To what extent do specific features of self- tracking technologies impact psychological well-being, focusing on body image concerns and self-esteem?

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TO WHAT EXTENT DO SPECIFIC FEATURES OF SELF-TRACKING TECHNOLOGIES IMPACT PSYCHOLOGICAL WELL-BEING, FOCUSING ON BODY IMAGE CONCERNS AND SELF-ESTEEM?

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Abstract

Self-tracking technologies have gained tremendous popularity in recent years as tools to encourage healthier lifestyles. While prior empirical research has highlighted the benefits these technologies can offer, growing concerns have emerged regarding their potential negative psychological effects on users. This thesis therefore investigates the extent to which self-tracking technology usage affects psychological well-being, specifically focusing on body image concerns and self-esteem. More precisely, it examines the impact of specific self-tracking features, namely fitspiration content, behavior change techniques, and gamified and social design, on these outcomes. Through an experimental quantitative study (N = 186), participants were exposed to one of three self-tracking technology features or to a control condition to assess whether certain features are more likely to exacerbate negative psychological outcomes. Additionally, the moderating effects of usage intensity and usage motivation were explored to better understand how individual differences influence these outcomes. Findings revealed no significant differences in body image concerns or self-esteem levels across the different self-tracking technology features. In addition, the moderating role of usage motivation could not be confirmed. However, higher usage intensity was associated with greater body image concerns in certain feature conditions, suggesting that individual engagement patterns may play a critical role in shaping users' psychological responses. Based on these insights, this study outlines implications for managers, policymakers, and health insurers, acknowledges its key limitations, and proposes directions for future research.

KEYWORDS: self-tracking technologies, psychological well-being, body image concerns, self-esteem, usage intensity, usage motivation

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List of abbreviations

Abbreviation	Definition
STTs	Self-tracking technologies
BCTs	Behavior change techniques
BE	Body esteem
SE	Self-esteem

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1. Introduction

1.1. Context

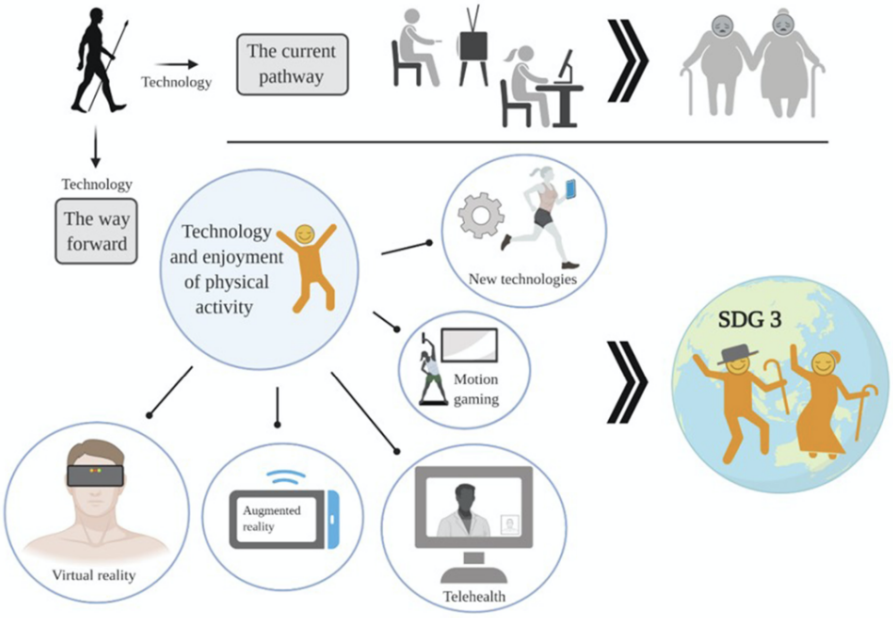
Despite growing awareness of the benefits of an active lifestyle, physical inactivity remains a significant global public health concern. According to the World Health Organization (2022), approximately 1.4 billion adults, representing 27.5% of the global adult population, fail to meet recommended physical activity levels. This figure has shown little improvement over the years, highlighting the persistent challenge of promoting active lifestyles. Alarmingly, 81% of adolescents also fall short of the minimum physical activity requirements, suggesting that inactivity is a growing concern across all age groups.

The health consequences of physical inactivity are profound, as it is a major risk factor for noncommunicable diseases, including cardiovascular disease, type 2 diabetes, various cancers, and mental health disorders such as depression and dementia. The World Health Organization (2022) estimates that meeting recommended physical activity levels could prevent 7-8% of cardiovascular disease, depression, and dementia cases, along with 5% of type 2 diabetes cases.

These modern physically inactive lifestyles are largely driven by technological advancements, such as labor-saving devices and transportation improvements (Ferguson et al., 2022; Woessner et al., 2021). While these innovations are initially designed to reduce physical labor and enhance convenience in daily life, ultimately leading to improved well-being and life expectancy, they also contribute to increased physical inactivity due to the growing automation of tasks (Woessner et al., 2021). Combined with the fast-paced nature of contemporary life, these factors significantly reinforce sedentary behavior. Additionally, the rise of the internet, mobile devices, and screen-based entertainment has further amplified this trend, particularly among children and adolescents (Woessner et al., 2021).

The United Nations Sustainable Development Goal (SDG) 3, which aims to “ensure healthy lives and promote well-being for all at all ages” (United Nations, n.d.), highlights the importance of addressing this issue on a global scale. In this context, while technological advancements have contributed to sedentary behavior, they also hold significant potential for promoting and facilitating physical activity. When leveraged effectively, technology can serve as a powerful tool to integrate physical activity into daily life, making active lifestyles more accessible, engaging, and sustainable (Woessner et al., 2021). This is illustrated in **Figure 1** below.

Figure 1 – From sedentary behavior to active living with digital technologies



Source: (Woessner et al., 2021, p.4)

Among the various emerging technologies, self-tracking technologies (STTs), such as wearable devices and fitness apps, have gained prominence as tools designed to promote physical activity and healthier lifestyles (Calvo & Peters, 2014). These technologies fall within the broader category of digital health innovations, which aim to empower individuals to monitor and enhance their well-being through real-time data tracking and personalized feedback (Lupton, 2016). Indeed, this self-monitoring of health parameters, such as heart rate, physical activity, and sleep patterns, also called "self-quantification", can ultimately promote healthier lifestyles and improve health outcomes by enhancing individuals' autonomy and motivation to engage in self-care and preventive health behaviors (Sharon, 2017).

In the past years, the market for STTs has grown rapidly, with global estimates showing that the wearable fitness technology industry is projected to surpass $74.61 billion by 2024, with nearly 287 million users worldwide in 2024 (Statista, 2024). Furthermore, previous research indicates that more than 60% of surveyed users track their data daily (Ajana, 2020), and 87% of wearables users specifically monitor health-related metrics (Abrams & Fera, 2024). This shift towards health-conscious behaviors is further evidenced by Euromonitor International, who identified healthy living as one of the eight global megatrends through 2030 (Boumphrey & Brehmer, 2017).

However, despite their growing popularity and many health benefits, concerns have emerged regarding the potential negative psychological and behavioral consequences of STT use. Scholars argue that, while these technologies are primarily designed with the promise of encouraging healthy behaviors and enhancing users' well-being, they may paradoxically lead to detrimental effects instead (McLean et al., 2025). For example, self-tracking can reduce the initial enjoyment in physical activity by shifting attention away from the enjoyment of the experience itself toward a preoccupation with numerical targets and performance outcomes (Etkin, 2016). Failure to achieve these goals can further lead to frustration, anxiety, and stress, which can ultimately diminish users' well-being (Chen et al., 2024). Considering these findings, it appears essential to gain a comprehensive understanding of the complex and multifaceted impact of these technologies on users' well-being and health outcomes.

1.2. Problem statement

Taking this context into account, the central research problem addressed in this study is:

"To what extent do specific features of self-tracking technologies impact psychological well-being, focusing on body image concerns and self-esteem?"

Specifically, this study focuses on three distinct features embedded within self-tracking technologies: fitspiration content, behavior change techniques (BCTs), and gamified and social elements.

Additionally, this research aims to explore the potential influencing role of individual factors, such as usage intensity and usage motivation, in shaping these well-being outcomes. Considering this, the underlying research questions of this study are:

- How do self-tracking technology features influence body image concerns?
- How do self-tracking technology features influence self-esteem?
- Does the type of motivation underlying self-tracking technology engagement moderate the effects on body image concerns and self-esteem?
- Does the intensity of self-tracking technology engagement moderate the effects on body image concerns and self-esteem?

By answering these questions, the present work contributes to a deeper understanding of how users interact with self-tracking technologies and how these interactions may affect their psychological well-being.

1.3. Research motivations

1.3.1. Managerial Motivations

From a managerial perspective, the insights derived from this study can, first of all, greatly benefit managers, marketers, and developers of companies marketing these self-tracking technologies. This study not only highlights the benefits of such technologies but also uncovers potential negative impacts related to their use. By understanding these risks, companies can design their products in a way that minimizes adverse effects for users while enhancing their overall user experience. This is especially crucial in today's post-pandemic era, where the pursuit of healthy living and well-being has become a central focus for individuals and has shaped new consumer behavior and expectations. (Pradhan, 2022). It has further been shown that negative user experiences with self-tracking technologies, such as stress, guilt, pressure, etc., which are emphasized by self-tracking design, can lead to product abandonment (Attig & Franke, 2023). Therefore, the results of this study can inform the design of more ethical and psychologically safe features. Overall, taking these insights into account can help managers and developers of current or future tech companies maintain long-term user engagement with their products, ultimately driving profitability.

Beyond the tech industry, health insurance companies that have started incorporating self-tracking technologies into their offerings can also benefit from this research. Indeed, this initiative is a means to encourage healthy behaviors among policyholders and thus reduce risks associated with physical inactivity, while also allowing insurers to better manage risk and potentially lower healthcare costs (Stiglbauer et al., 2019). For example, insurance programs can offer premium discounts and rewards to policyholders who regularly track and meet activity goals using wearable devices (Japsen, 2016). As such, it is crucial for insurers to ensure that the tools they promote do not inadvertently undermine policyholders' health and well-being. Indeed, if certain features negatively impact policyholders' psychological health, they may lead to higher healthcare utilization and, ultimately, higher insurance costs. This also raises an ethical concern as these devices are promoted by health insurers to improve health outcomes, yet they may ultimately cause harm instead.

Finally, by contributing to the growing literature about the dark side of self-tracking technologies, this study may also inform public policy makers. Currently, there is a lack of adequate regulations regarding self-tracking technologies, as they are often classified as consumer products and therefore exempt from regulatory standards applied to medical devices, even though they are primarily used for health purposes (Wieczorek et al., 2023). However, these technologies have largely proven to pose a risk to users' health and well-being. Consequently, by shedding light on these negative effects and what specific features exacerbate them, this research can help raise awareness among policymakers, emphasize the need for protective measures, and inform the development of these measures.

1.3.2. Academic motivations

From an academic point of view, knowledge regarding self-tracking technologies is considerably growing. In today's rapidly evolving digital economy, academic interest in these devices continues to rise. An extensive body of literature has already highlighted the benefits of self-tracking technologies on users' physical and psychological well-being (Constantiou et al., 2023; Ferguson et al., 2022; Stiglbauer et al., 2019). Additionally, a growing number of researchers have pointed out the existence of negative consequences these technologies may have on users. However, they call for further academic exploration (Chen et al., 2024; McLean et al., 2025; Mwangi et al., 2024).

Specifically, Chen et al. (2024), who conducted a systematic review of the literature about the dark side of self-tracking technologies, emphasize the need for more quantitative empirical research investigating the negative health outcomes associated with self-tracking technology usage. Notably, they highlight the lack of feature-specific examination of SSTs in the literature and urge researchers to move beyond treating self-tracking technology use as a uniform experience, and instead investigate how individual features may differentially impact user wellbeing. Additionally, Mwangi et al. (2024) explicitly call for more empirical research examining the psychological impact of wearable technologies, particularly focusing on micro-level conceptualizations of wellbeing, such as eudaimonic and emotional wellbeing.

Furthermore, Chen et al. (2024) also emphasize the need for more empirical testing of potential moderators, such as usage motivation, usage intensity, and user characteristics, in shaping the negative health outcomes of specific self-tracking technology features. Indeed, they highlight that existing quantitative studies often overlook these moderating effects, which leaves a gap in understanding how user engagement patterns influence negative outcomes.

1.4. Contributions

Considering these motivations, this research will add insights into the current academic knowledge about self-tracking technologies by filling some of the gaps identified in the literature. Specifically, this research will delve into a feature-specific examination of SSTs to yield more nuanced insights into their psychological impacts. Additionally, the present work will contribute to further assess the psychological consequences of STT features using a causal research design and quantitative method, an underrepresented approach in the current literature. Furthermore, by focusing on body image concerns and self-esteem, two key aspects of the self-acceptance dimension of eudaimonic psychological well-being, this study will contribute to filling the gap for more micro-level well-being research in the context of wearable technologies. Finally, this study will attempt to confirm the role of usage intensity and usage motivation as moderating variables to advance the current understanding of how these constructs might amplify or mitigate the psychological effects of specific self-tracking features.

Beyond researchers, this study can also benefit managers and marketers in the effective design of self-tracking technologies by clarifying which specific elements can trigger negative outcomes to their users. These insights can help them adapt and refine feature design to minimize their associated psychological risks and foster more positive, user-centered experiences. Similarly, these insights can help public policymakers establish targeted regulations by identifying which self-tracking features may pose psychological risks. The further investigation of usage motivation and intensity can provide extra evidence on the circumstances under which these risks arise, and thus inform guidelines that promote safer and more effective use of self-tracking technologies. Finally, health insurance companies can also adapt their packages including STTs based on these insights to avoid harming their policyholders' health, and ultimately increasing their costs.

1.5. Approach

To address the research questions of this study, a structured approach is followed. It begins with a literature review, which explores key theoretical perspectives on self-tracking technologies (STTs), user well-being, and user engagement. This chapter aims to provide a comprehensive overview of existing research while identifying potential gaps in the literature. Building on these insights, the study next presents its conceptual model and hypotheses, which outline the theoretical framework and proposed relationships between key variables of interest.

Following this, the research design is developed, outlining the methodology, data collection method, sampling technique, and measuring instruments employed in the study. This approach ensures methodological rigor and transparency in answering the research questions. The results emerging from the data collection are then analyzed and discussed, providing insights into their alignment with existing literature and identifying both anticipated and unexpected patterns.

Finally, the conclusion chapter provides a short summary of the study, discusses its theoretical and managerial implications, acknowledges its limitations, and suggests directions for future research.

2. Literature Review

2.1. Self-tracking technologies

2.1.1. The concept of self-tracking

The concept of self-tracking does not have a single, fixed definition. In the literature, it is described using various terms, and its meaning has evolved over time. In the 1970s, self-tracking first emerged as a practice used for personal surveillance purposes, via wearable computers (Krijnen et al., 2013). The practice gained momentum in the early 2000s, with the rise of digital technologies, and led to the emergence of the “quantified self” movement (Feng et al., 2021). The term "quantified self," was first introduced by Wolf and Kelly in 2007, with the intent to label this growing trend of digital self-observation (Feng et al., 2021). It embodies the notion of “self-knowledge through numbers”, where individuals use quantitative data to monitor and understand personal activities and health. Building on this, Lupton (2016, as cited in Feng et al., 2021, p.2.) defines self-tracking as the practice in which people “knowingly and purposively collect information about themselves, which they then review and consider applying in their lives”. The collected information generally involves biological, physical, behavioral, or environmental information (Pfeiffer et al., 2016; Swan, 2009).

According to Lupton (2016), more than to collect personal health information, self-tracking can be used in a social context (e.g., to monitor social interactions) or in a work context (e.g., to monitor productivity). However, health and well-being remain the primary focuses within self-tracking and the quantified self. Specifically, many individuals track health-related metrics such as heart rate, sleep quality, physical activity, calorie intake, symptoms, stress levels, and recovery, to reflect on and make adjustments in their daily lives.

In the literature, beyond the quantified self, the concept of self-tracking is also referred to as self-monitoring, lifelogging, personal analytics, and personal informatics. While these terms highlight different nuances, they all refer to the same core practice by which people seek to monitor their everyday life (Lupton, 2016).

2.1.2. Self-tracking technologies (STTs)

Building upon the conceptual foundation of self-tracking, self-tracking technologies (STTs) represent cutting-edge technologies designed to monitor various aspects of individuals’ everyday lives (Ameen et al., 2021), with a primary focus on healthcare (Ferreira et al., 2021). These technologies encompass a diverse range of tools and have completely transformed the way individuals monitor their data.

Among these tools, wearable devices are among the most prominent and widely adopted, with global shipments projected to reach around 560 million units in 2024 (Statista, 2024). These devices are defined as smart electronic monitoring devices, worn on the body, that use predictive technology (i.e., a form of artificial intelligence), to collect personal health data in real time (Mwangi et al., 2024). They include fitness trackers, smartwatches, fitness bands, among others. Additionally, smart objects such as sensor-equipped clothing, shoes, and home furniture, further integrate self-tracking into daily routines (e.g., a smart mattress can monitor users’ sleep patterns and body temperature). Finally, health and fitness mobile applications, whether used independently or in conjunction with wearable devices, represent another major category of self-tracking technologies (Chen et al., 2024). Their widespread availability and integration with smartphones, which are now owned by the vast majority of the global population, have made self-tracking more accessible and affordable than ever. Indeed, the smartphone penetration rate worldwide increased from 49.35% to 71% between 2016 and 2024 (Statista, 2025), and users can now choose from over 350,000 health-related apps (Olsen, 2021). Like

other self-tracking technologies discussed, these apps collect real-time biometric and behavioral data, enabling users to visualize and act upon insights about their physical and emotional states (Lupton, 2016). This ease of access has played a major role in the growing adoption of self-tracking practices in the past years, especially among physically active individuals (Attig & Franke, 2023; Toner, 2018).

In a nutshell, the emergence of self-tracking technologies, particularly wearable devices, has considerably reshaped how individuals monitor their health and well-being, notably, by significantly simplifying the self-quantification process (Stiglbauer et al., 2019). These tools enable users to gather data automatically with little to no manual input, which is then processed into personalized, visual feedback, available in an online or mobile application, or directly on the wearable device itself. This process allows consumers to easily interpret and reflect on their gathered data, ultimately encouraging behavior change or prompting specific actions.

2.1.3. Features of self-tracking technologies

Chen et al. (2024) classified the key features of health and fitness self-tracking technologies into three main categories: behavior change techniques, fitspiration content, and gamified and social design elements.

2.1.3.1. Behavior Change Techniques (BCTs)

Behavior change techniques (BCTs) are "interventions that promote behavioral change by manipulating the factors that affect behavior" (Carey et al., 2019, as cited in Chen et al., 2024, p.8). These techniques are commonly integrated into health and fitness apps to increase users' awareness of their performance and encourage the adoption of healthy habits and behaviors. In the context of self-tracking technologies, BCTs primarily focus on elements such as "goal setting, self-monitoring, awareness, feedback, and self-regulation" (Buckingham et al., 2020, p. 8). Examples include notifications, reminders, and continuous feedback mechanisms (Chen et al., 2024).

These features are often used to nudge users when their activity levels fall below certain standards (Toner, 2018). Nudging is described as "essentially a means of encouraging or guiding behavior but without mandating or instructing, and ideally, without the need for heavy financial incentives or sanctions" (Halpern, 2015, p. 22). For instance, a Fitbit smartwatch vibrates when users haven't met their step goals, while an Apple Watch sends reminders to stand and move if it detects prolonged inactivity (Toner, 2018). These alerts are powered by algorithms and sensors that monitor user activity and aim to encourage behavior change.

2.1.3.2. Fitspiration content

Many STTs incorporate fitspiration content, which promotes "idealized thinness and toned muscles with pictures of ideal thin body shapes and encouraging messages, inspiring users to maintain a 'healthy' body image and weight" (Berry et al., 2021, as cited in Chen et al., 2024). This concept is also referred to as thin-ideal internalization (Berry et al., 2021; Thompson & Stice, 2001) and reflects content encouraging users to pursue a thin or muscular physique, often through images and messages that celebrate fitness and thinness as markers of success and social acceptance (Hesse-Biber et al., 2006).

Additionally, self-trackers are often encouraged to share their progress on social media, where posts frequently showcase images of their bodies as visual evidence of transformation over time (Berry et al., 2021). This practice contributes to an online environment that emphasizes bodily transformation, performance, and commitment to fitness ideals, often framed through aspirational and motivational content.

2.1.3.3. Gamified and social design

Gamification, defined as "the application of game elements outside of a game setting" (Deterding et al., 2011, as cited in Chen et al., 2024, p.8), is another prominent feature of self-tracking technologies. Its core purpose is to motivate users, enhance the user experience, and increase sustained engagement with such tools by turning routine behaviors (e.g., walking, running, eating) into game-like experiences (Deterding et al., 2011). Game elements such as ranking boards, badges, and rewards (Attig & Franke, 2019) encourage users to track their data and engage in social comparison, either through leaderboard systems integrated into the app or wearable device, or within broader online communities (e.g., the "Communauté Garmin Connect" Facebook group) (Chen et al., 2024).

2.1.4. Benefits of self-tracking technologies

A growing body of research supports the potential of self-tracking technologies to enhance both physical and psychological well-being. Indeed, engaging with these tools has been shown to increase users' awareness of their health status (Stiglbauer et al., 2019), notably through the continuous, real-time feedback they provide. By continuously exposing users to their personal data, they become more aware of undesirable habits, such as insufficient physical activity or poor sleep quality, that might otherwise go unnoticed. Ultimately, this heightened awareness prompts individuals to make positive behavioral changes and adopt healthier routines (Constantiou et al., 2023), potentially leading to sustained lifestyle improvements over time. Additionally, as users begin to adopt healthier behaviors based on their collected data, they tend to feel more in control of their health and experience a heightened sense of empowerment and accomplishment, both of which can contribute to improved psychological well-being. (Stiglbauer et al., 2019).

Beyond increasing behavioral awareness, STTs have shown measurable impacts on physical activity, with improvements documented across several health metrics. Prior research reported that wearable devices led to an increase of around 1,800 extra steps per day and approximately 40 minutes of additional walking, alongside a moderate increase in moderate-to-vigorous physical activity (MVPA) by about six minutes daily (Ferguson et al., 2022). These increases are associated with improved physiological outcomes, such as reduced BMI, lower blood pressure, and enhanced aerobic capacity, all of which contribute to overall cardiovascular and metabolic health. Additionally, by promoting increased physical activity, STTs also have the potential to enhance psychosocial outcomes such as depression and anxiety, given that physical activity possesses both antidepressant effects and anxiolytic effects (Ferguson et al., 2022).

2.2. Well-being

While the benefits of self-tracking technologies are well-documented in the literature, their widespread adoption has also raised concerns about potential negative effects on users' well-being. Although these tools are often marketed as ways to enhance health and well-being (Spil et al., 2021), emerging research suggests that their impact is not universally positive, and may, in some cases, contribute to adverse health outcomes, often referred to as the "dark side" of self-tracking technologies (Chen et al., 2024; Mwangi et al., 2024).

This paradoxical interplay between technology and user well-being has emerged as a focal point in recent research. On one hand, STTs may enhance well-being by fostering health improvements (Ferguson et al., 2022; Stiglbauer et al., 2019). On the other hand, they can lead to increased stress, guilt, and other negative psychological outcomes (Chen et al., 2024). McLean et al. (2025) characterize this phenomenon as a "double-edged sword", referring to the dual potential of technology to both enhance and diminish well-being. They introduced the “Technology and Consumer Well-being Paradox Model” to illustrate this complexity, highlighting how factors such as the type of activity, the purpose of use, and the duration of exposure influence whether technology contributes positively or negatively to well-being.

Despite this complexity, much of the focus within marketing and technological research has focused on driving adoption and co-creating value between consumers and brands, often at the expense of considering broader implications for consumer well-being (McLean et al., 2025). As such, this section aims to examine the multifaceted concept of well-being and the nuanced role of self-tracking technologies in shaping it.

2.2.1. Definitions

The World Health Organization (n.d.) defines health as intrinsically linked to well-being, describing it as “a state of complete physical, mental, and social well-being and not merely the absence of disease or infirmity”.

