walking extra, skipping rest, or ignoring discomfort—just to meet a wearable goal?** *

- Yes
- No
- I'm not sure

33. **Would you like your wearable to support more balance—e.g., promoting rest, recovery, or moments without tracking?** *

- Yes, that would help
- Maybe
- No, I like it the way it is

34. **Do you plan to continue using a wearable in the long term?** *

- Yes, it helps me stay committed
- Maybe, if I can stay motivated
- No, I don't find it useful
- Not sure yet