Well-being is a highly complex concept that researchers have long struggled to define within the literature (Mwangi et al., 2024). The umbrella term “well-being” encompasses various types of well-being that are both complementary and distinct from one another (Gallagher et al., 2009, as cited in Mwangi et al., 2024). Building on this foundation, Mwangi et al. (2024) conducted an interdisciplinary systematic review and reported the different conceptualizations of well-being according to the discipline studied (see **Table 1**).

Table 1 – Conceptualizations of well-being by discipline

Conceptualization of wellbeing	Discipline	Characteristics	Focus/Level	Authors
Eudaimonic wellbeing	Neuroscience, psychology, and philosophy	cognitive driven; long term life satisfaction; human flourishing personal development/self-actualization.	Individual/micro	Huta and Waterman (2014)
Hedonic wellbeing	Psychology	affect/emotion driven; momentary; short stints of positive affect, alleviation of distress and boredom	Individual/micro	Waterman et al. (2010)
Subjective wellbeing	Psychology	Umbrella term for eudaimonic and hedonic wellbeing	Individual/micro	Waterman et al. (2010)
Social wellbeing	Sociology	social connectedness	Group/meso	Keyes, (1998).
Emotional wellbeing	Psychology, Clinical sciences	mental health and wellbeing	Individual/micro	Cemiloglu et al. (2022)
Digital wellbeing	Marketing, IT, psychology,	digital addiction, privacy	Individual/micro	Cemiloglu et al. (2022)
Collective wellbeing	Philosophy	positive relationships/institutions overall “health” of a community (vitality, opportunity, connectedness, contribution, and inspiration)	Group/meso	Roy et al. (2018)
Consumer wellbeing	Economics/Macromarketing	acquisition, possession, consumption, maintenance, and disposition of economic goods	Economic/macro	Sirgy and Lee (2006)

Source: Mwangi et al., 2024, p.2

Mwangi et al.'s (2024) systematic review underscores the complexity of well-being as a construct that operates on multiple levels and encompasses both individual and societal dimensions. At the individual level (micro perspective), the authors report that well-being is often framed through psychological constructs such as subjective well-being, which includes both hedonic and eudaimonic well-being. Hedonic well-being is driven by emotions and emphasizes the pursuit of pleasure, happiness, and the reduction of negative affect. In contrast, eudaimonic well-being is cognitively driven and is characterized by self-actualization, personal growth, and the realization of long-term goals. In addition to these, emotional well-being, often defined in relation to mental health, and digital well-being, which considers critical factors such as privacy and the risks of digital addiction, are also recognized as important facets of individual well-being.

Beyond the individual perspective, Mwangi et al. (2024) highlight that well-being has also been studied within the context of social relationships and communities (meso perspective), which are captured under the notions of social and collective well-being. Social well-being includes quality of life, social confidence, and a sense of connectedness, while collective well-being examines the vitality and functionality of groups, communities, and institutions.

At the macro level, Mwangi et al. (2024) report that well-being is situated within broader societal constructs. It considers consumer satisfaction with the entire consumption process, from the acquisition of goods and services to their disposal. This perspective aligns with macromarketing and economic approaches to well-being, which typically focus on aggregate societal outcomes and the broader impact of marketing practices on societal welfare.

2.2.2. Psychological well-being

The concept of psychological well-being (PWB) has been a cornerstone of eudaimonic well-being research since Carol Ryff introduced her psychological well-being model in 1989. Developed through an extensive synthesis of mental health, clinical, and life span development theories, this model draws heavily on Aristotle's notion of eudaimonia, which emphasizes living a virtuous and meaningful life (Van Dierendonck & Lam, 2023). Similarly, Ryff's conceptualization emphasizes long-term personal growth and flourishing as central components of well-being.

Specifically, a central instrument of Ryff's model is the Psychological Well-Being Scale (PWBS), which identifies six core dimensions of PWB: "(1) self-acceptance (being aware of and accept one's strengths and weaknesses), (2) positive relations (having deep, meaningful relationships with others), (3) autonomy (being self-determined and taking independent decisions), (4) environmental mastery (managing one's circumstances to take advantage of opportunities), (5) purpose in life (establishing and being guided by goals), and (6) personal growth (experiencing progress as a result of developing one's strengths)" (Blasco-Belled & Alsinet, 2022, p.1). Collectively, these dimensions assess an individual's psychological functioning and well-being (Van Dierendonck & Lam, 2023).

Grounded in the eudaimonic perspective, this model posits that well-being arises from the realization of personal potential, rather than the mere pursuit of pleasure (Ryan & Deci, 2001). Additionally, high PWB has been associated with numerous benefits, including its ability to protect against mental health issues, psychological disorders, and physical illnesses (Ryff, 2014; Weiss et al., 2016).

Investigating psychological well-being aligns with Mwangi et al.'s (2024) call for more nuanced consumer well-being research, particularly at the micro-level within the context of self-tracking technologies. While much of the current literature emphasizes behavioral outcomes, such as increased physical activity or healthier habits, a growing body of literature highlights the need to also examine

how these technologies shape deeper, internal dimensions of consumer experience. As self-tracking technologies include personalized features (Chen et al., 2024), they can influence not just what users do, but how they feel about themselves and assess their own development. Psychological well-being can provide a valuable lens for understanding these internal effects, particularly through dimensions such as autonomy, self-acceptance, and personal growth. Exploring PWB in the context of STTs is therefore essential to fully capture how these technologies shape users' self-perception and personal development.

To better situate the discussion, the next section presents an overview of the broader unintended consequences of self-tracking technologies, before narrowing the focus to the two psychological dimensions examined in this study.

2.2.3. Negative outcomes of self-tracking technologies

Chen et al. (2024) systematically reviewed the unintended negative outcomes of self-tracking technologies and found that specific features of such tools may trigger negative user responses. Based on their data structuring, the reported negative outcomes found in the literature can be classified into four categories: (1) negative psychological outcomes, (2) negative behavioral outcomes, (3) negative social outcomes, and (4) other negative outcomes.

To provide a more comprehensive overview, their findings have been supplemented with evidence from additional relevant studies identified in the literature (indicated in the "Article(s)" column of the table below). Furthermore, outcomes not explicitly detailed by Chen et al. (2024) were added in *italics* within the same table. A synthesis of these results is presented in **Table 2**.

Table 2 – Summary of negative outcomes associated with self-tracking technologies

Category	Specific outcomes	Description	Article(s)
Psychological	Guilt	Triggered by failure to achieve goals, negative feedback, or unmet expectations. Leads to self-blame and feelings of inadequacy.	Ryan et al. (2019)
	Stress/pressure	Caused by constant notifications, reminders, and comparisons with others. Results in heightened tension and inability to relax.	Constantiou et al. (2023); Ryan et al. (2019)
	Anxiety	Induced by self-comparisons, fear of underperformance, and societal pressures related to idealized body images.	Peterson Fronczek et al. (2022); Constantiou et al. (2023); Ryan et al. (2019)
	Frustration	Resulting from unmet performance or body shape goals, and failure to achieve desired ranking in gamified leaderboards.	
	Rumination	Persistent negative thoughts about performance gaps, often exacerbated by feedback from wearable trackers and apps.	Ryan et al. (2019)
	Body dissatisfaction	Caused by negative feedback, failure to achieve goals, and social comparison with idealized body representations.	Berry et al. (2021); Jain et al. (2025)

	Low self-esteem	*Triggered by performance pressure and social comparison, reinforced by ideal body or performance standards that tie self-worth to appearance and performance.*	*Algashami et al. (2018)*; *Jain et al. (2025); Kačerauskas et al. (2023)*
Behavioral	Compulsive exercise	Excessive physical activity driven by guilt or frustration, often beyond safe or healthy limits.	Berry et al. (2021); Toner (2018)
	Disordered eating	Includes excessive dieting, binge eating, overeating, and purging behaviors, triggered by idealized body goals and social comparison.	Berry et al. (2021)
	Data obsession	Over-focus on metrics and tracking results, leading to exacerbated negative emotions when faced with undesirable data. Neglect of intrinsic enjoyment of activities.	Etkin (2016); Peterson Fronczek et al. (2022); Toner (2018)
	Reduced motivation	Decline in intrinsic motivation to engage in physical activity, the activity becomes task-oriented rather than enjoyable.	Etkin (2016); Peterson Fronczek et al. (2022); Toner (2018)
	Loss of autonomy	*Dependency on tracking device. Loss of motivation for physical activities and frustration if unable to wear the wearable device.*	*Duus & Cooray (2015); Ryan et al. (2019)*
Social	Social isolation	Reduction in time and energy spent on social interactions due to obsession with tracking.	
	Psychosocial impairment	Harm to social relationships and interactions due to preoccupation with achieving personal health/fitness goals.	
Other	Negative physical outcomes	Physical discomfort such as skin irritation caused by wearable trackers.	Buckingham et al. (2020)

The most frequently reported negative emotions associated with self-tracking technologies include guilt, pressure, stress, anxiety, and frustration (Chen et al., 2024). As shown in **Table 2**, these emotional responses are primarily triggered by behavior change techniques (BCTs) and gamified features of STTs, such as goal reminders, competitive rankings, and performance feedback (Chen et al., 2024; Constantiou et al., 2023). Indeed, users often experience these emotions when faced with unsatisfactory results, especially compared to others, or when failing to meet predefined goals or targets. Additionally, constant notifications and comparison with peers foster pressure and anxiety (Chen et al., 2024). These emotional reactions are exacerbated by the gamified and social design of many STTs, which tend to emphasize underperformance and encourage users to strive for perfection. Elements such as leaderboards and rankings can create a sense of inadequacy in users who perceive themselves as lagging behind, leading to feelings of shame and despair.

Beyond emotional responses, self-tracking technologies can also lead to adverse cognitive outcomes, as these negative emotions often trigger maladaptive thought patterns, including persistent rumination and excessive preoccupation with body image (Chen et al., 2024). Many users internalize unrealistic body ideals, often propagated through fitspiration content, such as images and narratives embedded in these technologies and on social media (e.g., Berry et al., 2021). This internalization results in increased dissatisfaction with body image, particularly among users who perceive a significant gap between their current appearance and the societal standards promoted in their environment. Ultimately, such negative body image perceptions can erode self-esteem, especially when users begin to base their self-worth on how closely their appearance aligns with these externally imposed ideals (Jain et al., 2025).

On a behavioral level, dissatisfaction with body image can drive obsessive-compulsive behaviors, as users become overly focused on numerical data such as calorie counts and other physical activity metrics (Kanstrup et al., 2018). This focus not only exacerbates anxiety but also fosters disconnection from internal bodily cues (Zimdars, 2021) such as hunger or physical exhaustion, which further undermine well-being. Moreover, such prolonged and intense use of self-quantification practices may contribute to the normalization and objectification of the body, where individuals view themselves primarily through measurable attributes (Peterson Fronczek et al., 2022). This shift in perception reduces users' attention to how their body feel during movement, which ultimately distances them from their embodied experience and contribute to what's described as the "anaesthetisation" of human experience (Toner, 2018). This disconnection may prevent exercisers from being fully immersed in their environment (Little, 2017), and may trigger negative emotions, such as frustration and stress, particularly when goals are unmet (Goodyear et al., 2019). Ultimately, as users constantly focus on rigid external metrics, rather than on their personal enjoyment and satisfaction, their intrinsic motivation tends to decline, causing activities to feel more like work and diminishing the pleasure they once derived from it (Etkin, 2016). Over time, this may reduce subjective well-being and lead to disengagement from the activity altogether (Etkin, 2016; Toner, 2018).

Another behavioral outcome reported in the literature is the device dependency, where users feel that their physical efforts are meaningless unless tracked. Duus and Cooray (2015) found that some participants described feeling "naked" or that their activity was "wasted" when not captured by their wearable device. This loss of autonomy may further reduce users' sense of control over their health-related behaviors, as they become increasingly reliant on external validation from the device rather than internal cues or intrinsic motivation.

Finally, at the social level, engaging with STTs may harm social well-being, particularly when tracking behaviors becomes obsessive and begin to divert users' time and energy away from interpersonal relationships (Chen et al., 2024). This preoccupation with metrics can lead to social isolation and hinder users' ability to connect with others.

Overall, the literature suggests that many of the negative effects of STT use stem from how these technologies shape users' self-perception and self-evaluation. This is closely aligned with Ryff's (1989) conceptualization of the self-acceptance dimension of psychological well-being, which reflects individuals' ability to positively evaluate themselves and embrace both their strengths and weaknesses. Within this dimension, body image concerns and self-esteem are particularly salient, as they reflect how individuals asses their personal worth and accept their physical and personal attributes.

When self-tracking technologies contribute to greater body dissatisfaction and lower self-esteem, they risk undermining self-acceptance. Since self-acceptance is central to psychological well-being, these disruptions may further hinder individuals' capacity for personal growth, self-actualization, and the pursuit of meaningful life goals (McLean et al., 2025). Given that body image concerns and self-esteem play an essential role in shaping self-acceptance and sustaining psychological well-being, the present study focuses on these constructs as key psychological outcomes of STT use.

2.2.4. Body image concerns

Body image is defined as "a multidimensional construct encompassing the thoughts, feelings, and behaviors of an individual related to their own appearance" (Cash, 2004, as cited in Rodgers et al., 2023, p.1). It is typically conceptualized around two key aspects: an evaluative aspect, which includes satisfaction or concerns with appearance, and the degree to which body image is central to one's identity (Jarry et al., 2019).

As such, body image concerns refer to preoccupation and dissatisfaction with one's physical appearance, including shape, weight, and other features (Rodgers et al., 2023). This issue is globally widespread and is particularly emphasized by the presence of global societal pressures to adhere to appearance ideals. Although the expression of these concerns may differ across cultures, their prevalence and association with poor mental and physical health are universally recognized (Rodgers et al., 2023).

As previously noted, self-tracking technologies have become widely used as tools for monitoring health and fitness metrics. Prior market research indicates that the most popular reasons to engage with STTs are, in ranked order, tracking weight, calories burned, steps taken, and calories consumed (Berry et al., 2021). While tracking these metrics is intended to improve health and well-being, an emerging body of literature highlights their potential association with body image concerns. Specifically, building on Chen et al.'s (2024) proposed framework, several distinct features of self-tracking technologies can be identified as key contributors to the development of such concerns.

2.2.4.1. Fitspiration content

One prominent feature of self-tracking technologies that may contribute to body image concerns is fitspiration content, which promotes societal body ideals as personal standards to strive for. These visuals place users under the dual pressures of striving for thin-and-muscular ideals and conforming to the "healthy weight" discourse (Berry et al., 2021).

The thin and muscular ideal reflects a combination of minimal body fat and well-defined muscle tone, which are often equated with societal standards of beauty (Berry et al., 2021). In parallel, the promotion of a "healthy" weight as a normative goal reinforces the stigma toward larger bodies (i.e., "overweight" or "obese"), which are frequently perceived as deviating from this ideal (Crandall, 1994). This stigmatization not only fosters shame but also reinforces the belief that higher weight reflects personal failure (Magallares & Morales, 2013), often associated with negative traits such as laziness or lack of intelligence (Puhl et al., 2015). Such narratives often overlook the influence of broader external factors, including genetic predispositions, urban environments that may discourage physical activity, and unequal access to affordable, nutritious foods, which can significantly shape health outcomes (Berry et al., 2021).

Considering this, fitspiration content embedded in STTs can increase the risk of body image concerns such as appearance anxiety and body shame, as users internalize appearance standards and interpret deviations from these ideals as personal shortcomings (Jain et al., 2025). This may, in turn, lead to body change behaviors such as disordered eating or compulsive exercise (Berry et al., 2021).

2.2.4.2. Behavior change techniques

Behavior change techniques (BCTs) embedded in self-tracking technologies may also play an important role in shaping users' relationship with their bodies. Features such as goal setting, progress tracking, and regular reminder notifications encourage users to closely monitor their behaviors and assess success through predefined metrics (e.g., calories burned, steps taken, or weight changes) (Chen et al., 2024). While these mechanisms are intended to support healthy habits, they often convey the message that health and self-worth are conditional upon visible, quantifiable progress (Chen et al., 2024). This promotion of health as attainable through self-discipline and self-monitoring contributes to a cultural environment in which failing to meet normative standards of appearance is stigmatized (Rodgers, 2016). Consequently, BCTs reinforce compulsive monitoring and encourage users to assess their bodies not based on internal cues, but through externally imposed standards.

This shift reflects the concept of self-objectification, defined as "the treatment of a body as an object rather than a subject" (Nussbaum, 1995, as cited in Berry et al., 2021, p.5). In this context, self-trackers come to view their body as an external object to be monitored, evaluated, and improved, rather than as an integrated component of their lived experience (Lupton, 2013; Toner, 2018). This external perspective shifts the focus away from embodied, intuitive knowledge of the body and instead emphasizes quantifiable metrics, such as calories burned, steps taken, or body fat percentages as the primary indicators of health and success (Berry et al., 2021). Ultimately, when personal results fail to meet expectations or highlight areas of underperformance, users may experience frustration, body dissatisfaction, and broader body image concerns (Berry et al., 2021).

2.2.4.3. Gamified and social design

Finally, the gamified and social design of STTs may also foster body image concerns. These features include leaderboards, reward systems, streaks, badges, and social sharing options, all of which introduce elements of competition and comparison (Chen et al., 2024). While these tools initially intend to increase user engagement, they can also fuel social comparison, prompting users to evaluate their own bodies or performance against peers (Berry et al., 2021; Chen et al., 2024).

Similarly to behavior change techniques, these features promote a performance-oriented view of the body, in which value is linked to how well one ranks compared to others. As users strive to meet social or algorithmic standards, they may become increasingly focused on how their performance and appearance is perceived by others, often at the expense of their own physical or emotional well-being (Jain et al., 2025). This can reinforce self-objectification and lead to excessive self-monitoring, compulsive behaviors, and body image concerns, particularly when users perceive themselves as underperforming (Berry et al., 2021).

In light of this, the following hypotheses are proposed:

H1a: The behavior change techniques of STTs increase body image concerns.

H1b: The fitspiration content of STTs increases body image concerns.

H1c: The gamified and social design of STTs increases body image concerns.

2.2.5. Self-esteem

Self-esteem is defined as "an individual's subjective evaluation of their own worth" (Donnellan et al., 2015, as cited in Kim, 2024, p.2). Prior research has widely shown that self-esteem can shape positive physical and psychological well-being. Indeed, high self-esteem is associated with happiness, confidence, and resilience, while low self-esteem is associated with pessimism, self-doubt, and self-diminishing attitudes (Kim, 2024).

Self-esteem is deeply intertwined with body image perceptions. Individuals with low body satisfaction are often preoccupied about how they are perceived by others, what ultimately lowers their self-esteem (Ameen et al., 2022). As such, negative body image frequently correlates with low self-esteem, reflected in dissatisfaction with one's physical appearance and overall self-worth. In contrast, positive body image is associated with enhanced self-esteem, which in turn contributes to greater psychological resilience and life satisfaction (Merino et al., 2024). As such, similarly to body image concerns, self-tracking features can significantly impact self-esteem.

2.2.5.1. Fitspiration content

Fitspiration content, while initially aiming to inspire healthier lifestyles, frequently triggers upward social comparisons, as individuals measure themselves against body ideals, often unattainable (Kim, 2024). This can reinforce users' perception that self-worth is based on appearance, which may subsequently lower their self-esteem (Jain et al., 2025).

2.2.5.2. Behavior change techniques

Behavior change techniques can also significantly impact self-esteem. While these features may foster feelings of accomplishment and self-efficacy when users perform well, potentially boosting self-esteem, they can also elicit negative psychological reactions (Chen et al., 2024). For instance, constant and intrusive notifications and reminders about unmet goals or poor performance may trigger guilt, frustration, and anxiety (Berry et al., 2021; Chen et al., 2024), especially among users with preexisting body image concerns, which can diminish their sense of self-worth (Jain et al., 2025).

2.2.5.3. Gamified and social design

Finally, the gamified and social design of self-tracking technologies may also contribute to decreased self-esteem. Although gamification elements such as leaderboards, rewards, and point systems aim to enhance engagement and motivation to engage with these technologies (Grech et al., 2023), they often foster social comparison and competition, which can lead to stress, anxiety, and a diminished sense of self-worth, particularly when users perceive their performance as inferior (Kačerauskas et al., 2023). Persistent underperformance or failure to achieve a desired ranking may lead users to think negatively about themselves, which can in turn undermine their self-esteem (Algashami et al., 2018).

Consequently, the following hypotheses are proposed:

H2a: The behavior change techniques of STTs lower self-esteem.

H2b: The fitspiration content of STTs lowers self-esteem.

H2c: The gamified and social design of STTs lowers self-esteem.

2.3. User engagement

Research on user engagement has experienced significant growth over the past decade (Harmeling et al., 2017), and the field of self-tracking technologies is no exception to this trend. Although the concept appeared in academic discourse as early as 2006, it began receiving significant attention around 2010 (Lim et al., 2022). Despite this growing body of literature, there is still no universally accepted definition of user engagement (Lim et al., 2022).

2.3.1. Definitions

While social commerce research has mostly approached user engagement as a unidimensional construct, marketing literature tends to conceptualize it as a multidimensional construct including cognitive, emotional, and behavioral dimensions, to better reflect its complexity (Brodie et al., 2013; Hollebeek, 2011; Lim et al., 2022). Engagement is typically viewed as a dynamic, two-way interaction between an individual and a brand or a technology, shaped by specific contextual conditions (Brodie et al., 2011; Brodie et al., 2013; Hollebeek, 2011; O'Brien & Toms, 2008). This construct can vary in intensity and may be positively or negatively valenced (Brodie et al., 2011; Brodie et al., 2013; Hollebeek & Chen, 2014; O'Brien & Toms, 2008).

Cognitive engagement refers to user's mental involvement during the interaction, such as attention and information processing. Emotional engagement captures the positive or negative feelings users develop through their interaction with the object of engagement (i.e., a brand or technology). Finally, behavioral engagement reflects the energy, time, and effort dedicated to the brand or technology, often serving as a key indicator of engagement intensity (Hollebeek et al., 2014).

In the context of self-tracking technologies, user engagement is frequently measured through behavioral indicators (Gouveia et al., 2015). It is driven by motivational factors (Dessart et al., 2015), as individuals engage with STTs to achieve personal goals or satisfy specific needs, and is often measured through intensity indicators such as usage frequency, time spent on self-tracking activities, and duration of exposure to self-tracking content (Chen et al., 2024; Constantiou et al., 2023). Considering this, the present study adopts a behavioral perspective on engagement, focusing on how users interact with self-tracking technologies and the psychological outcomes derived from these usage patterns. Specifically, building on Chen et al.'s (2024) conceptual framework, this research investigates how users' motivation to engage with self-tracking technologies, along with the intensity of that engagement, may influence aspects of psychological well-being.

2.3.2. Motivations underlying user engagement with self-tracking technologies

The quantification journey begins with users' motivation to engage with self-tracking technologies and practices (Peterson Fronczek et al., 2022). This engagement, defined as a state involving deep, meaningful, and sustained interaction with a brand or a technology, is driven by both intrinsic and extrinsic motivations (Hollebeek, 2011). This conceptualization aligns with the Self-Determination Theory (SDT), which posits that behaviors are driven by either intrinsic or extrinsic motivation (Ryan & Deci, 2000).

Intrinsically motivated users participate in activities for the inherent satisfaction and personal fulfillment they derive from them (Ryan & Deci, 2000). In the realm of self-tracking technologies, such motivations are, for instance, pursuing better health and self-improvement. In contrast, extrinsically motivated users are influenced by external incentives or pressures, such as attaining a desirable appearance or avoiding an undesirable one (Ryan & Deci, 2000; Ryan & Deci, 2020). For instance, using

self-tracking technologies to enhance personal health reflects intrinsic motivation, while utilizing them primarily to achieve an idealized physical appearance is more aligned with extrinsic motivation (Chen et al., 2024).

Research on the impact of extrinsic factors has revealed that they can potentially undermine intrinsic motivation, a phenomenon known as the "overjustification effect" (Deci, 1971; Lepper et al., 1973). When individuals receive external rewards for engaging in activities they already find enjoyable, they may begin to attribute their actions to these rewards rather than to personal interest, thereby diminishing their intrinsic motivation (Etkin, 2016). In the context of STTs, even the act of measurement itself, without explicit incentives, can influence users' motivation by emphasizing quantitative outcomes. Prior research suggests that, while focusing on output metrics such as the number of steps taken or calories burned can initially increase the frequency of the behavior by providing immediate feedback (e.g., walking more steps), it may also shift users' perception of enjoyable activities, making them feel more like obligations or "work" (Etkin, 2016). This shift can reduce the enjoyment associated with the activity, which may ultimately decrease sustained engagement and lead to user disengagement altogether (Attig & Franke, 2023).

2.3.2.1. A potential moderator

Building on Chen et al. (2024), intrinsically motivated engagement may foster resilience against stressors linked to tracking metrics, as their engagement is not contingent on external validation. According to Self-Determination Theory (Ryan & Deci, 2000), individuals driven by intrinsic motivation may experience self-tracking in a more self-directed and fulfilling manner. In contrast, extrinsically motivated users may be more vulnerable to negative outcomes due to their heightened focus on external rewards and quantitative targets, such as step counts or calorie metrics, which STTs are often designed to emphasize. For these users, unmet goals or failure to achieve externally imposed standards can contribute to increased negative emotions and maladaptive thought patterns (Chen et al., 2024).

Consequently, the motivations underlying engagement with self-tracking technologies may serve as a key moderating factor in the relationship between user interaction with STTs and psychological well-being, as they can shape whether these technologies serve as tools for personal empowerment or sources of psychological distress.

Considering these insights, the following hypotheses are proposed:

H3a: The positive relationship between behavior change techniques and body image concerns is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.

H3b: The positive relationship between fitspiration content and body image concerns is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.

H3c: The positive relationship between gamified and social design and body image concerns is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.

H4a: The negative relationship between behavior change techniques and self-esteem is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.

H4b: The negative relationship between fitspiration content and self-esteem is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.

H4c: The negative relationship between gamified and social design and self-esteem is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.

2.3.3. Intensity of user engagement with self-tracking technologies

As engagement is a dynamic varying state of intensity (Brodie et al., 2011; Brodie et al., 2013; O'Brien & Toms, 2008), it is of interest to consider how intensity levels related to self-tracking technology usage may influence health outcomes.

Makkonen et al. (2016) categorized users of self-tracking technologies into four distinct segments based on their patterns of technology adoption: pro-trackers, semi-trackers, interested trackers, and non-trackers. Pro-trackers are highly engaged users who integrate multiple self-tracking devices into their daily routines. They exhibit a strong commitment to comprehensively monitoring various health and lifestyle metrics. Semi-trackers are users who engage intermittently and focus on specific health aspects (e.g., running performance) instead of maintaining consistent monitoring practices. Interested trackers are individuals curious about self-tracking but who have not yet fully adopted these tools, often due to barriers such as resource constraints, lack of motivation, or insufficient knowledge. Finally, non-trackers are those who neither use STTs nor express interest in adopting them, typically due to skepticism about their benefits or perceived lack of necessity.

2.3.3.1. A potential moderator

Chen et al. (2024) systematically reviewed the literature and raised concerns about how usage intensity might correlate with psychological outcomes. Prior research has shown that high usage intensity of social media is associated with poor body satisfaction (Marques et al., 2022) and mental health issues such as anxiety, depression, and low self-esteem (McLean et al., 2025), largely due to the ideal standards users are exposed to on these platforms and the pressure to engage in social comparison. In the context of self-tracking technologies, frequent and prolonged use exposes individuals to idealized body images and performance metrics, which they may compare against their own physical appearance and achievements. As a result, users may experience heightened feelings of anxiety, frustration, disappointment, and body dissatisfaction when they fail to meet personal or societal standards (Chen et al., 2024). Conversely, individuals who engage with these technologies infrequently or for shorter durations appear less likely to experience adverse psychological effects. For instance, studies with brief engagement periods—such as 10 days (Gittus et al., 2020) or one month (Hahn et al., 2021)—reported no negative impact on users' emotions or body image. Considering this, usage intensity may play a key moderating role in the relationship between STT use and users' psychological responses, such as body image concerns and self-esteem.

Consequently, the following hypotheses are proposed:

H5a: The positive relationship between behavior change techniques and body image concerns is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.

H5b: The positive relationship between fitspiration content and body image concerns is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.

H5c: The positive relationship between gamified and social design and body image concerns is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.

H6a: The negative relationship between behavior change techniques and self-esteem is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.

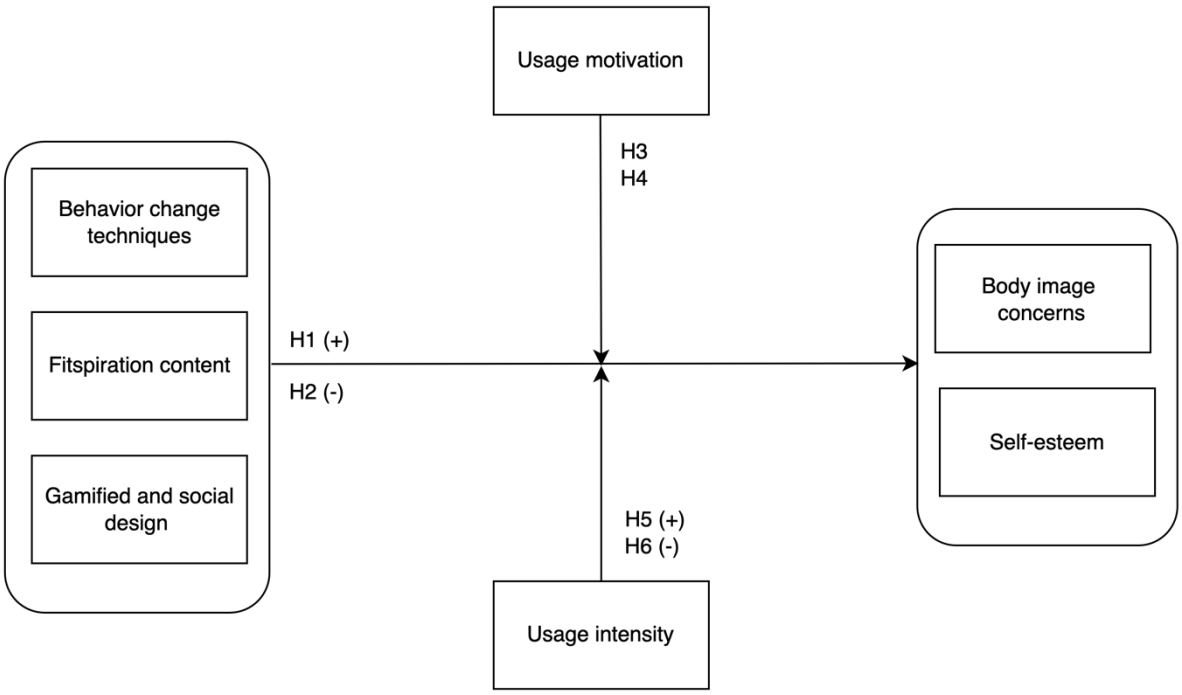
H6b: The negative relationship between fitspiration content and self-esteem is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.

H6c: The negative relationship between gamified and social design and self-esteem is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.

2.4. Research model and summary of proposed hypotheses

Based on the constructs discussed and the hypotheses developed in the literature review, a graphical model was developed (see **Figure 2**) to provide a visual representation of the research questions. In a nutshell, this study aims to examine the impact of three independent variables—the key features of self-tracking technologies identified in the literature: behavior change techniques (BCTs), fitspiration content, and gamified and social design—on two dependent variables: body image concerns and self-esteem. In addition, usage motivation and usage intensity are introduced as moderating variables, hypothesized to influence the strength or direction of the relationship between exposure to self-tracking features and psychological outcomes.

Figure 2 – Conceptual research model



Source: author's own illustration, based on the literature

Additionally, as discussed in the literature review, below are the proposed hypotheses for this study:

Table 3 – Summary of proposed hypotheses

H1a.	The behavior change techniques of STTs increase body image concerns.
H1b.	The fitspiration content of STTs increases body image concerns.
H1c.	The gamified and social design of STTs increases body image concerns.
H2a.	The behavior change techniques of STTs lower self-esteem.
H2b.	The fitspiration content of STTs lowers self-esteem.
H2c.	The gamified and social design of STTs lowers self-esteem.
H3a.	The positive relationship between behavior change techniques and body image concerns is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.
H3b.	The positive relationship between fitspiration content and body image concerns is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.
H3c.	The positive relationship between gamified and social design and body image concerns is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.
H4a.	The negative relationship between behavior change techniques and self-esteem is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.
H4b.	The negative relationship between fitspiration content and self-esteem is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.
H4c.	The negative relationship between gamified and social design and self-esteem is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.
H5a.	The positive relationship between behavior change techniques and body image concerns is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.
H5b.	The positive relationship between fitspiration content and body image concerns is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.
H5c.	The positive relationship between gamified and social design and body image concerns is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.
H6a.	The negative relationship between behavior change techniques and self-esteem is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.
H6b.	The negative relationship between fitspiration content and self-esteem is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.
H6c.	The negative relationship between gamified and social design and self-esteem is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.

Source: author's own formulation, based on the literature

3. Research Design

In this chapter, the development of the research design that has been elaborated to conduct this study will be outlined. A research design serves as a plan that specifies the set of procedures to conduct in order to obtain the information needed to address the marketing research problem (Malhotra et al., 2017).

First, the chosen methodology to carry out the research will be described. Then, a thorough analysis of the sample and data collection process will be provided, followed by a description of the research instruments used. Finally, the measurement methods used to assess the key constructs of this study will be discussed.

3.1. Methodology

The chosen research design to investigate the impact of self-tracking technologies on self-esteem and body image concerns is a quantitative research design, specifically, a conclusive research design. A conclusive research design aims to "describe specific phenomena, to test specific hypotheses and to examine specific relationships" (Malhotra et al., 2017, p.72), which aligns with the objectives of this study. The latter contains a subcategory, the causal research design, which is "used to obtain evidence of cause-and-effect (causal) relationships" (Malhotra et al., 2017, p.79). This type of research design is particularly suitable for identifying the nature of the relationship between causal variables and their expected effects. In other words, causal research is used to explain the impact of one or several independent variables on one or several dependent variables. This methodology is further appropriate as there is a growing call for more objective, quantitative studies to empirically examine the potential negative effects of self-tracking technologies on individuals. (Chen et al., 2024; Feng et al., 2021; Stiglbauer et al., 2019).

3.2. Sample

Due to the short time frame within which this research had to be conducted, a convenience sampling technique was chosen. A convenience sampling is "a non-probability sampling technique that attempts to obtain a sample of convenient elements" (Malhotra et al., 2017, p.420). In other words, this technique relies on participants who are easily accessible, available, and willing to respond to the survey at the time of data collection. Furthermore, this sampling method is the cheapest and least time-consuming to implement (Malhotra et al., 2017). For all these reasons, this method was perfectly suitable for this study.

3.2.1. Sample size determination

The required sample size for this study was determined using an a priori power analysis, following best practices in experimental research (Lakens, 2022). Indeed, the research questions of this study aim "to test whether certain effect sizes can be statistically rejected with a desired statistical power" (Lakens, 2022, p.2).

Given the study's factorial design, which examines the independent effects of three independent variables (behavior change techniques, fitspiration content, and gamified and social design) on two dependent variables (body image concerns and self-esteem), an Analysis of Variance (ANOVA) was selected as the suitable statistical test. This test is indeed appropriate to compare means across multiple categorical groups on continuous outcome variables (Baiwir, 2024). To ensure adequate statistical power and minimize both Type I errors (i.e., concluding that the means are different while they are in fact equal) and Type II errors (i.e., failing to detect a real difference among group means),

the required sample size was estimated using the tool G*Power 3.1, which was created by Erdfelder, Faul, and Buchner (1996) to conduct statistical power analyses for various tests.

For the power analysis, the following parameters were used:

1. **Effect size** (f): 0.25 (medium effect), based on Cohen's recommendations for studies in behavioral sciences (Cohen, 1988), where a medium effect refers to an effect likely to be visible to the naked eye of a careful observer.
2. **Alpha level** (α): 0.05, the conventional threshold for statistical significance (Cohen, 1988), which is used in all statistical tests of this study. A stricter level (e.g., $\alpha = 0.01$) was avoided to reduce the risk of Type II errors and overly demanding sample size requirements.
3. **Power** (1-β): 0.80, ensuring an 80% probability of detecting a true effect. This aligns with Cohen's convention, which balances the risks of Type I and Type II errors and reflects a standard practice in behavioral sciences. High power (e.g., 0.90-0.99) would usually require very large and impractical sample sizes (Cohen, 1988), they were thus avoided.
4. **Number of groups**: 4 (one for each STT feature, and one control group).

As a result, the power analysis yielded a required total sample size of N = 180 participants to detect a medium effect (see **Appendix A**).

3.2.2. Data collection

The data collection period for this study took place between March 31, 2025, and April 21, 2025. By the end of the 22-day period during which the survey remained open, a total of 316 answers were collected. However, due to incomplete questionnaires, only 186 fully completed responses were retained for analysis. This final sample size still exceeds the minimum required sample (N = 180) calculated in the power analysis, thereby ensuring adequate statistical power to detect medium-sized effects.

Out of the 186 respondents (N=186), the majority were women, representing 65.6% of the sample. Men accounted for 34.4%, with a total of 64 respondents. No respondents identified as non-binary or selected "prefer not to say". Regarding age, the participants ranged from 16 to 68 years old, with a mean age of 31.29 years. These demographics are illustrated in **Table 4** below.

Table 4 – Sample demographics

Gender	Male	34.4%
	Female	65.6%
	Non-binary	0.0%
	Prefer not to say	0.0%
Age	Mean	31.290
	Std deviation	11.437
	Minimum	16.000
	Maximum	68.000

Source: JASP output

The predominance of participants within the 25-34 age range is unsurprising, given that the survey was essentially distributed via Instagram and Facebook. Indeed, these platforms' audiences are mainly composed of individuals aged 18-34, with Instagram's second largest user group being 25-34 years old (30.6%), just after 18-24 group (31.7%) (Statista, 2024). Facebook's largest user group also falls within the 25-34 age range (31.1%) (Statista, 2024). Additionally, STTs are also more likely to be adopted by younger people, as older adults often report low perceived usability (e.g., ease of use, comfort) for such technologies (Rupp et al., 2018).

Finally, regarding scenario distribution, the majority of respondents were exposed to the fitspiration condition (31.2%). The control group represented the second largest segment with 28.5% of participants. The gamified and social design condition accounted for 20.4%, while the BCT scenario had the smallest group, with 19.9% of respondents. Results can be found in **Table 5** below.

Table 5 – Experimental condition distribution within the sample

Experimental condition	Control	28.5%
	Fitspiration content	31.2%
	Gamified and social design	20.4%
	Behavior change techniques	19.9%

Source: JASP output

3.3. Research instrument

To collect the necessary data for this study, a self-administered survey was chosen. This method is appropriate for quantitative research and aims to collect reliable and unbiased data (Burns et al., 2008). The survey took the form of a questionnaire, which is "a structured technique for data collection consisting of a series of questions, written or verbal, that a participant answers" (Malhotra et al.,2017, p.374). As a structured data collection method, the questionnaire followed a formal design with a prearranged sequence of questions (Malhotra et al., 2017). The questionnaire was created through the online survey tool LimeSurvey.

The survey was distributed online for participants to complete, mostly through social media and word-of-mouth. Online surveys offer multiple benefits, as they are typically quick to administer, cost-effective, and known to generate high-quality responses (Malhotra et al., 2017). The chosen social media platforms were Facebook and Instagram. Facebook was selected for its broad reach across different age groups, ensuring a diverse pool of respondents. To further reach individuals likely to engage in physical activity and track their health metrics, the survey was shared in health- and fitness-oriented Facebook groups, such as "Bref, je fais du running", "Team Belgium Running", "Communauté Garmin Connect", among others. Additionally, the survey was shared via Instagram stories to broaden its reach and attract more respondents.

The questionnaire was drafted in English as it is the most widely spoken language worldwide (Statista, 2025) and the primary language of publication for most of the academic literature on this research topic. This maximized the number of potential respondents who could complete the survey. Additionally, a French version of the questionnaire was created to allow people who are less familiar with English to complete it. This was particularly important because, as above-mentioned, the survey was mostly shared via social media and word-of-mouth, leading to a large portion of respondents coming from the investigator's personal network, which mainly consists of French speakers.

Before publicly administering the survey, it was pilot tested in order to identify and eliminate potential issues (Malhotra et al., 2017). Pre-testing ensures that respondents interpret the questions as intended by the investigator (Burns et al., 2008). Through this process, ambiguous questions can be revised and reformulated to enhance respondents' understanding. To this end, the survey was first distributed to six individuals from the target population. This included two English-speaking and four French-speaking participants. By the end of the pre-testing phase, and based on participants' feedback, no questions required reformulation.

The questionnaire consisted of ten pages and started with an introductory section outlining the objectives of the research. This section also provided a definition of STTs to ensure that all respondents shared a common understanding of the concept. Following this, participants were randomly assigned to one of four experimental conditions corresponding either to one of the three specific features of STTs or to a control group. Each condition included a standardized introductory scenario designed to immerse participants in a particular context related to self-tracking. Participants were then shown a screenshot from the self-tracking application "Fitbit" illustrating the feature relevant to their assigned condition. In the gamified and social condition, participants were shown a screenshot displaying a badge awarded for having walked 20,000 steps. In the BCT condition, the screenshot represented a performance feedback accompanied by a message encouraging the user to exercise more in order to reach their daily goal. For the fitspiration condition, given that such content is mainly present on social media (Berry et al., 2021), the stimulus consisted of two images (one male, one female) sourced from a Fitbit Community Instagram account (@fitbitanz), showcasing users' sharing their physical progress. Finally, the control group was not exposed to any specific screenshot.

Following this, participants were invited to respond to a series of questions assessing their self-esteem, body esteem (i.e., the variable measuring body image concerns in the analyses), motivation to engage with STTs, and their intensity of engagement with such technologies.

Subsequently, demographic questions including age and gender were presented at the end of the questionnaire as control variables. These were included as prior research has shown that young women represent the demographic group most at risk for negative outcomes associated with self-tracking technologies, compared to older men. Indeed, younger users are more vulnerable to appearance-oriented societal pressures than older adults, while women are typically more concerned about their physical appearance than men (Chen et al., 2024). Placing these questions at the end of the survey allowed to prioritize the most critical items first, while minimizing feelings of intrusion and reducing the likelihood of early drop-out. Finally, respondents were thanked for their participation. The entire questionnaire, available in both English and French, is provided in **Appendix B**.

3.4. Measures

As previously noted, the three independent variables: behavior change techniques, fitspiration content, and gamified and social design, were manipulated through an experimental design in which participants were randomly assigned to one of four conditions, including a control group. This design enabled the establishment of four distinct experimental groups and allowed for the assessment of whether exposure to different self-tracking features resulted in statistically significant differences in self-esteem and body image concerns across groups.

The dependent variables were measured through scientifically validated scales. First, the variable "self-esteem" was measured using the Rosenberg Self-Esteem Scale (1965). Respondents were asked to what extent they agreed or disagreed with each statement based on a 4-point Likert scale, which is a type of scale measuring levels of agreement with a series of statements related to a particular topic (Malhotra et al., 2017). Second, the variable "body image concerns" was measured with the Body-Esteem Scale for Adolescents and Adults proposed by Mendelson et al. (2001). For this variable, respondents were asked how often each statement applies to them, based on a 6-point Likert scale ranging from "Never" to "Always". Since higher scores on this scale indicate greater body esteem, results were interpreted in the opposite direction: higher body esteem scores were considered indicative of lower levels of body image concerns.

Third, the moderating variable "usage motivation" was assessed with a scientifically validated scale developed by Gimpel et al. (2013), known as the "Five-Factor Framework of Self-Tracking Motivations", which encompasses five motivational dimensions: self-entertainment, self-association, self-design, self-discipline, and self-healing. Here, respondents were asked how much they agreed or disagreed with each statement based on a 5-point Likert scale ranging from "Disagree strongly" to "Agree strongly". As this study focuses on the differences between intrinsic and extrinsic motivation for self-tracking, the original five-factor structure was not retained in the analysis. Instead, each item was classified based on whether it aligned more closely with intrinsic or extrinsic motivation. To ensure that all items reflected the same underlying construct, all items needed to be coded in the same direction, with higher scores indicating stronger intrinsic motivation. Therefore, items that originally reflected extrinsic motivation were reverse scored within the Excel dataset to align them conceptually with intrinsic motivation. The items concerned — MOTIV06, MOTIV07, MOTIV08, MOTIV09, MOTIV16, MOTIV18, and MOTIV19 — are indicated in *italics* in **Table 6**, which provides a complete overview of all measurement items of every scale used.

Fourth, the moderating variable "usage intensity" was measured using three multiple-choice questions (MCQs). Two of these questions, which addressed the self-tracking metrics monitored and the devices used to self-track, were designed as "select all that apply" items allowing respondents to indicate multiple applicable options. The third question, which addressed the frequency of checking self-tracking data, was a single-response item requiring participants to select one answer that best reflected their usage patterns. The questionnaire also included a fourth question asking participants how long they had been using STTs, but this item was ultimately excluded from the analysis, as it was not deemed a valid indicator of current engagement intensity.

Finally, the demographic control variables were collected. For age, participants were asked to provide their exact age via a numerical input field. Regarding gender, respondents selected one answer from the following options: male, female, non-binary, or prefer not to say.

Table 6 – Summary of measurement scales

Variable	Author	Code	Items
Self-esteem	Rosenberg, M. (1965).	SE01	I feel that I'm a person of worth, at least on an equal plane with others.
		SE02	I feel that I have a number of good qualities.
		SE03	I am inclined to feel that I am a failure. (-)[1]
		SE04	I am able to do things as well as most other people.
		SE05	I do not have much to be proud of. (-)
		SE06	I take a positive attitude toward myself.
		SE07	On the whole, I am satisfied with myself.
		SE08	I certainly feel useless at times. (-)
		SE09	I wish I had more respect for myself. (-)
		SE10	At times I think I am no good at all. (-)
Body image concerns	Mendelson, B. K., Mendelson, M. J., & White, D. R. (2001).	BE01	I wish I looked like someone else. (-)
		BE02	There are lots of things I would change about my look if I could. (-)

[1] (-) Indicates that the item was reverse scored according to the original scale's scoring instructions

		BE03	I wish I looked better (-)
		BE04	My looks upset me (-)
		BE05	I feel ashamed of how I look (-)
		BE06	I worry about the way I look (-)
		BE07	I like what I see when I look in the mirror
		BE08	I'm looking as nice as I would like to
		BE09	I'm pretty happy about the way I look
		BE10	I like what I look like in pictures
		BE11	I am satisfied with my weight
		BE12	I really like what I weigh
		BE13	I feel I weigh the right amount for my height
		BE14	My weight makes me unhappy (-)
		BE15	I am preoccupied with trying to change my body weight (-)
		BE16	Weighing myself depresses me (-)
		BE17	I think I have a good body
		BE18	I'm proud of my body
		BE19	Other people consider me good looking
		BE20	My looks help me get dates
		BE21	People my own age like my looks
		BE22	I think my appearance would help me get a job
		BE23	I'm as nice looking as most people
Usage motivation	Gimpel, H., Nißen, M., & Görlitz, R. (2013).	MOTIV01	I enjoy getting lost totally in self-tracking activities.
		MOTIV 02	I like playing around with numbers/statistics, etc.
		MOTIV03	I like playing around with my smartphone/technical device, etc.
		MOTIV04	I enjoy forgetting about time while doing so.
		MOTIV 05	It is fun and entertaining.
		MOTIV 06	*I want to help/inspire others.*
		MOTIV 07	*The way I'm doing it is interesting for others/might help others.*
		MOTIV 08	*I want to compare my results to others.*
		MOTIV 09	*I want to present myself to others.*
		MOTIV 10	I want to control what I'm doing with my life.
		MOTIV 11	I try to manipulate certain aspects in my life.
		MOTIV 12	I enjoy being my own master.
		MOTIV 13	I'm interested in how certain things in (my) life interact.
		MOTIV 14	It helps me to optimize the way I'm living.
		MOTIV 15	It motivates me to keep on working for a goal.
		MOTIV 16	*It allows me to reward myself.*
		MOTIV 17	It facilitates my self-discipline.
		MOTIV 18	*I don't trust in the healthcare system/classic therapies.*
		MOTIV 19	*I want to be independent from traditional medical treatments.*

4. Results

This chapter presents the results of the statistical analyses conducted to test the proposed research hypotheses. It begins with a description of the data preparation and cleansing procedures carried out prior to the statistical analyses. Next, a descriptive analysis of this data is provided, followed by a correlation analysis to explore relationships between variables. Finally, the chapter concludes with the hypothesis testing through the appropriate statistical tests.

The majority of statistical analyses were conducted using the JASP software. However, the moderation analyses were performed using the PROCESS macro (Hayes, 2018) within IBM SPSS Statistics, as it is specifically designed for such analyses and is widely accepted in psychological, marketing, and social sciences research.

4.1. Data preparation

According to Malhotra et al. (2017), ensuring data integrity is essential before proceeding with more advanced analyses. Considering this, a data cleanse was realized in Excel before importing the clean dataset into the JASP software.

First, the option to export only fully completed questionnaires from the LimeSurvey platform was selected to ensure the Excel file contained no missing values. This resulted in a total of 186 fully completed questionnaires, while the 130 incomplete responses, most participants having dropped out early in the survey, typically at the first set of questions, were excluded from the analysis.

Second, in Excel, all irrelevant columns such as submit date, last page, date stamp, start language, and start date were removed to ensure clarity in the dataset. Once only the relevant columns remained, the data was quantitatively coded to convert non-numerical responses (e.g., “Agree,” “Disagree”) into numerical values. A consistent coding scheme was used, where 1 represented the lowest level (e.g., lowest agreement or frequency) and the highest number (4 or 5) indicated the highest level, depending on the scale.

Third, all negatively worded items were reverse scored so that all items represent positive statements. This allowed for consistency in the interpretation of values and ensure that higher values uniformly reflected higher levels of the measured variable. A quick review of the final dataset was then conducted to identify any potential inconsistencies or errors in the responses. As a result, three mistakes were detected and corrected.

Finally, the mean of all items corresponding to each variable was calculated, so that each variable was represented by a single composite score in the dataset. After completing these steps, the final dataset was saved as a CSV file and imported into JASP for statistical analysis.

4.1.1. Normality of measuring instruments

The first step of the data preparation process in JASP was to assess whether the variables used in this study followed a normal distribution. This indicator is particularly important as many statistical techniques commonly employed in market research rely on the assumption of normally distributed data (Malhotra et al., 2017).

To evaluate this, the Shapiro-Wilk test was conducted. In this test, a p-value greater than 0.05 indicates that the variable does not significantly deviate from normality. Additionally, according to George and Mallery (2019), skewness and kurtosis values, which provide additional insights into the symmetry and

peakedness of distributions, are considered acceptable to assume normality if they fall between -2 and 2. Finally, a visual inspection of distribution plots was performed, where a bell-shaped curve suggests normal distribution. All distribution plots are provided in **Appendix C**.

As shown in **Table 7,** according to the Shapiro-Wilk test, only the variable body esteem (BE) is normally distributed, with a p-value of 0.325 > 0.05. This finding is further confirmed by the distribution plot of this variable, which displays a bell-shaped curve. The negative Skewness value for this variable indicates that the distribution is slightly skewed to the left, which means that the tail extends more toward the lower values (see **Appendix C**).

Regarding usage motivation (MOTIV_INTR), the Shapiro-Wilk test yielded a p-value of 0.05, which falls exactly at the conventional threshold for normality. While this suggests that the distribution does not significantly deviate from normality, it remains a borderline case. However, the skewness and kurtosis values fall within the acceptable range of -2 to +2, which supports the assumption of normality. The distribution plot further reinforces this, as the data display an approximately bell-shaped curve, though with slight deviations from perfect symmetry.

With regard to self-esteem (SE) and usage intensity (USAGE_INT), the Shapiro-Wilk test rejects normality, both p-values of Shapiro-Wilk being below 0.05. However, both skewness and kurtosis values fall within the acceptable range of -2 to +2, normality is thus still considered acceptable, and statistical tests can thus be conducted.

Table 7 – Shapiro-Wilk, Skewness, and Kurtosis analyses

	SE	BE	MOTIV_INTR	USAGE_INT
Valid	186	186	186	186
Missing	0	0	0	0
Mean	3.024	3.042	3.443	3.287
Std. Deviation	0.498	0.725	0.312	1.048
Skewness	-0.465	-0.156	-0.327	0.079
Std. Error of Skewness	0.178	0.178	0.178	0.178
Kurtosis	0.855	-0.356	-0.257	-0.686
Std. Error of Kurtosis	0.355	0.355	0.355	0.355
Shapiro-Wilk	0.975	0.991	0.985	0.979
P-value of Shapiro-Wilk	0.002	0.325	0.050	0.008
Minimum	1.300	1.174	2.632	1.000
Maximum	4.000	5.000	4.158	5.667

Source: JASP output

4.1.2. Reliability of measuring instruments

Secondly, the reliability of the measurement items from the validated scales was assessed, as it is a fundamental criterion for evaluating measurement instruments. Reliability refers to the extent to which a scale produces consistent results under consistent conditions (Malhotra et al., 2017). To assess internal consistency reliability, Cronbach's alpha coefficients were computed. In general, a scale will show low internal consistency if respondents tend to strongly agree with some items and strongly disagree with others that are supposed to measure the same construct (Malhotra et al., 2017). Cronbach's alpha coefficients range from 0 to 1, with values of 0.70 or above considered acceptable to assume the internal consistency reliability of a scale (Nunnally, 1978).

Regarding the variables of interest in this study measured using validated scales, i.e., self-esteem, body-esteem, and usage motivation, the reliability of the items is supported by Cronbach's alpha coefficients, which are above the commonly accepted threshold of 0.70. Specifically, the reliability estimates are 0.862 for self-esteem, 0.945 for body-esteem, and 0.809 for usage motivation, which indicate satisfactory to excellent internal consistency. Further details on Cronbach's alpha coefficients for individual items are provided in **Appendix D**.

It is also worth noting that Cronbach's alpha is sensitive to the number of items in a scale, with longer scales more likely to yield higher coefficients, even when item correlations are moderate (Malhotra et al., 2017). Therefore, these values must be interpreted with caution.

4.1.3. Validity of measuring instruments

Thirdly, a validity check was performed to ensure that measurement scales accurately capture the construct it is intended to measure, not just consistently (reliability), but also correctly. This step is essential as reliability is a necessary but not sufficient condition to assess validity, (Malhotra et al., 2017), since a scale may consistently measure the wrong concept. Considering this, convergent validity was assessed using Pearson correlation analyses to determine whether items within each scale are positively correlated, indicating that they measure the same underlying construct (Malhotra et al., 2017). All results can be found in **Appendix E**.

Regarding self-esteem and body-esteem, nearly all item pairs showed positive and statistically significant correlations (at the 0.001 level), as their p-values were below the required 0.05 threshold. Only 2 exceptions were observed within the self-esteem scale: the correlations between SE01 and SE08 (p = .133), and SE02 and SE08 (p = .072) were not significant. These observations may result from item phrasing or minor conceptual divergence between the items. However, given the overwhelmingly significant and positive correlations across the scale, the overall convergent validity remains well supported. For body-esteem, all correlations were positive and highly significant, with positive Pearsons' r values and p-values below 0.001. These results support the convergent validity of both self-esteem and body esteem scales used in this study.

Regarding usage motivation, the majority of item pairs demonstrated statistically significant correlations (p < .05), despite the observation of several weaker or non-significant correlations. However, negative correlations were observed for item pairs including one item that was reverse scored in the Excel dataset to reflect intrinsic motivation, rather than extrinsic. Yet, these negative correlations are generally weak, with Pearsons' r values typically around r = -0.1. This could suggest that some of these items may still not fully capture the underlying construct of intrinsic motivation, possibly due to the fact their wording leaned more toward either intrinsic or extrinsic motivation, rather than clearly and consistently representing one or the other. As such, despite efforts to align the direction of measurement, residual conceptual ambiguity may have limited their alignment with other scale items. In light of this, the convergent validity of the usage motivation scale should be interpreted with caution.

4.2. Descriptive statistics

Although they do not allow for drawing conclusions, descriptive statistics provide a clear overview of the data and help identify preliminary patterns in the results.

Descriptive analysis of the mean scores highlights the overall tendencies across self-esteem, body esteem, usage motivation, and usage intensity among the surveyed self-trackers. Specifically, the average self-esteem score is *M* = 3.024 (*SD* = 0,498) on a 4-point Likert scale, indicating a relatively high level of self-esteem, as this value is positioned above the "agree" point on the scale. For body esteem, the average is *M* = 3.04 (*SD* = 0.725), calculated on a 5-point Likert scale, suggesting a moderate level of body esteem among respondents, and thus moderate levels of body image concerns, as the mean is close to the neutrality point of the scale. Regarding usage motivation, the mean score of *M* = 3.443 (*SD* = 0.312) on a 5-point scale indicates a slight tendency for participants to engage with self-tracking technologies primarily for intrinsic rather than extrinsic reasons, as higher scores on the usage motivation scale reflect stronger intrinsic motivation. Finally, the mean for usage intensity is *M* = 3.287 (*SD* = 1.048), on a scale with a maximum possible value of 6.67[2], suggesting a relatively moderate level of engagement intensity with STTs among respondents. All descriptive statistics are provided in **Table 8** below.

Table 8 – Descriptive statistics

	SE	BE	MOTIV_INTR	USAGE_INT
Valid	186	186	186	186
Missing	0	0	0	0
Mean	3.024	3.042	3.443	3.287
Std. Deviation	0.498	0.725	0.312	1.048
Minimum	1.300	1.174	2.632	1.000
Maximum	4.000	5.000	4.158	5.667

Source : JASP output

4.2.1. Split descriptives

In line with the objectives of this research, it is relevant to examine split descriptive statistics. Specifically, this involves comparing the means of the dependent variables self-esteem and body image concerns across the four distinct conditions, each representing either a specific feature of self-tracking technologies or a control condition.

As shown in **Table 9**, the lowest mean for both SE and BE are observed in the fitspiration content condition, with means of *M* = 2.938 for SE and *M* = 2.991 for BE. This suggests that exposure to idealized thin and muscular bodies may be associated with lower self-esteem and body esteem compared to the other conditions. Conversely, SE scores are the highest in the behavior change techniques (BCT) condition with a mean of *M* = 3.149, while the highest BE score was recorded in the gamified and social design condition, with a mean of *M* = 3.089, closely followed by the BCT group with a mean of *M* = 3.076. This may indicate that behavior change techniques might be less harmful to SE and BE than other conditions. Overall, while the fitspiration condition showed the lowest means, BE scores remained close to the neutral point of the scale across all groups. Similarly, SE levels showed little variation across condition groups, with values remaining generally high. This suggests that none of the

[2] The usage intensity construct was measured using three multiple-choice questions with respectively 6, 5, and 9 answer options. The total maximum score was therefore 20, resulting in a maximum possible mean value of 6.67 when divided by the number of items (20/3 = 6.67).

tested STT features produced substantial differences in either body esteem or self-esteem levels, both of which remained relatively stable across conditions. However, these observations remain preliminary, as no statistical tests of significance have yet been conducted to confirm differences between experimental conditions.

Table 9 – Descriptive statistics by experimental condition

	SE				BE			
	Control	Fitspiration	Gamified	BCT	Control	Fitspiration	Gamified	BCT
Valid	53	58	38	37	53	58	38	37
Missing	0	0	0	0	0	0	0	0
Mean	3.042	2.938	3.008	3.149	3.039	2.991	3.089	3.076
Std. Dev.	0.494	0.547	0.441	0.467	0.766	0.627	0.727	0.823
Minimum	1.300	1.300	1.700	2.100	1.174	1.435	1.522	1.174
Maximum	3.800	4.000	3.900	4.000	4.435	4.304	5.000	4.217

Source: JASP output

4.3. Correlation analysis

The final step before proceeding to hypothesis testing is to examine whether some of the key variables are interrelated. **Table 10** below presents the correlations between the variables of interest in this study. As a reference, a p-value below 0.05 indicates that the correlation between the two variables is statistically significant. Pearson's *r* further describes the strength and direction of this relationship: the closer *r* is to ±1, the stronger the correlation (Baiwir, 2024).

Table 10 – Correlation analysis

Variable		SE	BE	MOTIV_INTR	USAGE_INT
1. SE	Pearson's r	—			
	p-value	—			
2. BE	Pearson's r	0.469	—		
	p-value	< .001	—		
3. MOTIV_INTR	Pearson's r	0.100	0.014	—	
	p-value	0.174	0.845	—	
4. USAGE_INT	Pearson's r	0.091	-0.098	0.348	—
	p-value	0.217	0.185	< .001	—

Source: JASP output

As shown in **Table 10**, self-esteem and body esteem are significantly and positively correlated, at a moderate level ($r = 0.469$, $p < .001$). This means that higher levels of self-esteem tend to be associated with higher levels of body esteem—and thus lower body image concerns—and vice versa. Similarly, usage intensity and usage motivation also show a significant moderate positive correlation ($r = 0.348$, $p < .001$). This suggests that individuals who are more intrinsically motivated tend to engage more intensively with STTs. Conversely, lower intrinsic motivation, i.e., higher levels of extrinsic motivation, is associated with lower usage intensity. No other variable pairs are significantly correlated ($p > .05$), which is further confirmed by the Pearson's *r* values being very close to zero, indicating weak or no linear relationships.

It is worth noting that, although correlation analysis reveals linear associations between variables and indicates the strength and direction of these relationships, it does not imply causality in any way (Malhotra et al., 2017).

4.4. Analysis of Variance (ANOVA)

To test the proposed hypotheses, an Analysis of Variance (ANOVA) will be conducted. This test is particularly appropriate as the aim of this study is to determine whether the different experimental conditions, each representing a distinct feature of self-tracking technologies or a control condition, lead to statistically significant differences in self-esteem and body image concerns. As the ANOVA enables the comparison of means across more than two groups (Baiwir, 2024), it is perfectly suited for this research design. **Tables 11** and **12** below present the results of this analysis.

Table 11 – ANOVA body esteem

Cases	Sum of Squares	df	Mean Square	F	p
randnbr	0.280	3	0.093	0.175	0.913
Residuals	96.869	182	0.532		

Source: JASP output

Table 12 – ANOVA self-esteem

Cases	Sum of Squares	df	Mean Square	F	p
randnbr	1.031	3	0.344	1.397	0.245
Residuals	44.765	182	0.246		

Source: JASP output

Based on the ANOVA results presented in **Table 11**, there is no statistically significant difference in body esteem scores across the different condition groups ($p > .05$), i.e., the various STT features and the control group. Consequently, hypotheses H1a, H1b, and H1c are not supported. This finding is not surprising, as it aligns with the descriptive statistics discussed above, which showed minimal variation in body esteem levels between groups.

A similar pattern was observed for self-esteem (see **Table 12**), where the ANOVA also yielded a non-significant result ($p > .05$). This suggests that differences in self-esteem levels across groups are not statistically significant, which, again, is consistent with the relatively stable scores observed in the descriptive statistics. As a result, hypotheses H2a, H2b, and H2c are not supported.

In other words, the specific STT feature respondents were exposed to did not lead to statistically significant differences in body esteem (and thus body image concerns) or self-esteem levels.

4.5. Multiple regression analysis

To examine whether the proposed moderating variables—usage motivation (MOTIV_INTR) and usage intensity (USAGE_INT)—contribute to the prediction of self-esteem (SE) and body esteem (BE) levels, a multiple linear regression analysis was conducted. This step provides an initial evaluation of the extent to which these individual differences (predictors) explain variance in the outcome variables, prior to testing interaction effects.

As shown in **Appendix F**, the regression results indicate that the model did not significantly predict body esteem levels, $F(5, 180) = 0.531$, $p = .753$ (> .05), with a low explained variance ($R^2 = .015$), meaning that only 1.5% of the variance in body esteem was explained by the predictors. Neither intrinsic motivation ($p = .527$) nor usage intensity ($p = .148$) showed a significant effect, suggesting that these individual characteristics did not meaningfully predict body esteem levels, irrespective of the STT feature participants were exposed to.

Similarly, the regression model did not significantly predict self-esteem levels, $F(5, 180) = 1.384$, $p = .232$ (> .05), with a low explained variance ($R^2 = .037$), meaning that only 3.7% of the variance in self-esteem was explained by the predictors. Again, neither intrinsic motivation ($p = .404$) nor usage intensity ($p = .305$) showed a significant effect, suggesting that these individual characteristics also did not meaningfully predict self-esteem levels across conditions.

However, these results only reflect the main effects of the predictors (i.e., usage motivation and usage intensity) on the dependent variables (DVs), without accounting for any potential interaction effects. Yet, to conduct a proper test of moderation, it is essential to include interaction terms between the independent variables (IVs) and the proposed moderators, as main effects alone cannot determine whether a moderator influences the strength or direction of the relationship between the IVs and the DVs (Hayes, 2018). Therefore, to statistically assess moderation, the PROCESS macro, an SPSS extension for conducting regression-based moderation and mediation analysis, was employed to test interaction terms and determine whether usage motivation and usage intensity significantly moderate the relationship between exposure to self-tracking features and body esteem or self-esteem levels. The results of this analysis are presented and interpreted in the following section.

4.6. Moderation analysis

The results of the moderation analysis are presented in **Appendix G.** For body esteem, these results show that usage motivation (MOTIV) does not significantly moderate the relationship between exposure to self-tracking features and body esteem (and thus body image concerns), across any of the experimental conditions, as the p-values for each interaction term (*Int_1, Int_2*, and *Int_3*) exceed the 0.05 significance threshold. Therefore, hypotheses H3a, H3b, H3c are not supported.

However, usage intensity (USAGE) demonstrated a statistically significant moderating effect for two self-tracking conditions. Specifically, the interaction between usage intensity and the gamified and social design (*Int_5*, $p = .0235$, $B = –0.3691$), as well as the interaction with the behavior change techniques condition (*Int_6*, $p = .0376$, $B = –0.2950$), were both significant. These negative coefficients indicate that, as participants' usage intensity increased, their reported body esteem decreased in these conditions, meaning their body image concerns increased. No significant moderation effect was observed for the fitspiration condition (*Int_4*, $p = .5274$, $B = –0.0971$), which suggests that the intensity of engagement did not meaningfully alter the relationship between fitspiration exposure and body image concerns. Considering these results, H5a and H5c are supported, while H5b is not supported.

Regarding self-esteem, the moderation analysis results revealed that neither usage motivation nor usage intensity significantly moderated the relationship between exposure to self-tracking features and self-esteem in any of the experimental conditions, all p-values for the interaction terms being greater than 0.05. As a result, hypotheses H4a, H4b, H4c, as well as H6a, H6b, and H6c, are not supported.

4.7. Summary of hypothesis testing

To conclude this analytical chapter, **Table 13** provides an overview of all proposed hypotheses and summarizes the corresponding results from the analysis.

Table 13 – Summary of hypothesis testing

H1a. The behavior change techniques of STTs increase body image concerns.	Not supported
H1b. The fitspiration content of STTs increases body image concerns.	Not supported
H1c. The gamified and social design of STTs increases body image concerns.	Not supported
H2a. The behavior change techniques of STTs lower self-esteem.	Not supported
H2b. The fitspiration content of STTs lowers self-esteem.	Not supported
H2c. The gamified and social design of STTs lowers self-esteem.	Not supported
H3a. The positive relationship between behavior change techniques and body image concerns is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.	Not supported
H3b. The positive relationship between fitspiration content and body image concerns is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.	Not supported
H3c. The positive relationship between gamified and social design and body image concerns is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.	Not supported
H4a. The negative relationship between behavior change techniques and self-esteem is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.	Not supported
H4b. The negative relationship between fitspiration content and self-esteem is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.	Not supported
H4c. The negative relationship between gamified and social design and self-esteem is moderated by usage motivation, such that the relationship is weaker at higher levels of intrinsic motivation.	Not supported
H5a. The positive relationship between behavior change techniques and body image concerns is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.	Supported
H5b. The positive relationship between fitspiration content and body image concerns is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.	Not supported
H5c. The positive relationship between gamified and social design and body image concerns is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.	Supported
H6a. The negative relationship between behavior change techniques and self-esteem is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.	Not supported
H6b. The negative relationship between fitspiration content and self-esteem is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.	Not supported
H6c. The negative relationship between gamified and social design and self-esteem is moderated by usage intensity, such that the relationship is stronger at higher levels of usage intensity.	Not supported

5. Discussion

5.1. Rethinking the experimental approach

This study aimed to investigate the effects of engagement with self-tracking technologies (STTs) on psychological well-being, focusing specifically on body image concerns and self-esteem. Based on the literature review (see Chapter 2), it was expected that engaging with specific self-tracking technology features, namely fitspiration content, gamified and social design, and behavior change techniques, would increase users' body image concerns (H1a, H1b, H1c) and lower their self-esteem (H2a, H2b, H2c), by reinforcing idealized body standards, promoting social comparison, and pressuring users to pursue sometimes unattainable performance or appearance goals (e.g., Berry et al., 2021; Chen et al., 2024; Jain et al., 2025).

In line with Chen et al.'s (2024) call for feature-specific research, a quantitative experimental design was employed to isolate effects of each STT feature on these psychological outcomes, rather than focusing on general usage. However, despite the anticipated effects, findings revealed no significant differences in body esteem or self-esteem levels across the four experimental groups, suggesting that exposure to different STT features did not produce significantly different psychological outcomes.

The discrepancy between the expected results derived from the literature and the findings observed in this experimental study may be attributed to several factors. A main potential explanation is the way participants were exposed to the self-tracking feature (or the control condition). Indeed, each group encountered a brief written scenario putting respondents into a self-tracking situation, accompanied by a screenshot illustrating the feature of interest. However, this stimulus, limited to a single image and short description, may not have been immersive, emotionally engaging, or dynamic enough to evoke a meaningful psychological response. In other words, the mere exposure to a static representation of a self-tracking feature may not have been impactful enough to influence body esteem or self-esteem levels. This interpretation aligns with prior neuroscientific research which has shown that dynamic stimuli activate emotion-related brain regions more strongly than static ones. Indeed, static images elicited lower neural engagement, whereas dynamic stimuli were shown to be more effective at triggering emotional responses (Goldberg et al., 2015; Sato et al., 2004). As such, this may partly explain the absence of significant effects on body image concerns and self-esteem in the present study.

Furthermore, the lack of personal relevance in the situation presented to participants may have also contributed to the absence of significant effects on body image and self-esteem. The scenario shown to participants was centered around going for a walk, and the accompanying screenshots primarily focused on step count data (except the fitspiration condition), as step count is one of the most tracked metrics (Chan et al., 2022). However, for users who engage with STTs mainly for other purposes, such as tracking calories, heart rate, running performance, or sleep patterns, this specific context may have felt disconnected from their typical self-tracking habits. As a result, the stimulus may have failed to evoke the thoughts and emotions that users usually associate with their actual self-tracking experiences.

5.2. The role of usage motivation

To deepen the understanding of how self-tracking technologies relate to psychological outcomes such as body image concerns and self-esteem, the usage motivation was examined as a potential moderating variable. Based on the literature review, intrinsic motivation was expected to buffer the potential negative effects of STT usage on psychological outcomes, such as body image (H3a, H3b, H3c) and self-esteem (H4a, H4b, H4c) levels, in line with Self-Determination Theory (SDT), which links intrinsic motivation to enhanced well-being and resilience to external pressures (Etkin, 2016; Ryan & Deci, 2000).

However, contrary to expectations, the motivation type did not exhibit any statistically significant moderating effect. Indeed, whether participants were more intrinsically or more extrinsically motivated to self-track had no significant impact on their body image concerns and self-esteem, regardless of the self-tracking feature they were exposed to.

One possible explanation is that the reverse scoring of certain items to align them with intrinsic motivation (see Research Design) may have introduced conceptual inconsistencies in how motivation was measured. As noted in the Results section, the scale items tended to lean more toward one motivational type or the other, rather than clearly representing a distinct category (i.e., intrinsic or extrinsic). Therefore, some conceptual ambiguity may have been introduced. In addition, some conceptualizations of motivation are closely related and may overlap. Prior research has shown that certain forms of extrinsic motivation, such as integrated regulation, are highly autonomous and thus closely aligned with intrinsic motivation on the SDT continuum (Ryan & Deci, 2000). Such conceptual overlaps may have made it difficult to clearly distinguish the motivation type captured by each item, potentially compromising the scale's internal validity and its ability to accurately reflect participants' true motivational orientations, and, consequently, detect any moderating effects.

Another potential factor is the personality traits of users, which were not measured in this study. Prior research has shown that individual characteristics such as neuroticism, conscientiousness, perfectionism, locus of control, and coping style can influence users' vulnerability or resilience to negative psychological outcomes (Chen et al., 2024; Ryan et al., 2019). For instance, perfectionism has been associated with a heightened sensitivity to feedback, which may lead to body dissatisfaction and maladaptive behaviors such as excessive exercising or restrictive dieting as a means of compensating for perceived failure, which, in turn, may contribute to anxiety and depression (Chen et al., 2024). Similarly, coping style, which shapes how individuals respond to stressors, also plays a critical role. Individuals adopting problem-focused coping strategies tend to be more resilient (e.g., to negative self-tracking feedback), whereas those who avoid or escape from stressors are more prone to negative emotions and thought patterns (Algorani & Gupta, 2023). These findings suggest that intrinsic motivation alone may not be sufficient to buffer negative effects, as personality traits can significantly shape how users interpret and respond to self-tracking experiences. This may help explain the absence of any significant moderating effect of intrinsic motivation on body image concerns and self-esteem in the present study.

5.3. The role of usage intensity

Another moderating variable examined in this study is the usage intensity, i.e., users' level of engagement with self-tracking technologies. Based on the literature review, higher usage intensity is expected to reinforce the likelihood of poor psychological outcomes (Chen et al., 2024), such as body image concerns (H5a, H5b, H5c) and low self-esteem (H6a, H6b, H6c). Indeed, users who engage more intensively with STTs are more frequently exposed to idealized performance metrics and body ideals, which can reinforce upward comparison and low self-acceptance (Kim, 2024).

However, the results of this study provided only partial support for these expectations. Usage intensity significantly moderated the effect of exposure to behavior change techniques and gamified and social design on body esteem, but not the effect of exposure to fitspiration content. Additionally, no significant moderating effects were observed for self-esteem, across any of the experimental conditions.

This distinction between body esteem and self-esteem results may be explained by the nature of the psychological constructs being measured. Indeed, self-esteem has been widely regarded as a trait-like construct (i.e., an internal characteristic of a person) that is relatively stable over time and across contexts (Trzesniewski et al., 2003). As such, it may be less susceptible to situational influences such as brief exposure to self-tracking features or varying levels of engagement with self-tracking technologies. Research has shown that, even during periods of significant life transition, such as emerging adulthood, self-esteem maintains a high degree of rank-order stability (Chung et al., 2014), which means that people showed consistent level of self-worth across time. Considering this, even high levels of usage intensity may not be sufficient to meaningfully alter individuals' global self-evaluations. In contrast, body image is more context-sensitive, particularly in environments that emphasize appearance ideals and performance monitoring (e.g., social media). It is strongly shaped by external feedback and societal pressures to conform to aesthetic norms (Berry et al., 2021; Rodgers et al., 2023), which are frequently emphasized in the design of self-tracking technologies. Taking this into account, intensive engagement with STTs, and thus repeated exposure to appearance-related or goal-driven features, may heighten body image concerns more directly than they affect self-esteem.

The absence of a moderation effect in the fitspiration condition, even for body esteem, may be explained by the nature of fitspiration content itself, which might be less influenced by usage intensity, compared to gamification and behavior change techniques features. A systematic review of experimental studies regarding exposure to body ideals revealed that even a brief, one-time exposure to idealized body images on social networks can lead to immediate increases in body dissatisfaction (Fioravanti et al., 2022). In contrast, features such as gamification and behavior change techniques may rely more heavily on sustained engagement to meaningfully influence psychological outcomes. In the literature, negative effects on body image linked to these features are often described as arising from *constant* feedback, *constant* self-surveillance, or *constant* notifications and reminders (e.g., Berry et al., 2021), which highlights the importance of continuous engagement, and therefore usage intensity, as a key factor in their psychological impact. This suggests that the impact of usage intensity may be more pronounced for features like gamification and BCTs, which tend to rely more on sustained interaction, whereas fitspiration may influence body esteem, even at lower levels of engagement. However, it is worth noting that the usage intensity measured in this study captured general engagement with self-tracking technologies, rather than feature-specific usage intensity. As such, the moderating effects observed may reflect general usage patterns, rather than direct interaction with the specific feature to which participants were exposed.

6. Conclusion

6.1. Short summary

In a context where self-tracking technologies are increasingly used to promote health and well-being, growing concerns have emerged in the literature regarding their potential to contribute to negative psychological outcomes.

A review of the literature revealed that engagement with self-tracking technologies is often associated with increased negative emotional, cognitive, and behavioral reactions, such as stress, anxiety, rumination, and disordered eating behaviors. However, several authors call for more empirical research examining the effects of self-tracking technologies on psychological well-being, with particular attention to which specific design features that may contribute to these outcomes (e.g., Chen et al., 2024; Mwangi et al., 2024).

As such, the present study investigates how self-tracking technologies may contribute to negative psychological outcomes, with a focus on two key components of the self-acceptance dimension of eudaimonic psychological well-being: body image concerns and self-esteem. Specifically, it examines how distinct design elements, such as fitspiration content, behavior change techniques, and gamified and social features, can evoke negative psychological reactions independently, rather than attributing these effects to overall patterns of self-tracking technology use. Furthermore, this study examines the potential moderating role of individual characteristics such as usage motivation (i.e., intrinsic or extrinsic) and usage intensity, in shaping the psychological impact of specific self-tracking technology features.

To investigate these effects, a one-way fixed effects experimental design was used, in which participants were randomly assigned to one of four experimental conditions, that is, one of the three self-tracking technology features or a control group. Furthermore, data were collected through a quantitative online survey, distributed via social media.

After conducting thorough statistical analyses, the results revealed that, contrary to expectations derived from the literature, there were no significant differences in body image concerns and self-esteem across the different experimental conditions. This indicates that the specific self-tracking feature participants were exposed to did not significantly affect these outcomes. Additionally, higher levels of intrinsic motivation did not significantly buffer the negative effects of self-tracking exposure on body image or self-esteem, despite anticipated moderation effects. Finally, the usage intensity significantly moderated the effect of exposure to the gamified and social design condition as well as the behavior change techniques condition on body image, but not in the fitspiration condition, nor in any condition for self-esteem. In other words, higher levels of engagement intensity with self-tracking technologies were associated with lower body image (i.e., greater body image concerns), as expected, but only in the gamified and social design and behavior change techniques conditions.

6.2. Managerial implications

Despite the absence of significant differences in body image concerns and self-esteem across specific self-tracking features, this study revealed that higher levels of intensity of STT use were associated with lower body esteem in certain conditions (i.e., gamified and social design, and behavior change techniques). This highlights that usage intensity plays a role in exacerbating some negative psychological outcomes among users. Therefore, marketers and developers should consider designing features that promote balanced usage and avoid encouraging excessive engagement. For example, they could reduce the frequency and intrusiveness of notifications and performance reminders that prompt users to check their data, especially when goals are unmet, as they may evoke feelings of failure, dissatisfaction, or guilt. Such reactions may in turn encourage obsessive self-surveillance and social comparison, all of which may contribute to psychological risks. Ultimately, shifting the focus away from intensive engagement and constant performance pressure may reduce negative emotions felt by users, which may in turn lower product abandonment (Attig & Franke, 2023) and support the long-term profitability of companies marketing self-tracking technologies.

These insights can also inform public policy makers about the risks associated with high intensity usage and support the development of regulations for marketers and developers aimed at limiting the promotion of excessive engagement with self-tracking devices. Building on the previous example, a regulation could require marketers to limit the number of push notifications and reminders to a predetermined daily threshold. Another potential regulation could mandate that self-tracking tools display warning messages after an extended period of use, in order to raise users' awareness about their usage patterns and transparently communicate the potential risks associated with high-intensity engagement. Overall, these findings suggest that engaging with self-tracking technologies can be harmful to users. Although this was demonstrated only under specific conditions (i.e., gamified and social design and behavior change techniques), the results support existing literature and confirm the potential for psychological harm. This should thus encourage public policymakers to further investigate the risks associated with STT use and consider appropriate protective measures.

Finally, these findings should also prompt health insurance companies that include STTs in their packages to avoid encouraging overly ambitious physical activity goals for their policyholders, as this may unintentionally backfire and harm their psychological health. For example, insurers could set more personalized and flexible targets and tie incentives (e.g., premium discounts) to consistent, moderate activity rather than high-intensity performance goals.

6.3. Theoretical implications

Beyond managerial implications, this study also adds to the academic knowledge about the dark side of self-tracking technologies.

First, to the best of current knowledge, this study is one of the few studies examining the impact of self-tracking features in isolation, rather than considering STT usage as a uniform experience. While prior research has identified specific elements that may trigger or aggravate negative psychological outcomes, such as receiving negative feedback, failing to achieve a certain ranking, or exposure to idealized body images, few studies have employed a randomized experimental design to directly compare the effects of distinct self-tracking features. By adopting this approach, the present study makes an early contribution to the empirical investigation of feature-specific effects in self-tracking technologies. Even though the results revealed no significant differences in body image concerns and self-esteem across the different self-tracking feature conditions, this may suggest that the relationship between STT features and psychological outcomes could be better captured through an improved experimental design, for example, by using more dynamic or immersive stimuli, rather than static ones. In light of this, the present study offers useful methodological guidance, as researchers can build on

this research to refine experimental designs and further explore the psychological effects of individual STT features.

Furthermore, the significant moderating effect of usage intensity in the gamified and behavior change conditions for body image concerns supports Chen et al.'s (2024) proposed conceptual framework, which posits that higher levels of STT usage intensity may exacerbate negative health outcomes. Conversely, the non-significant effects observed for self-esteem and within the fitspiration condition in general add nuance to this framework and suggests that the impact of usage intensity may vary depending on the self-tracking feature involved and the nature of the psychological construct being measured. Additionally, although no significant moderating effects were found for usage motivation, its inclusion addresses Chen et al.'s (2024) call to examine motivational moderators of STT use. The lack of significant findings may stem from limitations in the measurement scale and thus informs scholars about the potential need for more robust and valid instruments in future research.

Overall, the present work contributes to the literature on self-tracking technologies by responding to recent calls for more quantitative research on the impact of STT features (Chen et al., 2024), particularly at the micro-level of well-being, such as eudaimonic psychological well-being (Mwangi et al., 2024), and by addressing the broader paradox of technology's dual impact on consumer well-being (McLean et al., 2025). While the findings did not reveal many significant effects, this study nonetheless provides a valuable foundation for future research in this emerging field.

6.4. Limitations and suggestions for future research

Although this research offers insights into the impact of self-tracking technologies on psychological well-being, some limitations must be acknowledged and can serve as a foundation for future research.

First, a key limitation lies in the design of the experimental study used to test the impact of exposure to self-tracking features on body image concerns and self-esteem. Specifically, the emotional valence of the screenshots varied across conditions (e.g., positive reward in the gamification condition, negative feedback in the BCT condition), which may have influenced participants' responses and made it difficult to isolate the effects of the feature type alone. Additionally, as mentioned in the "Discussion" section, the use of more dynamic stimuli could have evoked stronger emotional responses compared to the brief written scenario and static screenshot that were presented. As such, future research should consider using more immersive formats, such as short, animated videos simulating a self-tracking situation and typical interactions with a distinct feature, while ensuring consistent emotional valence across conditions to better isolate the impact of each feature.

Alternatively, negative outcomes associated with specific self-tracking features may develop gradually (Chen et al., 2024) and may not be fully captured in a cross-sectional design, which only collects data at a single point in time, as was the case in this research. In this regard, a longitudinal study could offer more detailed insights by observing sustained engagement and capturing the cumulative effects on body image concerns and self-esteem that may emerge over time. For example,[3] a longitudinal field experiment could equip participants with a self-tracking device (e.g., a smartwatch) for an extended period, during which they complete periodic surveys to track the evolving psychological effects of continued exposure to a specific STT feature. This approach could yield more accurate insights by capturing immediate reactions after interactions with self-tracking features. Additionally, it could allow for a better understanding of the role of usage intensity and motivations, as these constructs could be monitored over time and linked to evolving psychological outcomes. In this regard, future research

[3] This approach is inspired by an ongoing research project developed by Baiwir, Dessart, and Delcourt (HEC Liège), which investigates the effects of gamified wearables on well-being through a longitudinal field experiment using Fitbits.

should adopt a longitudinal approach to examine more effectively how specific self-tracking features contribute to body image concerns and self-esteem.

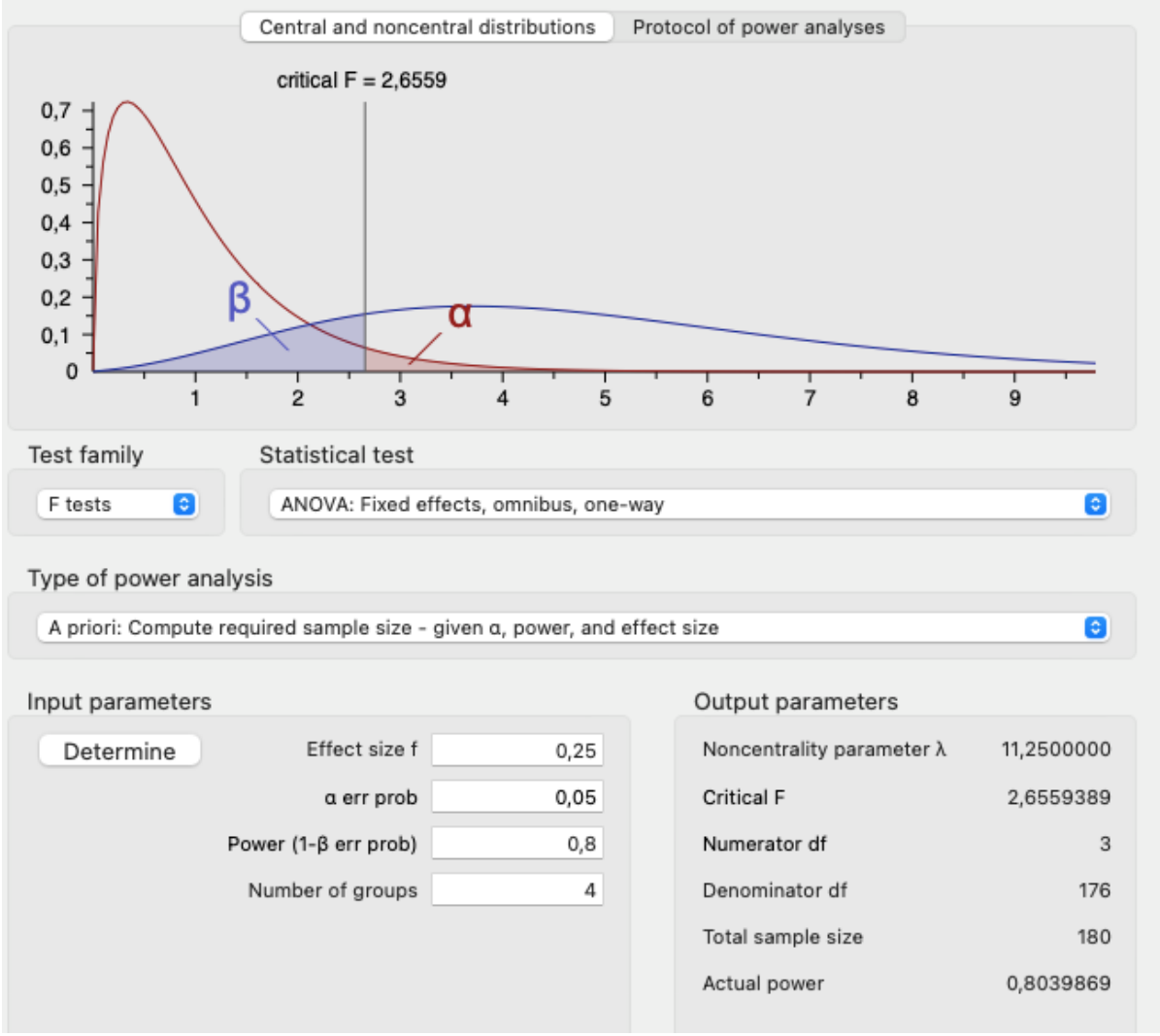
Another limitation concerns the sampling method used in this study (i.e., convenience sampling), which was chosen as it is a cost-effective and time-saving method, allowing to rapidly collect easily accessible data. However, it is not recommended for causal research designs due to its inherent limitations (Malhotra et al., 2017). This method can introduce selection bias and may not provide a representative sample of the target population. In this study, for example, the sample is predominantly composed of women (65.6% versus 34.4% of men) and likely consists mostly of Belgian individuals, given that the survey was distributed within a predominantly Belgian social media network. In addition, 72.83% of respondents are under the age of 35, indicating that younger users are overly represented in this study compared to older age groups. These sampling imbalances compromise the generalizability of the findings the ability to establish cause-and-effect relationships. Considering this, future research adopting a probability sampling technique is required to enhance the representativeness of the sample and strengthen the validity of the conclusions.

A further methodological concern involves the variable “usage motivation”, which showed limited internal validity, likely due to conceptual ambiguity when attempting to align the direction of measurement items. This may explain why no moderating effects were observed in this study. Future research should consider refining the measurement scale or adopting alternative validated instruments to improve internal validity.

Finally, as highlighted by Chen et al. (2024) in their systematic literature review, user characteristics may play a crucial moderating role in the relationship between self-tracking features and health outcomes. However, within the scope of this study, these characteristics were not comprehensively measured. Indeed, only age and gender were included, and these were treated solely as control variables rather than potential moderators. As mentioned in the “Discussion” section of this work, additional individual differences, such as personality traits (e.g., perfectionism, locus of control, intolerance of uncertainty) and coping mechanisms, may significantly influence how users interpret and respond to their self-tracking data, potentially contributing to negative psychological outcomes. In light of this, future research should integrate these user characteristics as moderating variables to develop a more holistic understanding of when and for whom self-tracking technologies may carry psychological risks.

7. Appendices

Appendix A: Sample size determination with G*power 3.1.



Source: G*power 3.1.

Appendix B: Questionnaire

English version

The Impact of Self-Tracking Technologies on Psychological Well-being

Dear participant,

As part of my master's thesis in International Strategic Marketing at HEC Liège, I am conducting a study on self-tracking technologies and their influence on users' psychological well-being. Self-tracking technologies refer to devices and applications that allow users to collect and analyze their own data, such as physical activity (step count, calories burned, distance traveled, etc.), heart rate, sleep quality, etc.

Notable examples of these technologies include Strava, Fitbit, Garmin Connect, WeWard, Apple Watch, Oura Ring, and Apple Health, among others.

To this end, I am seeking your help by inviting you to complete a questionnaire. You will be asked to answer a few questions about your experience with these technologies.

This survey will take no more than 5 minutes to complete and is completely anonymous.

There are no right or wrong answers, what matters most is your honest and thoughtful responses. Please take the time to read each question carefully and answer as sincerely as possible.

Thank you in advance for your participation.

Salomé Beltran

Self-tracking Technology

randomization

Scenario 0

Imagine that you've just wrapped up a busy day—whether it was spent at work, in class, running errands, or handling personal projects. You finally have a moment to yourself, and with the weather being nice, you decide to go for a walk after dinner.

As you head back home, feeling refreshed, you take out your phone and open your self-tracking app to check in on your activity for the day.

Take a moment to consider the situation above, then continue.

Only answer this question if the following conditions are met:
randnbr == 1

Scenario 1

Imagine that you've just wrapped up a busy day—whether it was spent at work, in class, running errands, or handling personal projects. You finally have a moment to yourself, and with the weather being nice, you decide to go for a walk after dinner.

As you head back home, feeling refreshed, you take out your phone and open your self-tracking app to check in on your activity for the day. You then scroll through the app's community feed and come across the following posts:

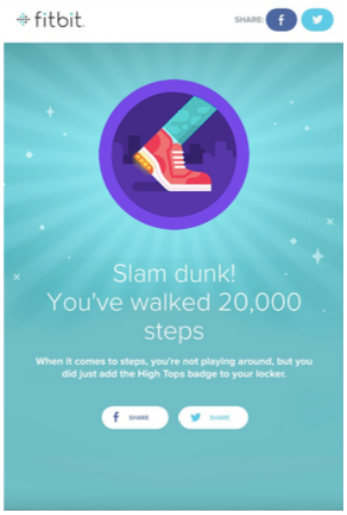
Take a moment to consider the situation above, then continue.

Only answer this question if the following conditions are met:
randnbr == 2

Scenario 2

Imagine that you've just wrapped up a busy day—whether it was spent at work, in class, running errands, or handling personal projects. You finally have a moment to yourself, and with the weather being nice, you decide to go for a walk after dinner.

As you head back home, feeling refreshed, you take out your phone and open your self-tracking app to check in on your activity for the day. As the app loads, you come across the following message:



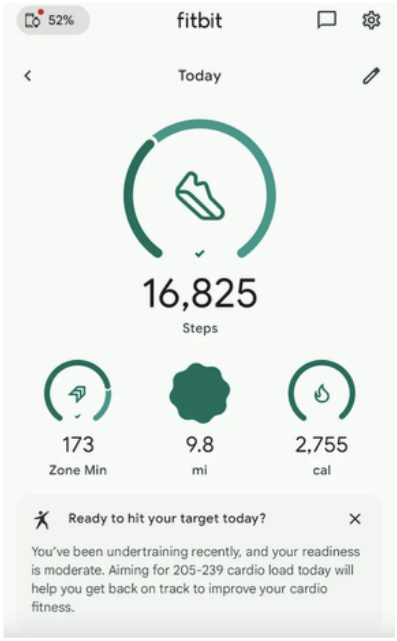
Take a moment to consider the situation above, then continue.

Only answer this question if the following conditions are met:
randnbr == 3

Scenario 3

Imagine that you've just wrapped up a busy day—whether it was spent at work, in class, running errands, or handling personal projects. You finally have a moment to yourself, and with the weather being nice, you decide to go for a walk after dinner.

As you head back home, feeling refreshed, you take out your phone and open your self-tracking app to check in on your activity for the day. As the app loads, you come across the following message:



Take a moment to consider the situation above, then continue.

Only answer this question if the following conditions are met:
randnbr == 4

Self-esteem

Below is a list of statements dealing with your general feelings about yourself. Please indicate how strongly you agree or disagree with each statement.

*

Please choose the appropriate response for each item:

	Strongly disagree	Disagree	Agree	Strongly agree
I feel that I'm a person of worth, at least on an equal plane with others.	◯	◯	◯	◯
I feel that I have a number of good qualities.	◯	◯	◯	◯
I am inclined to feel that I am a failure.	◯	◯	◯	◯
I am able to do things as well as most other people.	◯	◯	◯	◯
I do not have much to be proud of.	◯	◯	◯	◯
I take a positive attitude toward myself.	◯	◯	◯	◯
On the whole, I am satisfied with myself.	◯	◯	◯	◯
I certainly feel useless at times.	◯	◯	◯	◯
I wish I had more respect for myself.	◯	◯	◯	◯
At times I think I am no good at all.	◯	◯	◯	◯

Body Esteem - Appearance

Below is a list of statements dealing with your general feelings about your body and appearance. Please indicate how often this statement applies to you. *

Please choose the appropriate response for each item:

	Never	Seldom	Sometimes	Often	Always
I wish I looked like someone else.	◯	◯	◯	◯	◯
There are lots of things I would change about my look if I could.	◯	◯	◯	◯	◯
I wish I looked better.	◯	◯	◯	◯	◯
My looks upset me.	◯	◯	◯	◯	◯
I feel ashamed of how I look.	◯	◯	◯	◯	◯
I worry about the way I look.	◯	◯	◯	◯	◯
I like what I see when I look in the mirror.	◯	◯	◯	◯	◯
I'm looking as nice as I would like to.	◯	◯	◯	◯	◯
I'm pretty happy about the way I look.	◯	◯	◯	◯	◯
I like what I look like in pictures.	◯	◯	◯	◯	◯

Body Esteem - Weight

Below is a list of statements dealing with your general feelings about your body and appearance. Please indicate how often this statement applies to you.

*

Please choose the appropriate response for each item:

	Never	Seldom	Sometimes	Often	Always
I am satisfied with my weight.	◯	◯	◯	◯	◯
I really like what I weigh.	◯	◯	◯	◯	◯
I feel I weigh the right amount for my height.	◯	◯	◯	◯	◯
My weight makes me unhappy.	◯	◯	◯	◯	◯
I am preoccupied with trying to change my body weight.	◯	◯	◯	◯	◯
Weighing myself depresses me.	◯	◯	◯	◯	◯
I think I have a good body.	◯	◯	◯	◯	◯
I'm proud of my body.	◯	◯	◯	◯	◯

Body Esteem - Attribution

Below is a list of statements dealing with your general feelings about your body and appearance. Please indicate how often this statement applies to you.

*

Please choose the appropriate response for each item:

	Never	Seldom	Sometimes	Often	Always
Other people consider me good looking.	◯	◯	◯	◯	◯
My looks help me get dates.	◯	◯	◯	◯	◯
People my own age like my looks.	◯	◯	◯	◯	◯
I think my appearance would help me get a job.	◯	◯	◯	◯	◯
I'm as nice looking as most people.	◯	◯	◯	◯	◯

Usage Motivations

Please indicate how much you agree or disagree with the following statements regarding your use of self-tracking technologies.

I'm self-tracking because ...

*

Please choose the appropriate response for each item:

	Disagree strongly	Disagree a little	Neither agree nor disagree	Agree a little	Agree strongly
... I enjoy getting lost totally in self-tracking activities.	◯	◯	◯	◯	◯
... I like playing around with numbers/statistics, etc.	◯	◯	◯	◯	◯
... I like playing around with my smartphone/technical device, etc.	◯	◯	◯	◯	◯
... I enjoy forgetting about time while doing so.	◯	◯	◯	◯	◯
... it is fun and entertaining.	◯	◯	◯	◯	◯
... I want to help/inspire others.	◯	◯	◯	◯	◯
... the way I'm doing it is interesting for others/might help others.	◯	◯	◯	◯	◯
... I want to compare my results to others.	◯	◯	◯	◯	◯
... I want to present myself to others.	◯	◯	◯	◯	◯
... I want to control what I'm doing with my life.	◯	◯	◯	◯	◯
... I try to manipulate certain aspects in my life.	◯	◯	◯	◯	◯
... I enjoy being my own master.	◯	◯	◯	◯	◯
... I'm interested in how certain things in (my) life interact.	◯	◯	◯	◯	◯
... it helps me to optimize the way I'm living.	◯	◯	◯	◯	◯
... it motivates me to keep on working for a goal.	◯	◯	◯	◯	◯
... it allows me to reward myself.	◯	◯	◯	◯	◯
... it facilitates my self-discipline.	◯	◯	◯	◯	◯
... I don't trust in the healthcare system/classic therapies.	◯	◯	◯	◯	◯
... I want to be independent from traditional medical treatments.	◯	◯	◯	◯	◯

Usage Intensity

How long have you been using self-tracking technologies? *

Please choose **only one** of the following:

- ◯ Less than a month
- ◯ About 1 to 3 months
- ◯ About 3 to 12 months
- ◯ About 1 to 2 years
- ◯ More than 2 years

Which self-tracking device(s) do you use?

*

Please choose **all** that apply:

- ☐ Application
- ☐ Smartwatch
- ☐ Smart ring
- ☐ Smart scale
- ☐ Fitness band
- ☐ Other: _____

Which metric(s) do you track? *

Please choose **all** that apply:

- ☐ Step count
- ☐ Calories burned
- ☐ Distance traveled
- ☐ Physical activity duration
- ☐ Heart rate
- ☐ Sleep quality
- ☐ Body temperature
- ☐ Blood pressure
- ☐ Calorie intake
- ☐ Other: _____

How often do you check your self-tracking data?

*

Please choose **only one** of the following:

- ◯ Never
- ◯ Rarely (e.g., less than once a month)
- ◯ Occasionally (e.g., a few times a month)
- ◯ Regularly (e.g., once a week)
- ◯ Often (e.g., several times a week)
- ◯ Very often (e.g., daily or more)

About you

What is your gender? *

Please choose **only one** of the following:

- ◯ Male
- ◯ Female
- ◯ Non-binary
- ◯ Prefer not to say

How old are you? *

Please write your answer here:

Thank you for your participation!

Your responses have been succesfully saved. If you have any questions or would like to receive the study results, feel free to contact me at salome.beltran@student.uliege.be

Salomé Beltran.

Source: LimeSurvey

French version

L'impact des technologies de self-tracking sur le bien-être psychologique

Cher(e) participant(e),

Dans le cadre de mon mémoire en Marketing Stratégique International à HEC Liège, je mène une étude sur les technologies de self-tracking et leur influence sur le bien-être psychologique des utilisateurs. Les technologies de self-tracking désignent les dispositifs et applications permettant aux utilisateurs de collecter et d'analyser leurs propres données, telles que l'activité physique (nombre de pas, calories brûlées, distance parcourue), la fréquence cardiaque, la qualité du sommeil, etc.

Parmi les exemples notables de ces technologies figurent Strava, Fitbit, Garmin Connect, WeWard, Oura Ring, Apple Watch, et Apple Santé, entre autres.

À cette fin, je sollicite votre aide en vous invitant à répondre à un questionnaire. Vous serez amené(e) à répondre à quelques questions sur votre expérience avec ces technologies.

Ce questionnaire ne prendra pas plus de 5 minutes à compléter et est entièrement anonyme.

Il n'y a pas de bonnes ou de mauvaises réponses, l'important est de répondre avec honnêteté. Lisez chaque question attentivement et répondez aussi sincèrement que possible.

Merci d'avance pour votre participation.

Salomé Beltran

Self-tracking Technology

randomisation

Scénario 0

Imaginez que vous venez de terminer une journée bien remplie—que ce soit au travail, en cours, à faire des courses ou à gérer des projets personnels. Vous avez enfin un moment pour vous, et comme le temps est agréable, vous décidez d'aller faire une promenade après le dîner.

En rentrant chez vous, ressourcé(e), vous sortez votre téléphone et ouvrez votre application de self-tracking pour vérifier votre activité de la journée.

Prenez un moment pour considérer cette situation, puis continuez.

Répondre à cette question seulement si les conditions suivantes sont réunies :
randnbr == 1

Scénario 1

Imaginez que vous venez de terminer une journée bien remplie—que ce soit au travail, en cours, à faire des courses ou à gérer des projets personnels. Vous avez enfin un moment pour vous, et comme le temps est agréable, vous décidez d'aller faire une promenade après le dîner.

En rentrant chez vous, ressourcé(e), vous sortez votre téléphone et ouvrez votre application de self-tracking pour vérifier votre activité de la journée. Vous explorez ensuite le fil d'actualité de la communauté et voyez les publications suivantes:

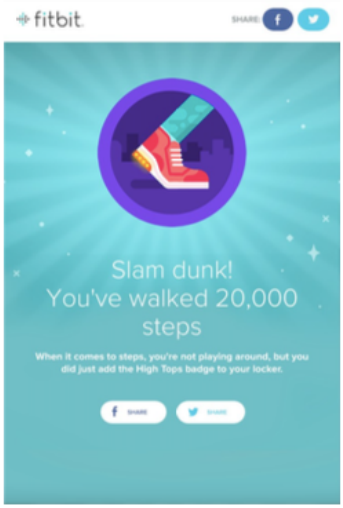
Prenez un moment pour considérer cette situation, puis continuez.

Répondre à cette question seulement si les conditions suivantes sont réunies :
randnbr == 2

Scénario 2

Imaginez que vous venez de terminer une journée bien remplie—que ce soit au travail, en cours, à faire des courses ou à gérer des projets personnels. Vous avez enfin un moment pour vous, et comme le temps est agréable, vous décidez d'aller faire une promenade après le dîner.

En rentrant chez vous, ressourcé(e), vous sortez votre téléphone et ouvrez votre application de self-tracking pour vérifier votre activité de la journée. Lorsque l'application se charge, vous tombez sur le message suivant :



Vous avez atteint les 20 000 pas !
Le message vous félicite avec enthousiasme : « Coup de maître ! Vous avez marché 20 000 pas. Quand il s'agit de faire des pas, vous ne plaisantez pas — vous venez d'ajouter le badge High Tops à votre collection. »

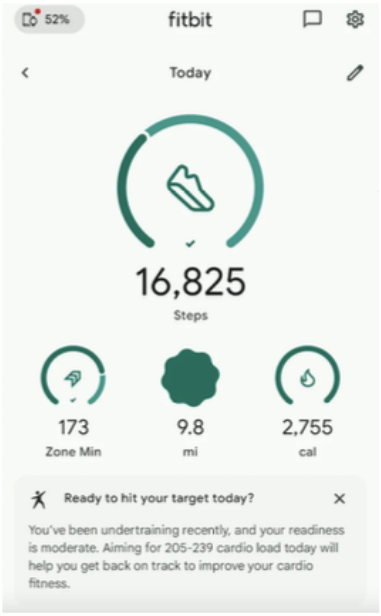
Prenez un moment pour considérer cette situation, puis continuez.

Répondre à cette question seulement si les conditions suivantes sont réunies :
randnbr == 3

Scénario 3

Imaginez que vous venez de terminer une journée bien remplie—que ce soit au travail, en cours, à faire des courses ou à gérer des projets personnels. Vous avez enfin un moment pour vous, et comme le temps est agréable, vous décidez d'aller faire une promenade après le dîner.

En rentrant chez vous, ressourcé(e), vous sortez votre téléphone et ouvrez votre application de self-tracking pour vérifier votre activité de la journée. Lorsque l'application se charge, vous tombez sur le message suivant :



Votre app vous indique que vous avez marché 16 825 pas, parcouru près de 16 kilomètres, brûlé 2 755 calories et passé 173 minutes dans une zone d'effort cardio. Un message vous informe que vous avez été moins actif(ve) ces derniers temps, et vous recommande d'augmenter votre activité aujourd'hui pour améliorer votre forme physique.

Prenez un moment pour considérer cette situation, puis continuez.

Répondre à cette question seulement si les conditions suivantes sont réunies :
randnbr == 4

Estime de soi

Vous trouverez ci-dessous une liste d'affirmations concernant vos ressentis généraux à votre sujet. Veuillez indiquer dans quelle mesure vous êtes d'accord ou non avec chaque affirmation.

*

Choisissez la réponse appropriée pour chaque élément :

	Tout à fait en désaccord	Plutôt en désaccord	Plutôt en accord	Tout à fait en accord
Je pense que je suis une personne de valeur, au moins égal(e) à n'importe qui d'autre.	○	○	○	○
Je pense que je possède un certain nombre de belles qualités.	○	○	○	○
Tout bien considéré, je suis porté(e) à me considérer comme un(e) raté(e).	○	○	○	○
Je suis capable de faire les choses aussi bien que la majorité des gens.	○	○	○	○
Je sens peu de raisons d'être fier(e) de moi.	○	○	○	○
J'ai une attitude positive vis-à-vis de moi-même.	○	○	○	○
Dans l'ensemble, je suis satisfait(e) de moi.	○	○	○	○
Parfois je me sens vraiment inutile.	○	○	○	○
J'aimerais avoir plus de respect pour moi-même.	○	○	○	○
Il m'arrive de penser que je suis un(e) bon(ne) à rien.	○	○	○	○

Estime corporelle - Apparence

Vous trouverez ci-dessous une liste d'affirmations concernant vos sentiments généraux à propos de votre corps et de votre apparence. Veuillez indiquer à quelle fréquence chaque affirmation s'applique à vous. *

Choisissez la réponse appropriée pour chaque élément :

	Jamais	Rarement	Parfois	Souvent	Toujours
J'aimerais ressembler à quelqu'un d'autre.	○	○	○	○	○
Il y a beaucoup de choses que je changerais dans mon apparence si je le pouvais.	○	○	○	○	○
J'aimerais avoir une meilleure apparence.	○	○	○	○	○
Mon apparence me contrarie.	○	○	○	○	○
J'ai honte de mon apparence.	○	○	○	○	○
Je m'inquiète de mon apparence.	○	○	○	○	○
J'aime ce que je vois quand je me regarde dans le miroir.	○	○	○	○	○
J'ai l'apparence que je souhaiterais avoir.	○	○	○	○	○
Je suis plutôt satisfait(e) de mon apparence.	○	○	○	○	○
J'aime mon apparence sur les photos.	○	○	○	○	○

Estime corporelle - Poids

Vous trouverez ci-dessous une liste d'affirmations concernant vos sentiments généraux à propos de votre corps et de votre apparence. Veuillez indiquer à quelle fréquence chaque affirmation s'applique à vous.

*

Choisissez la réponse appropriée pour chaque élément :

	Jamais	Rarement	Parfois	Souvent	Toujours
Je suis satisfait(e) de mon poids.	◯	◯	◯	◯	◯
J'aime vraiment mon poids.	◯	◯	◯	◯	◯
J'ai l'impression que mon poids est adapté à ma taille.	◯	◯	◯	◯	◯
Mon poids me rend malheureux(se).	◯	◯	◯	◯	◯
Je suis préoccupé(e) par l'idée d'essayer de changer mon poids.	◯	◯	◯	◯	◯
Me peser me déprime.	◯	◯	◯	◯	◯
Je pense que j'ai un beau corps.	◯	◯	◯	◯	◯
Je suis fier(e) de mon corps.	◯	◯	◯	◯	◯

Estime corporelle - Attribution

Vous trouverez ci-dessous une liste d'affirmations concernant vos sentiments généraux à propos de votre corps et de votre apparence. Veuillez indiquer à quelle fréquence chaque affirmation s'applique à vous.

*

Choisissez la réponse appropriée pour chaque élément :

	Jamais	Rarement	Parfois	Souvent	Toujours
Les autres me trouvent beau/belle.	◯	◯	◯	◯	◯
Mon apparence m'aide à avoir des rendez-vous.	◯	◯	◯	◯	◯
Les gens de mon âge aiment mon apparence.	◯	◯	◯	◯	◯
Je pense que mon apparence m'aiderait à obtenir un emploi.	◯	◯	◯	◯	◯
Je suis aussi beau/belle que la plupart des gens.	◯	◯	◯	◯	◯

Motivations d'utilisation

Veuillez indiquer dans quelle mesure vous êtes d'accord ou non avec les affirmations suivantes concernant votre utilisation des technologies de self-tracking.

Je pratique le self-tracking parce que...

*

Choisissez la réponse appropriée pour chaque élément :

	Tout à fait en désaccord	Plutôt en désaccord	Ni d'accord ni en désaccord	Plutôt d'accord	Tout à fait d'accord
... j'aime me perdre totalement dans les activités de self-tracking.	◯	◯	◯	◯	◯
... j'aime jouer avec des nombres/statistiques, etc.	◯	◯	◯	◯	◯
... j'aime jouer avec mon smartphone/dispositif technologique, etc.	◯	◯	◯	◯	◯
... j'aime oublier le temps qui passe en faisant cela.	◯	◯	◯	◯	◯
... c'est amusant et divertissant.	◯	◯	◯	◯	◯
... je veux aider/inspirer les autres.	◯	◯	◯	◯	◯
... la manière dont je le fais est intéressante pour les autres/peut les aider.	◯	◯	◯	◯	◯
... je veux comparer mes résultats à ceux des autres.	◯	◯	◯	◯	◯
... je veux me présenter aux autres.	◯	◯	◯	◯	◯
... je veux contrôler ce que je fais de ma vie.	◯	◯	◯	◯	◯
... j'essaie de manipuler certains aspects de ma vie.	◯	◯	◯	◯	◯
... j'aime être mon propre maître.	◯	◯	◯	◯	◯
... je suis intéressé(e) par la manière dont certaines choses de (ma) vie interagissent.	◯	◯	◯	◯	◯
... cela m'aide à optimiser ma façon de vivre.	◯	◯	◯	◯	◯
... cela me motive à continuer à travailler pour atteindre un objectif.	◯	◯	◯	◯	◯
... cela me permet de me récompenser.	◯	◯	◯	◯	◯
... cela facilite mon autodiscipline.	◯	◯	◯	◯	◯
... je ne fais pas confiance au système de santé/thérapies classiques.	◯	◯	◯	◯	◯
... je veux être indépendant(e) des traitements médicaux traditionnels.	◯	◯	◯	◯	◯

Intensité d'utilisation

Depuis combien de temps utilisez-vous des technologies de self-tracking ? *

Veuillez sélectionner une réponse ci-dessous.
Veuillez sélectionner une seule des propositions suivantes :

- ◯ Moins d'un mois
- ◯ Environ 1 à 3 mois
- ◯ Environ 3 à 12 mois
- ◯ Environ 1 à 2 ans
- ◯ Plus de 2 ans

Quel(s) dispositif(s) de self-tracking utilisez-vous ? *

Cochez tout ce qui s'applique.
Veuillez choisir toutes les réponses qui conviennent :

- ☐ Application
- ☐ Montre connectée
- ☐ Bague connectée
- ☐ Balance connectée
- ☐ Bracelet connecté
- ☐ Autre: _____

Quelle(s) donnée(s) mesurez-vous ? *

Cochez tout ce qui s'applique.
Veuillez choisir toutes les réponses qui conviennent :

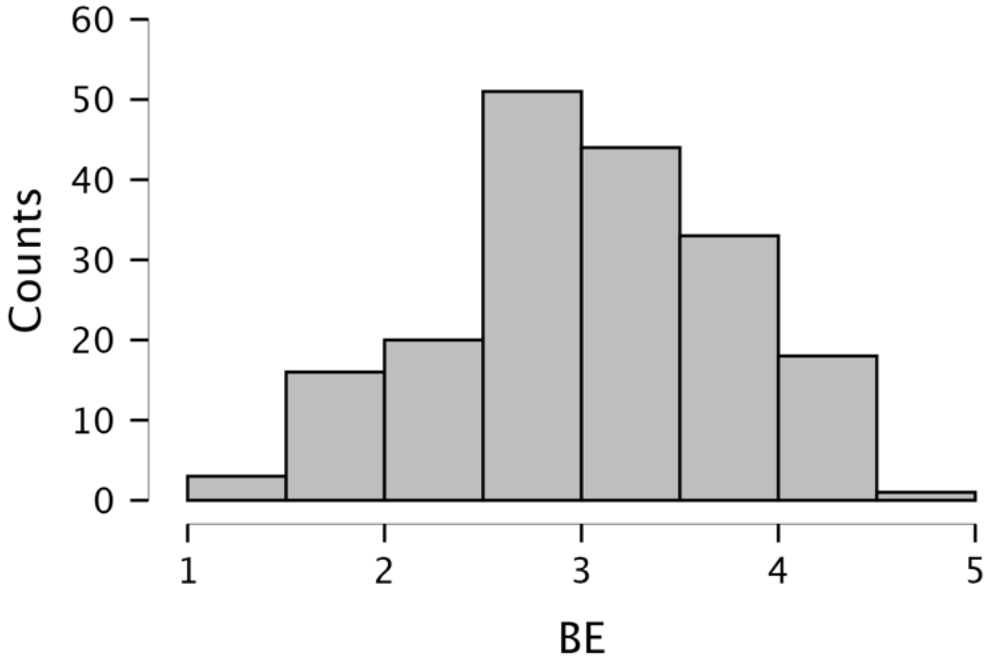
- ☐ Nombre de pas
- ☐ Calories brûlées
- ☐ Distance parcourue
- ☐ Durée de l'activité physique
- ☐ Fréquence cardiaque
- ☐ Qualité du sommeil
- ☐ Température corporelle
- ☐ Pression artérielle
- ☐ Apport calorique
- ☐ Autre: _____

À propos de vous

Source: LimeSurvey

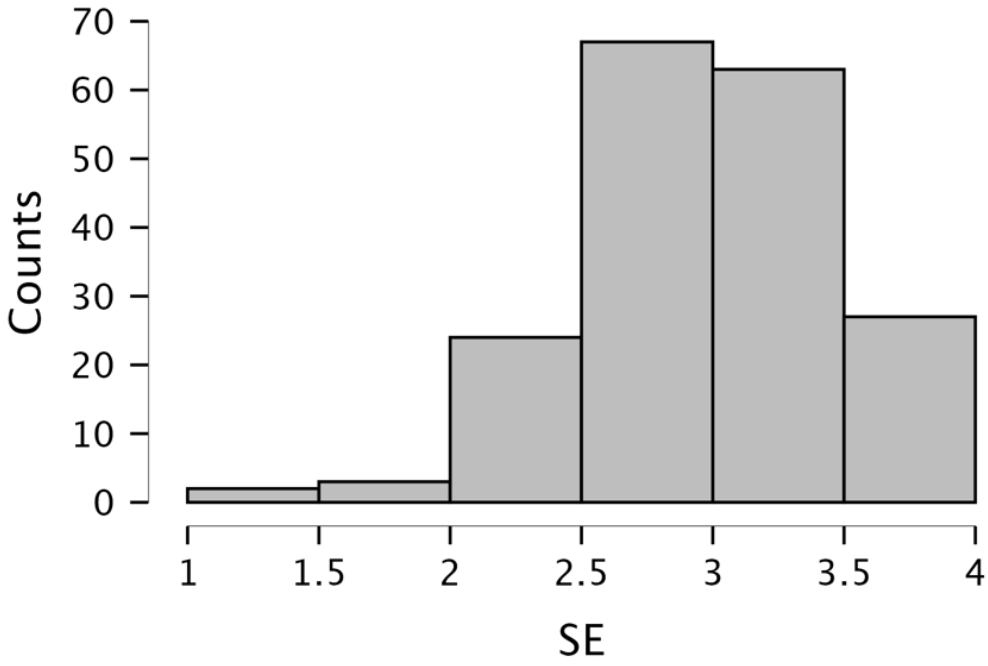
Appendix C: Normality assessment - distribution plots

Body esteem (BE)



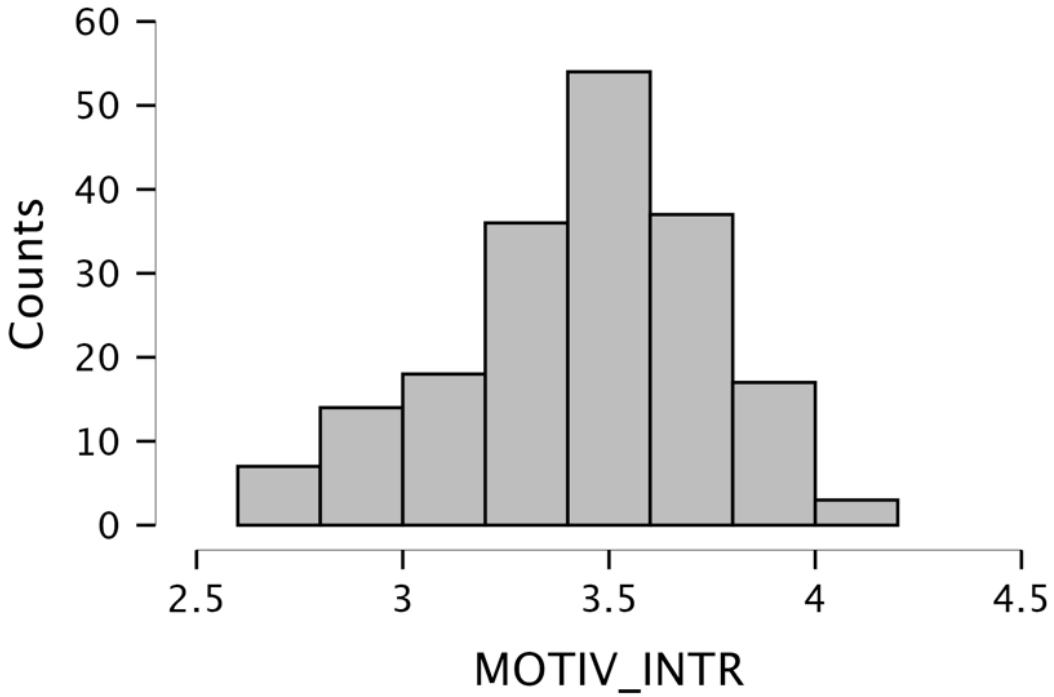
Source: JASP output

Self-esteem (SE)



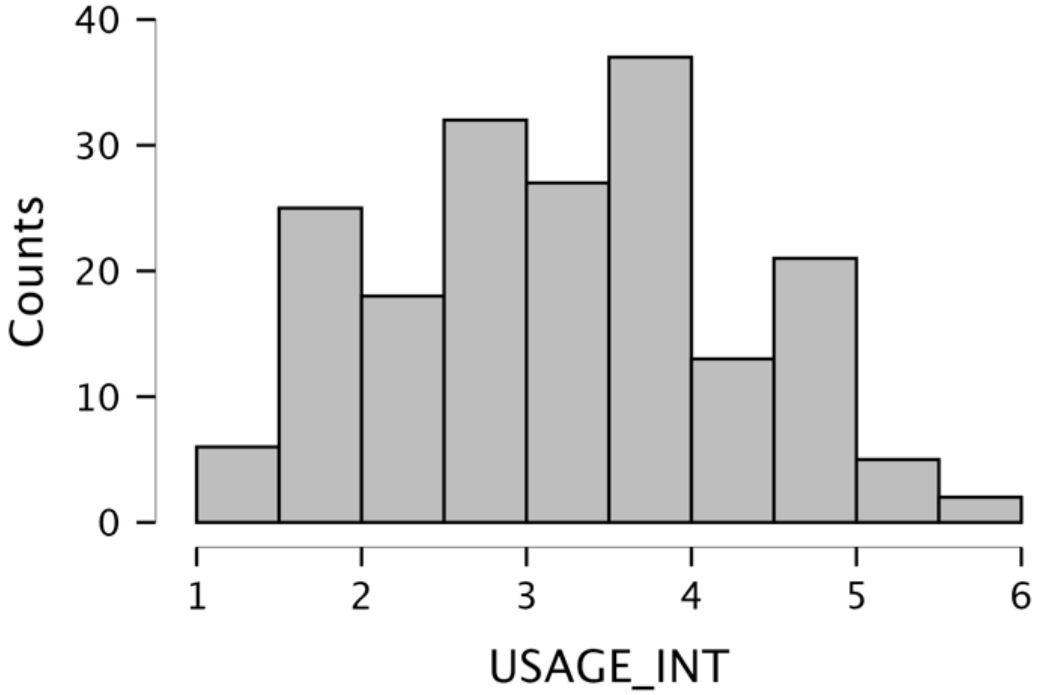
Source: JASP output

Usage motivation



Source: JASP output

Usage intensity



Source: JASP output

Appendix D: Cronbach's alphas

Self-esteem (SE)

Frequentist Scale Reliability Statistics				
			95% CI	
Coefficient	Estimate	Std. Error	Lower	Upper
Coefficient α	0.862	0.019	0.825	0.899

Source: JASP output

Frequentist Individual Item Reliability Statistics			
	Coefficient α (if item dropped)		
Item	Estimate	Lower 95% CI	Upper 95% CI
SE01	0.864	0.827	0.901
SE02	0.860	0.825	0.895
SE03	0.848	0.804	0.892
SE04	0.848	0.808	0.888
SE05	0.844	0.803	0.885
SE06	0.839	0.795	0.882
SE07	0.841	0.800	0.883
SE08	0.848	0.807	0.889
SE09	0.850	0.807	0.892
SE10	0.843	0.801	0.886

Source: JASP output

Body esteem (BE)

Frequentist Scale Reliability Statistics				
			95% CI	
Coefficient	Estimate	Std. Error	Lower	Upper
Coefficient α	0.945	0.006	0.933	0.956

Source: JASP output

Frequentist Individual Item Reliability Statistics			
	Coefficient α (if item dropped)		
Item	Estimate	Lower 95% CI	Upper 95% CI
BE01	0.944	0.932	0.957
BE02	0.941	0.929	0.954
BE03	0.942	0.929	0.954
BE04	0.941	0.928	0.953
BE05	0.941	0.929	0.954
BE06	0.944	0.932	0.956
BE07	0.942	0.929	0.954
BE08	0.941	0.928	0.953
BE09	0.940	0.928	0.953
BE10	0.943	0.931	0.955
BE11	0.941	0.928	0.953
BE12	0.941	0.928	0.953
BE13	0.941	0.928	0.954
BE14	0.940	0.928	0.953
BE15	0.942	0.930	0.954
BE16	0.941	0.928	0.953
BE17	0.940	0.927	0.953
BE18	0.940	0.927	0.953
BE19	0.945	0.933	0.956
BE20	0.947	0.936	0.958
BE21	0.945	0.933	0.956
BE22	0.947	0.936	0.958
BE23	0.943	0.931	0.955

Source: JASP output

Usage motivation

Frequentist Scale Reliability Statistics				
			95% CI	
Coefficient	Estimate	Std. Error	Lower	Upper
Coefficient α	0.809	0.024	0.761	0.856

Source: JASP output

Frequentist Individual Item Reliability Statistics			
	Coefficient α (if item dropped)		
Item	Estimate	Lower 95% CI	Upper 95% CI
MOTIV01	0.797	0.747	0.848
MOTIV02	0.808	0.761	0.856
MOTIV03	0.801	0.751	0.850
MOTIV04	0.800	0.750	0.850
MOTIV05	0.803	0.753	0.853
MOTIV06	0.796	0.745	0.847
MOTIV07	0.793	0.741	0.845
MOTIV08	0.808	0.760	0.856
MOTIV09	0.796	0.744	0.847
MOTIV10	0.796	0.745	0.846
MOTIV11	0.803	0.754	0.853
MOTIV12	0.795	0.743	0.846
MOTIV13	0.792	0.740	0.844
MOTIV14	0.799	0.748	0.849
MOTIV15	0.803	0.754	0.852
MOTIV16	0.796	0.745	0.847
MOTIV17	0.803	0.753	0.853
MOTIV18	0.807	0.761	0.853
MOTIV19	0.808	0.762	0.855
Note. The following items were reverse scaled: MOTIV06, MOTIV07, MOTIV08, MOTIV09, MOTIV16, MOTIV18, MOTIV19.			

Source: JASP output

Appendix E: Pearson's correlations

Body esteem (BE)

Pearson's Correlations ▼

Variable		BE01	BE02	BE03	BE04	BE05	BE06	BE07	BE08	BE09	BE10	BE11	BE12	BE13	BE14	BE15	BE16	BE17
1. BE01	Pearson's r	—																
	p-value	—																
2. BE02	Pearson's r	0.541	—															
	p-value	< .001	—															
3. BE03	Pearson's r	0.519	0.789	—														
	p-value	< .001	< .001	—														
4. BE04	Pearson's r	0.441	0.676	0.655	—													
	p-value	< .001	< .001	< .001	—													
5. BE05	Pearson's r	0.442	0.577	0.625	0.719	—												
	p-value	< .001	< .001	< .001	< .001	—												
6. BE06	Pearson's r	0.461	0.440	0.507	0.566	0.517	—											
	p-value	< .001	< .001	< .001	< .001	< .001	—											
7. BE07	Pearson's r	0.366	0.594	0.510	0.633	0.599	0.403	—										
	p-value	< .001	< .001	< .001	< .001	< .001	< .001	—										
8. BE08	Pearson's r	0.381	0.650	0.620	0.674	0.621	0.413	0.723	—									
	p-value	< .001	< .001	< .001	< .001	< .001	< .001	< .001	—									
9. BE09	Pearson's r	0.403	0.663	0.610	0.678	0.682	0.427	0.766	0.797	—								
	p-value	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	—								
10. BE10	Pearson's r	0.273	0.444	0.333	0.486	0.406	0.312	0.520	0.505	0.600	—							
	p-value	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	—							
11. BE11	Pearson's r	0.282	0.490	0.471	0.474	0.440	0.252	0.439	0.591	0.485	0.358	—						
	p-value	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	—						
12. BE12	Pearson's r	0.308	0.515	0.484	0.462	0.402	0.309	0.433	0.564	0.500	0.385	0.916	—					
	p-value	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	—					
13. BE13	Pearson's r	0.251	0.443	0.452	0.437	0.449	0.266	0.443	0.569	0.499	0.352	0.869	0.852	—				
	p-value	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	—				
14. BE14	Pearson's r	0.356	0.509	0.560	0.560	0.583	0.431	0.469	0.544	0.536	0.366	0.729	0.705	0.731	—			
	p-value	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	—			
15. BE15	Pearson's r	0.400	0.479	0.506	0.474	0.434	0.420	0.321	0.478	0.405	0.310	0.707	0.674	0.587	0.662	—		
	p-value	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	—		
16. BE16	Pearson's r	0.348	0.519	0.513	0.618	0.517	0.433	0.439	0.530	0.546	0.373	0.679	0.700	0.618	0.704	0.651	—	
	p-value	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	—	
17. BE17	Pearson's r	0.259	0.504	0.399	0.578	0.462	0.302	0.603	0.615	0.611	0.509	0.724	0.711	0.660	0.580	0.526	0.634	—
	p-value	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	—
18. BE18	Pearson's r	0.295	0.534	0.499	0.564	0.534	0.364	0.566	0.592	0.621	0.473	0.707	0.697	0.648	0.655	0.577	0.643	0.854
	p-value	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001
19. BE19	Pearson's r	0.154	0.231	0.152	0.264	0.295	0.108	0.409	0.359	0.437	0.509	0.198	0.192	0.204	0.186	0.172	0.204	0.398
	p-value	0.035	0.002	0.039	< .001	< .001	0.142	< .001	< .001	< .001	< .001	0.007	0.009	0.005	0.011	0.019	0.005	< .001
20. BE20	Pearson's r	0.013	0.145	0.131	0.237	0.209	0.020	0.265	0.195	0.276	0.322	0.082	0.066	0.102	0.093	0.067	0.128	0.251
	p-value	0.864	0.048	0.074	0.001	0.004	0.785	< .001	0.008	< .001	< .001	0.266	0.370	0.166	0.208	0.361	0.082	< .001
21. BE21	Pearson's r	0.087	0.234	0.195	0.345	0.296	0.099	0.448	0.377	0.468	0.492	0.181	0.172	0.216	0.221	0.131	0.168	0.380
	p-value	0.238	0.001	0.008	< .001	< .001	0.179	< .001	< .001	< .001	< .001	0.013	0.019	0.003	0.002	0.074	0.022	< .001
22. BE22	Pearson's r	−0.078	0.165	0.128	0.248	0.140	0.104	0.238	0.238	0.273	0.354	0.105	0.138	0.162	0.122	0.061	0.148	0.312
	p-value	0.290	0.024	0.082	< .001	0.056	0.157	0.001	0.001	< .001	< .001	0.153	0.060	0.027	0.097	0.407	0.044	< .001
23. BE23	Pearson's r	0.283	0.419	0.346	0.456	0.499	0.304	0.527	0.497	0.556	0.527	0.275	0.287	0.338	0.379	0.286	0.358	0.406
	p-value	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001

—							
—							
0.317	—						
< .001	—						
0.141	0.471	—					
0.055	< .001	—					
0.284	0.725	0.534	—				
< .001	< .001	< .001	—				
0.187	0.319	0.382	0.366	—			
0.010	< .001	< .001	< .001	—			
0.353	0.621	0.366	0.567	0.370	—		
< .001	< .001	< .001	< .001	< .001	—		

Source: JASP output

Self-esteem (SE)

Pearson's Correlations

Variable		SE01	SE02	SE03	SE04	SE05	SE06	SE07	SE08	SE09	SE10
1. SE01	Pearson's r	—									
	p-value	—									
2. SE02	Pearson's r	0.580	—								
	p-value	< .001	—								
3. SE03	Pearson's r	0.155	0.221	—							
	p-value	0.035	0.002	—							
4. SE04	Pearson's r	0.327	0.392	0.453	—						
	p-value	< .001	< .001	< .001	—						
5. SE05	Pearson's r	0.290	0.296	0.431	0.480	—					
	p-value	< .001	< .001	< .001	< .001	—					
6. SE06	Pearson's r	0.302	0.332	0.477	0.465	0.515	—				
	p-value	< .001	< .001	< .001	< .001	< .001	—				
7. SE07	Pearson's r	0.276	0.354	0.469	0.443	0.521	0.717	—			
	p-value	< .001	< .001	< .001	< .001	< .001	< .001	—			
8. SE08	Pearson's r	0.110	0.132	0.427	0.303	0.463	0.423	0.467	—		
	p-value	0.133	0.072	< .001	< .001	< .001	< .001	< .001	—		
9. SE09	Pearson's r	0.154	0.159	0.372	0.360	0.409	0.531	0.406	0.543	—	
	p-value	0.036	0.030	< .001	< .001	< .001	< .001	< .001	< .001	—	
10. SE10	Pearson's r	0.242	0.256	0.508	0.390	0.396	0.449	0.436	0.581	0.501	—
	p-value	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	—

Source: JASP output

Usage motivation

Pearson's Correlations ▼

Variable		MOTIV01	MOTIV02	MOTIV03	MOTIV04	MOTIV05	MOTIV06	MOTIV07	MOTIV08	MOTIV09	MOTIV10	MOTIV11	MOTIV12	MOTIV13	MOTIV14	MOTIV15
1. MOTIV01	Pearson's r	—														
	p-value	—														
2. MOTIV02	Pearson's r	0.388	—													
	p-value	< .001	—													
3. MOTIV03	Pearson's r	0.170	0.296	—												
	p-value	0.020	< .001	—												
4. MOTIV04	Pearson's r	0.364	0.084	0.377	—											
	p-value	< .001	0.254	< .001	—											
5. MOTIV05	Pearson's r	0.178	0.235	0.358	0.378	—										
	p-value	0.015	0.001	< .001	< .001	—										
6. MOTIV06	Pearson's r	−0.239	−0.012	−0.139	−0.353	−0.153	—									
	p-value	0.001	0.866	0.058	< .001	0.037	—									
7. MOTIV07	Pearson's r	−0.302	−0.026	−0.124	−0.304	−0.060	0.678	—								
	p-value	< .001	0.723	0.092	< .001	0.419	< .001	—								
8. MOTIV08	Pearson's r	−0.175	−0.174	−0.076	−0.133	−0.162	0.144	0.217	—							
	p-value	0.017	0.017	0.306	0.071	0.028	0.050	0.003	—							
9. MOTIV09	Pearson's r	−0.231	−0.186	−0.098	−0.134	−0.037	0.357	0.398	0.516	—						
	p-value	0.002	0.011	0.182	0.067	0.618	< .001	< .001	< .001	—						
10. MOTIV10	Pearson's r	0.159	0.087	0.147	0.236	0.052	−0.300	−0.246	−0.082	−0.208	—					
	p-value	0.030	0.236	0.046	0.001	0.482	< .001	< .001	0.266	0.004	—					
11. MOTIV11	Pearson's r	0.056	0.052	0.192	0.121	0.108	−0.083	−0.149	−0.065	−0.173	0.469	—				
	p-value	0.448	0.480	0.009	0.101	0.141	0.262	0.042	0.378	0.018	< .001	—				
12. MOTIV12	Pearson's r	0.257	0.128	0.230	0.131	0.175	−0.153	−0.241	−0.096	−0.157	0.453	0.408	—			
	p-value	< .001	0.082	0.002	0.074	0.017	0.037	< .001	0.192	0.032	< .001	< .001	—			
13. MOTIV13	Pearson's r	0.247	0.239	0.212	0.178	0.157	−0.270	−0.283	−0.121	−0.205	0.447	0.401	0.426	—		
	p-value	< .001	0.001	0.004	0.015	0.032	< .001	< .001	0.099	0.005	< .001	< .001	< .001	—		
14. MOTIV14	Pearson's r	0.099	0.109	0.064	−0.018	0.173	−0.198	−0.210	−0.062	−0.202	0.379	0.296	0.390	0.519	—	
	p-value	0.177	0.138	0.386	0.809	0.018	0.007	0.004	0.399	0.006	< .001	< .001	< .001	< .001	—	
15. MOTIV15	Pearson's r	0.122	0.151	0.018	−0.134	0.118	−0.084	−0.184	−0.163	−0.179	0.209	0.141	0.247	0.338	0.499	—
	p-value	0.096	0.040	0.805	0.069	0.108	0.256	0.012	0.026	0.014	0.004	0.055	< .001	< .001	< .001	—
16. MOTIV16	Pearson's r	−0.205	−0.199	−0.195	−0.085	−0.213	0.215	0.225	0.147	0.325	−0.207	−0.097	−0.199	−0.288	−0.374	−0.450
	p-value	0.005	0.007	0.008	0.250	0.004	0.003	0.002	0.045	< .001	0.005	0.186	0.007	< .001	< .001	< .001
17. MOTIV17	Pearson's r	0.152	0.226	0.017	−0.026	0.049	−0.090	−0.177	−0.019	−0.175	0.324	0.134	0.130	0.369	0.365	0.544
	p-value	0.038	0.002	0.818	0.727	0.507	0.224	0.016	0.793	0.017	< .001	0.068	0.078	< .001	< .001	< .001
18. MOTIV18	Pearson's r	−0.142	0.093	−0.205	−0.344	−0.143	0.285	0.283	−0.004	0.115	−0.038	−0.040	−0.129	−0.081	0.029	0.155
	p-value	0.053	0.205	0.005	< .001	0.052	< .001	< .001	0.962	0.117	0.604	0.589	0.078	0.270	0.695	0.034
19. MOTIV19	Pearson's r	−0.130	0.099	−0.212	−0.215	−0.093	0.127	0.212	0.037	0.141	−0.088	−0.096	−0.262	−0.079	0.034	0.109
	p-value	0.076	0.177	0.004	0.003	0.206	0.083	0.004	0.613	0.056	0.232	0.194	< .001	0.283	0.646	0.139

—				
—				
−0.494	—			
< .001	—			
0.105	0.081	—		
0.155	0.272	—		
0.099	0.046	0.616	—	
0.178	0.530	< .001	—	

Source: JASP output

Appendix F: Multiple linear regression

Body esteem (BE)

Model Summary – BE

Model	R	R^2	Adjusted R^2	RMSE
M_0	0.000	0.000	0.000	0.725
M_1	0.121	0.015	−0.013	0.729

Note. M_1 includes MOTIV_INTR, USAGE_INT, randnbr

Source: JASP output

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_1	Regression	1.411	5	0.282	0.531	0.753
	Residual	95.738	180	0.532		
	Total	97.149	185			

Note. M_1 includes MOTIV_INTR, USAGE_INT, randnbr
Note. The intercept model is omitted, as no meaningful information can be shown.

Source: JASP output

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
M_0	(Intercept)	3.042	0.053		57.244	< .001
M_1	(Intercept)	2.883	0.617		4.670	< .001
	MOTIV_INTR	0.118	0.186	0.051	0.635	0.527
	USAGE_INT	−0.080	0.055	−0.116	−1.453	0.148
	randnbr (2)	−0.022	0.141		−0.159	0.874
	randnbr (3)	0.068	0.155		0.439	0.662
	randnbr (4)	0.041	0.157		0.264	0.792

[a] Standardized coefficients can only be computed for continuous predictors.

Source: JASP output

Self-esteem (SE)

Model Summary - SE

Model	R	R^2	Adjusted R^2	RMSE
M_0	0.000	0.000	0.000	0.498
M_1	0.192	0.037	0.010	0.495

Note. M_1 includes MOTIV_INTR, USAGE_INT, randnbr

Source: JASP output

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_1	Regression	1.696	5	0.339	1.384	0.232
	Residual	44.100	180	0.245		
	Total	45.796	185			

Note. M_1 includes MOTIV_INTR, USAGE_INT, randnbr

Note. The intercept model is omitted, as no meaningful information can be shown.

Source: JASP output

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
M_0	(Intercept)	3.024	0.036		82.882	< .001
M_1	(Intercept)	2.550	0.419		6.085	< .001
	MOTIV_INTR	0.106	0.126	0.066	0.837	0.404
	USAGE_INT	0.038	0.037	0.081	1.028	0.305
	randnbr (2)	-0.098	0.096		-1.026	0.306
	randnbr (3)	-0.041	0.106		-0.393	0.695
	randnbr (4)	0.117	0.106		1.102	0.272

[a] Standardized coefficients can only be computed for continuous predictors.

Source: JASP output

Appendix G: Moderation analysis with PROCESS macro

Body esteem (BE)

```
Model  : 2
    Y  : BE
    X  : randnbr
    W  : MOTIV
    Z  : USAGE

Sample
Size:  186

Coding of categorical X variable for analysis:
 randnbr      X1      X2      X3
   1.000    .000    .000    .000
   2.000   1.000    .000    .000
   3.000    .000   1.000    .000
   4.000    .000    .000   1.000

**************************************************************************
OUTCOME VARIABLE:
 BE

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2336      .0546      .5279      .9130    11.0000   174.0000      .5291

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.0512      .1022    29.8538      .0000     2.8494     3.2529
X1           -.0587      .1424     -.4122      .6807     -.3397      .2223
X2            .0585      .1571      .3720      .7103     -.2517      .3686
X3            .0005      .1581      .0032      .9974     -.3114      .3125
MOTIV        -.1198      .3782     -.3167      .7518     -.8661      .6266
Int_1         .1291      .5171      .2497      .8031     -.8914     1.1496
Int_2         .5107      .5367      .9515      .3427     -.5487     1.5701
Int_3         .3407      .5510      .6183      .5372     -.7469     1.4283
USAGE         .0849      .0932      .9110      .3636     -.0991      .2689
Int_4        -.0971      .1534     -.6332      .5274     -.3999      .2057
Int_5        -.3691      .1615    -2.2859      .0235     -.6878     -.0504
Int_6        -.2950      .1408    -2.0949      .0376     -.5729     -.0171

Product terms key:
 Int_1    :        X1       x        MOTIV
 Int_2    :        X2       x        MOTIV
 Int_3    :        X3       x        MOTIV
 Int_4    :        X1       x        USAGE
 Int_5    :        X2       x        USAGE
 Int_6    :        X3       x        USAGE
```

Source: PROCESS macro output

Self-esteem (SE)

```
Model  : 2
    Y  : SE
    X  : randnbr
    W  : MOTIV
    Z  : USAGE

Sample
Size:  186

Coding of categorical X variable for analysis:
 randnbr      X1      X2      X3
   1.000    .000    .000    .000
   2.000   1.000    .000    .000
   3.000    .000   1.000    .000
   4.000    .000    .000   1.000

**************************************************************************
OUTCOME VARIABLE:
 SE

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2604      .0678      .2454     1.1502    11.0000   174.0000      .3254

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.0500      .0697    43.7721      .0000     2.9125     3.1875
X1           -.1144      .0971    -1.1791      .2400     -.3060      .0771
X2           -.0570      .1071     -.5325      .5951     -.2685      .1544
X3            .0932      .1078      .8650      .3882     -.1195      .3059
MOTIV         .0264      .2578      .1023      .9186     -.4825      .5352
Int_1        -.0133      .3525     -.0377      .9700     -.7090      .6825
Int_2         .4531      .3659     1.2381      .2174     -.2692     1.1753
Int_3        -.1150      .3757     -.3061      .7599     -.8565      .6265
USAGE         .1238      .0636     1.9473      .0531     -.0017      .2492
Int_4        -.0821      .1046     -.7848      .4337     -.2885      .1244
Int_5        -.1751      .1101    -1.5905      .1135     -.3924      .0422
Int_6        -.1470      .0960    -1.5314      .1275     -.3365      .0425

Product terms key:
 Int_1    :        X1       x        MOTIV
 Int_2    :        X2       x        MOTIV
 Int_3    :        X3       x        MOTIV
 Int_4    :        X1       x        USAGE
 Int_5    :        X2       x        USAGE
 Int_6    :        X3       x        USAGE
```

Source: PROCESS macro output

8. Bibliography

Abrams, K., & Fera, B. (2024, July 25). *The future of clinicians in the era of consumer-centric health*. Deloitte. https://www2.deloitte.com/us/en/blog/health-care-blog/2024/the-future-of-clinicians-in-the-era-of-consumer-centric-health.html

Ajana, B. (2020). Personal metrics: Users' experiences and perceptions of self-tracking practices and data. *Social Science Information*, *59*(4), 654–678. https://doi.org/10.1177/0539018420959522

Algashami, A., Cham, S., Vuillier, L., Stefanidis, A., Phalp, K., & Ali, R. (2018). Conceptualising Gamification Risks to Teamwork within Enterprise. In R. A. Buchmann, D. Karagiannis, & M. Kirikova (Eds.), *The Practice of Enterprise Modeling* (Vol. 335, pp. 105–120). Springer International Publishing. https://doi.org/10.1007/978-3-030-02302-7_7

Algorani, E. B., & Gupta, V. (2023). Coping Mechanisms. In *StatPearls*. StatPearls Publishing. https://www.ncbi.nlm.nih.gov/books/NBK559031/

Ameen, N., Cheah, J., & Kumar, S. (2022). It's all part of the customer journey: The impact of augmented reality, chatbots, and social media on the body image and self-esteem of Generation Z female consumers. *Psychology & Marketing*, *39*(11), 2110–2129. https://doi.org/10.1002/mar.21715

Ameen, N., Hosany, S., & Tarhini, A. (2021). Consumer interaction with cutting-edge technologies: Implications for future research. *Computers in Human Behavior*, *120*, 106761. https://doi.org/10.1016/j.chb.2021.106761

Attig, C., & Franke, T. (2019). I track, therefore I walk – Exploring the motivational costs of wearing activity trackers in actual users. *International Journal of Human-Computer Studies*, *127*, 211–224. https://doi.org/10.1016/j.ijhcs.2018.04.007

Attig, C., & Franke, T. (2023). Why Do People Abandon Activity Trackers? The Role of User Diversity in Discontinued Use. *International Journal of Human–Computer Interaction*, *39*(8), 1662–1674. https://doi.org/10.1080/10447318.2022.2067935

Baiwir, L. (2024). *Data analysis for your (KIC) research project — Introduction to JASP*. [PowerPoint slides]. HEC Liège – Université de Liège.

Berry, R. A., Rodgers, R. F., & Campagna, J. (2021). Outperforming iBodies: A Conceptual Framework Integrating Body Performance Self-Tracking Technologies with Body Image and Eating Concerns. *Sex Roles*, *85*(1–2), 1–12. https://doi.org/10.1007/s11199-020-01201-6

Blasco-Belled, A., & Alsinet, C. (2022). The architecture of psychological well-being: A network analysis study of the Ryff Psychological Well-Being Scale. *Scandinavian Journal of Psychology*, *63*(3), 199–207. https://doi.org/10.1111/sjop.12795

Boumphrey, S., & Brehmer, Z. (2017). *Megatrend analysis: Putting the consumers at the heart of the business*. http://go.euromonitor.com/white-paper-2017- megatrend-analysis.html

Brodie, R. J., Hollebeek, L. D., Jurić, B., & Ilić, A. (2011). Customer Engagement: Conceptual Domain, Fundamental Propositions, and Implications for Research. *Journal of Service Research*, *14*(3), 252–271. https://doi.org/10.1177/1094670511411703

Brodie, R. J., Ilic, A., Juric, B., & Hollebeek, L. (2013). Consumer engagement in a virtual brand community: An exploratory analysis. *Journal of Business Research*, *66*(1), 105–114. https://doi.org/10.1016/j.jbusres.2011.07.029

Buckingham, S. A., Morrissey, K., Williams, A. J., Price, L., & Harrison, J. (2020). The Physical Activity Wearables in the Police Force (PAW-Force) study: Acceptability and impact. *BMC Public Health*, *20*(1), 1645. https://doi.org/10.1186/s12889-020-09776-1

Burns, K. E. A., Duffett, M., Kho, M. E., Meade, M. O., Adhikari, N. K. J., Sinuff, T., Cook, D. J., & for the ACCADEMY Group. (2008). A guide for the design and conduct of self-administered surveys of clinicians. *Canadian Medical Association Journal*, *179*(3), 245–252. https://doi.org/10.1503/cmaj.080372

Calvo, R. A., & Peters, D. (2014). *Positive computing: Technology for wellbeing and human potential*. MIT Press.

Chan, A., Chan, D., Lee, H., Ng, C. C., & Yeo, A. H. L. (2022). Reporting adherence, validity and physical activity measures of wearable activity trackers in medical research: A systematic review. *International Journal of Medical Informatics*, *160*, 104696. https://doi.org/10.1016/j.ijmedinf.2022.104696

Chung, J. M., Robins, R. W., Trzesniewski, K. H., Noftle, E. E., Roberts, B. W., & Widaman, K. F. (2014). Continuity and change in self-esteem during emerging adulthood. *Journal of Personality and Social Psychology*, *106*(3), 469–483. https://doi.org/10.1037/a0035135

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences*. Routledge Academic.

Constantiou, I., Mukkamala, A., Sjöklint, M., & Trier, M. (2023). Engaging with self-tracking applications: How do users respond to their performance data? *European Journal of Information Systems*, *32*(6), 941–961. https://doi.org/10.1080/0960085X.2022.2081096

Crandall, C. S. (1994). Prejudice against fat people: Ideology and self-interest. *Journal of Personality and Social Psychology*, *66*(5), 882–894. https://doi.org/10.1037/0022-3514.66.5.882

Deci, E. L. (1971). Effects of externally mediated rewards on intrinsic motivation. *Journal of Personality and Social Psychology*, *18*(1), 105–115. https://doi.org/10.1037/h0030644

Dessart, L., Veloutsou, C., & Morgan-Thomas, A. (2015). Consumer engagement in online brand communities: A social media perspective. *Journal of Product & Brand Management*, *24*(1), 28–42. https://doi.org/10.1108/JPBM-06-2014-0635

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness: Defining "gamification." *Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments*, 9–15. https://doi.org/10.1145/2181037.2181040

Duus, R., & Cooray, M. (2015). *How we discovered the dark side of wearable fitness trackers*. *The Conversation*. https://theconversation.com/how-we-discovered-the-dark-side-of-wearable-fitness-trackers-43363

Erdfelder, E., Faul, F., & Buchner, A. (1996). GPOWER: A general power analysis program. *Behavior Research Methods, Instruments, & Computers*, *28*(1), 1–11. https://doi.org/10.3758/BF03203630

Etkin, J. (2016). The Hidden Cost of Personal Quantification. *Journal of Consumer Research*, *42*(6), 967–984. https://doi.org/10.1093/jcr/ucv095

Feng, S., Mäntymäki, M., Dhir, A., & Salmela, H. (2021). How Self-tracking and the Quantified Self Promote Health and Well-being: Systematic Review. *Journal of Medical Internet Research*, *23*(9), e25171. https://doi.org/10.2196/25171

Ferguson, T., Olds, T., Curtis, R., Blake, H., Crozier, A. J., Dankiw, K., Dumuid, D., Kasai, D., O'Connor, E., Virgara, R., & Maher, C. (2022). Effectiveness of wearable activity trackers to increase physical activity and improve health: A systematic review of systematic reviews and meta-analyses. *The Lancet Digital Health*, *4*(8), e615–e626. https://doi.org/10.1016/S2589-7500(22)00111-X

Ferreira, J. J., Fernandes, C. I., Rammal, H. G., & Veiga, P. M. (2021). Wearable technology and consumer interaction: A systematic review and research agenda. *Computers in Human Behavior*, *118*, 106710. https://doi.org/10.1016/j.chb.2021.106710

Fioravanti, G., Bocci Benucci, S., Ceragioli, G., & Casale, S. (2022). How the Exposure to Beauty Ideals on Social Networking Sites Influences Body Image: A Systematic Review of Experimental Studies. *Adolescent Research Review*, *7*(3), 419–458. https://doi.org/10.1007/s40894-022-00179-4

George, D., & Mallery, P. (2019). *IBM SPSS statistics 26 step by step: A simple guide and reference*. Routledge.

Gimpel, H., Nißen, M., & Görlitz, R. (2013). Quantifying the quantified self: A study on the motivations of patients to track their own health. *Healthcare Information Systems*.

Gittus, M., Fuller-Tyszkiewicz, M., Brown, H. E., Richardson, B., Fassnacht, D. B., Lennard, G. R., Holland, E., & Krug, I. (2020). Are Fitbits implicated in body image concerns and disordered eating in women? *Health Psychology*, *39*(10), 900–904. https://doi.org/10.1037/hea0000881

Goldberg, H., Christensen, A., Flash, T., Giese, M. A., & Malach, R. (2015). Brain activity correlates with emotional perception induced by dynamic avatars. *NeuroImage*, *122*, 306–317. https://doi.org/10.1016/j.neuroimage.2015.07.056

Goodyear, V. A., Kerner, C., & Quennerstedt, M. (2019). Young people's uses of wearable healthy lifestyle technologies; surveillance, self-surveillance and resistance. *Sport, Education and Society*, *24*(3), 212–225. https://doi.org/10.1080/13573322.2017.1375907

Gouveia, R., Karapanos, E., & Hassenzahl, M. (2015). How do we engage with activity trackers?: A longitudinal study of Habito. *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, 1305–1316. https://doi.org/10.1145/2750858.2804290

Grech, E. M., Briguglio, M., & Said, E. (2023). Self-tracking and gamification of physical activity: Effects on wellbeing. In *GamiFIN* (pp. 119-131).

Hahn, S. L., Kaciroti, N., Eisenberg, D., Weeks, H. M., Bauer, K. W., & Sonneville, K. R. (2021). Introducing Dietary Self-Monitoring to Undergraduate Women via a Calorie Counting App Has No Effect on Mental Health or Health Behaviors: Results From a Randomized Controlled Trial. *Journal of the Academy of Nutrition and Dietetics*, *121*(12), 2377–2388. https://doi.org/10.1016/j.jand.2021.06.311

Halpern, D. (2015). *Inside the nudge unit: How small changes can make a big difference*. Random House.

Harmeling, C. M., Moffett, J. W., Arnold, M. J., & Carlson, B. D. (2017). Toward a theory of customer engagement marketing. *Journal of the Academy of Marketing Science*, *45*(3), 312–335. https://doi.org/10.1007/s11747-016-0509-2

Hayes, A. F. (2018). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach* (2nd ed.). The Guilford Press.

Hesse-Biber, S., Leavy, P., Quinn, C. E., & Zoino, J. (2006). The mass marketing of disordered eating and Eating Disorders: The social psychology of women, thinness and culture. *Women's Studies International Forum*, *29*(2), 208–224. https://doi.org/10.1016/j.wsif.2006.03.007

Hollebeek, L. D. (2011). Demystifying customer brand engagement: Exploring the loyalty nexus. *Journal of Marketing Management*, *27*(7–8), 785–807. https://doi.org/10.1080/0267257X.2010.500132

Hollebeek, L.D., & Chen, T. (2014). Exploring positively- versus negatively-valenced brand engagement: A conceptual model. *Journal of Product & Brand Management*, *23*(1), 62–74. https://doi.org/10.1108/JPBM-06-2013-0332

Hollebeek, L. D., Glynn, M. S., & Brodie, R. J. (2014). Consumer Brand Engagement in Social Media: Conceptualization, Scale Development and Validation. *Journal of Interactive Marketing*, *28*(2), 149–165. https://doi.org/10.1016/j.intmar.2013.12.002

Jain, A., Pradhan, D., Kuanr, A., & Singh, S. (2025). Self-quantification and consumer well-being: A meta-analytic review. *Psychology & Marketing*, *42*(2), 514–538. https://doi.org/10.1002/mar.22141

Japsen, B. (2016, March 01). *UnitedHealth, Qualcomm launch wearable device coverage plan*. Forbes. https://www.forbes.com/sites/brucejapsen/2016/03/01/unitedhealth-qualcomm-launch-wearable-device-coverage-plan/

Jarry, J. L., Dignard, N. A. L., & O'Driscoll, L. M. (2019). Appearance investment: The construct that changed the field of body image. *Body Image*, *31*, 221–244. https://doi.org/10.1016/j.bodyim.2019.09.001

Kačerauskas, T., Sederevičiūtė-Pačiauskienė, Ž., & Šliogerienė, J. (2023). Gamification in management: Positive and negative aspects. *E+M Ekonomie a Management*, *26*(4), 86–98. https://doi.org/10.15240/tul/001/2023-4-006

Kanstrup, A. M., Bertelsen, P., & Jensen, M. B. (2018). Contradictions in digital health engagement: An activity tracker's ambiguous influence on vulnerable young adults' engagement in own health. *DIGITAL HEALTH*, *4*, 2055207618775192. https://doi.org/10.1177/2055207618775192

Kim, Y. (2024). The Moderating Role of Self-Esteem in the Relationship Between Social Media Use and Life Satisfaction Among Older Adults. *Social Science Computer Review*, 08944393241301045. https://doi.org/10.1177/08944393241301045

Krijnen, D., Riphagen, M., van Hout, M., & Gootjes, G. (2013). Learning tomorrow: Visualising student and staff physical activity. In *EDULEARN13 Proceedings* (pp. 3209-3214). IATED.

Lakens, D. (2022). Sample Size Justification. *Collabra: Psychology*, *8*(1), 33267. https://doi.org/10.1525/collabra.33267

Lepper, M. R., Greene, D., & Nisbett, R. E. (1973). Undermining children's intrinsic interest with extrinsic reward: A test of the "overjustification" hypothesis. *Journal of Personality and Social Psychology*, *28*(1), 129–137. https://doi.org/10.1037/h0035519

Lim, W. M., Rasul, T., Kumar, S., & Ala, M. (2022). Past, present, and future of customer engagement. *Journal of Business Research*, *140*, 439–458. https://doi.org/10.1016/j.jbusres.2021.11.014

Little, J. (2017). Running, health and the disciplining of women's bodies: The influence of technology and nature. *Health & Place*, *46*, 322–327. https://doi.org/10.1016/j.healthplace.2016.11.011

Lupton, D. (2013). Quantifying the body: Monitoring and measuring health in the age of mHealth technologies. *Critical Public Health*, *23*(4), 393–403. https://doi.org/10.1080/09581596.2013.794931

Lupton, D. (2016). The diverse domains of quantified selves: Self-tracking modes and dataveillance. *Economy and Society*, *45*(1), 101–122. https://doi.org/10.1080/03085147.2016.1143726

Lupton, D. (2016). *The quantified self*. John Wiley & Sons.

Magallares, A., & Morales, J.-F. (2013). Gender differences in antifat attitudes. *International Journal of Social Psychology: Revista de Psicología Social*, *28*(1), 113–119. https://doi.org/10.1174/021347413804756014

Makkonen, M., Kari, T., Frank, L., & Moilanen, P. (2016). Adoption and Adoption Interests of Self--Tracking Technologies: Single and Multiple Technology Perspectives. *BLED 2016 Proceedings*. https://aisel.aisnet.org/bled2016/17

Malhotra, N.K., Nunan, D., & Birks, D.F. (2017). *Marketing research: An applied approach* (5th ed.). Pearson Education.

Marques, M. D., Paxton, S. J., McLean, S. A., Jarman, H. K., & Sibley, C. G. (2022). A prospective examination of relationships between social media use and body dissatisfaction in a representative sample of adults. *Body Image*, *40*, 1–11. https://doi.org/10.1016/j.bodyim.2021.10.008

McLean, G., Krey, N., & Barhorst, J. B. (2025). Revealing the double-edged sword: Introducing the Technology and Consumer Well-being Paradox Model. *Psychology & Marketing*, *42*(1), 5–20. https://doi.org/10.1002/mar.22110

Mendelson, B. K., Mendelson, M. J., & White, D. R. (2001). Body-Esteem Scale for Adolescents and Adults. *Journal of Personality Assessment*, *76*(1), 90–106. https://doi.org/10.1207/S15327752JPA7601_6

Merino, M., Tornero-Aguilera, J. F., Rubio-Zarapuz, A., Villanueva-Tobaldo, C. V., Martín-Rodríguez, A., & Clemente-Suárez, V. J. (2024). Body Perceptions and Psychological Well-Being: A Review of the Impact of Social Media and Physical Measurements on Self-Esteem and Mental Health with a Focus on Body Image Satisfaction and Its Relationship with Cultural and Gender Factors. *Healthcare*, *12*(14), 1396. https://doi.org/10.3390/healthcare12141396

Mwangi, V. N., Millard, R., & Histon, W. (2024). Prevalent elements of consumer wellbeing in wearable technology use: An interdisciplinary systematic review and future research agenda. *Psychology & Marketing*, *41*(5), 1006–1021. https://doi.org/10.1002/mar.21962

Nunnaly, J. C. (1978). *Psychometric Theory* (2nd ed.). McGraw-Hill.

O'Brien, H. L., & Toms, E. G. (2008). What is user engagement? A conceptual framework for defining user engagement with technology. *Journal of the American Society for Information Science and Technology*, *59*(6), 938–955. https://doi.org/10.1002/asi.20801

Olsen, E. (2021, August 4). *Digital health apps balloon to more than 350,000 available on the market, according to IQVIA report*. MobiHealthNews. https://www.mobihealthnews.com/news/digital-health-apps-balloon-more-350000-available-market-according-iqvia-report

Peterson Fronczek, L., Mende, M., & Scott, M. L. (2022). From self-quantification to self-objectification? Framework and research agenda on consequences for well-being. *Journal of Consumer Affairs*, *56*(3), 1356–1374. https://doi.org/10.1111/joca.12478

Pfeiffer, J., von Entress-Fuersteneck, M., Urbach, N., & Buchwald, A. (2016). Quantify-me: consumer acceptance of wearable self-tracking devices. In *Proceedings of the 24th European Conference on Information Systems*. http://hdl.handle.net/20.500.12127/6458

Pradhan, D. (2022). Pandemics and consumer well-being: Provenance and research priorities. *Journal of Consumer Affairs*, *56*(1), 28–33. https://doi.org/10.1111/joca.12445

Puhl, R. M., Latner, J. D., O'Brien, K., Luedicke, J., Danielsdottir, S., & Forhan, M. (2015). A multinational examination of weight bias: Predictors of anti-fat attitudes across four countries. *International Journal of Obesity*, *39*(7), 1166–1173. https://doi.org/10.1038/ijo.2015.32

Rodgers, R. F. (2016). The role of the "Healthy Weight" discourse in body image and eating concerns: An extension of sociocultural theory. *Eating Behaviors*, *22*, 194–198. https://doi.org/10.1016/j.eatbeh.2016.06.004

Rodgers, R. F., Laveway, K., Campos, P., & De Carvalho, P. H. B. (2023). Body image as a global mental health concern. *Cambridge Prisms: Global Mental Health*, *10*, e9. https://doi.org/10.1017/gmh.2023.2

Rosenberg, M. (2011). *Rosenberg Self-Esteem Scale* [Dataset]. https://doi.org/10.1037/t01038-000

Rupp, M. A., Michaelis, J. R., McConnell, D. S., & Smither, J. A. (2018). The role of individual differences on perceptions of wearable fitness device trust, usability, and motivational impact. *Applied Ergonomics*, *70*, 77–87. https://doi.org/10.1016/j.apergo.2018.02.005

Ryan, J., Edney, S., & Maher, C. (2019). Anxious or empowered? A cross-sectional study exploring how wearable activity trackers make their owners feel. *BMC Psychology*, *7*(1), 42. https://doi.org/10.1186/s40359-019-0315-y

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, *55*(1), 68–78. https://doi.org/10.1037/0003-066X.55.1.68

Ryan, R. M., & Deci, E. L. (2001). On Happiness and Human Potentials: A Review of Research on Hedonic and Eudaimonic Well-Being. *Annual Review of Psychology*, *52*(1), 141–166. https://doi.org/10.1146/annurev.psych.52.1.141

Ryan, R. M., & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. *Contemporary Educational Psychology*, *61*, 101860. https://doi.org/10.1016/j.cedpsych.2020.101860

Ryff, C. D. (1989). Happiness is everything, or is it? Explorations on the meaning of psychological well-being. *Journal of Personality and Social Psychology*, *57*(6), 1069–1081. https://doi.org/10.1037/0022-3514.57.6.1069

Ryff, C. D. (2014). Psychological Well-Being Revisited: Advances in the Science and Practice of Eudaimonia. *Psychotherapy and Psychosomatics*, *83*(1), 10–28. https://doi.org/10.1159/000353263

Sato, W., Kochiyama, T., Yoshikawa, S., Naito, E., & Matsumura, M. (2004). Enhanced neural activity in response to dynamic facial expressions of emotion: An fMRI study. *Cognitive Brain Research*, *20*(1), 81–91. https://doi.org/10.1016/j.cogbrainres.2004.01.008

Sharon, T. (2017). Self-Tracking for Health and the Quantified Self: Re-Articulating Autonomy, Solidarity, and Authenticity in an Age of Personalized Healthcare. *Philosophy & Technology*, *30*(1), 93–121. https://doi.org/10.1007/s13347-016-0215-5

Spil, T. A. M., Romijnders, V., Sundaram, D., Wickramasinghe, N., & Kijl, B. (2021). Are serious games too serious? Diffusion of wearable technologies and the creation of a diffusion of serious games model. *International Journal of Information Management*, *58*, 102202. https://doi.org/10.1016/j.ijinfomgt.2020.102202

Statista. (2024, May 2). *Distribution of Instagram users worldwide as of April 2024, by age group*. https://www.statista.com/statistics/325587/instagram-global-age-group/

Statista. (2024, May 16). *Wearables - statistics & facts*. https://www.statista.com/topics/1556/wearable-technology

Statista. (2024, May 22). *Distribution of Facebook users worldwide as of April 2024, by age and gender*. https://www.statista.com/statistics/376128/facebook-global-user-age-distribution/

Statista. (2025, March 24). *Smartphone penetration worldwide as a share of global population 2016-2024*. https://www.statista.com/statistics/203734/global-smartphone-penetration-per-capita-since-2005/

Statista. (2025, April 14). *The most spoken languages worldwide in 2025*. https://www.statista.com/statistics/266808/the-most-spoken-languages-worldwide/

Stiglbauer, B., Weber, S., & Batinic, B. (2019). Does your health really benefit from using a self-tracking device? Evidence from a longitudinal randomized control trial. *Computers in Human Behavior*, *94*, 131–139. https://doi.org/10.1016/j.chb.2019.01.018

Swan, M. (2009). Emerging Patient-Driven Health Care Models: An Examination of Health Social Networks, Consumer Personalized Medicine and Quantified Self-Tracking. *International Journal of Environmental Research and Public Health*, *6*(2), 492–525. https://doi.org/10.3390/ijerph6020492

Thompson, J. K., & Stice, E. (2001). Thin-Ideal Internalization: Mounting Evidence for a New Risk Factor for Body-Image Disturbance and Eating Pathology. *Current Directions in Psychological Science*, *10*(5), 181–183. https://doi.org/10.1111/1467-8721.00144

Toner, J. (2018). Exploring the dark-side of fitness trackers: Normalization, objectification and the anaesthetisation of human experience. *Performance Enhancement & Health*, *6*(2), 75–81. https://doi.org/10.1016/j.peh.2018.06.001

Trzesniewski, K. H., Donnellan, M. B., & Robins, R. W. (2003). Stability of self-esteem across the life span. *Journal of Personality and Social Psychology*, *84*(1), 205–220. https://doi.org/10.1037/0022-3514.84.1.205

United Nations. (n.d.). *THE 17 GOALS | Sustainable Development*. https://sdgs.un.org/goals

Van Dierendonck, D., & Lam, H. (2023). Interventions to enhance eudaemonic psychological well-being: A meta-analytic review with Ryff's Scales of Psychological Well-being. *Applied Psychology: Health and Well-Being*, *15*(2), 594–610. https://doi.org/10.1111/aphw.12398

Weiss, L. A., Westerhof, G. J., & Bohlmeijer, E. T. (2016). Can We Increase Psychological Well-Being? The Effects of Interventions on Psychological Well-Being: A Meta-Analysis of Randomized Controlled Trials. *PLOS ONE*, *11*(6), e0158092. https://doi.org/10.1371/journal.pone.0158092

Wieczorek, M., O'Brolchain, F., Saghai, Y., & Gordijn, B. (2023). The ethics of self-tracking. A comprehensive review of the literature. *Ethics & Behavior*, *33*(4), 239–271. https://doi.org/10.1080/10508422.2022.2082969

Woessner, M. N., Tacey, A., Levinger-Limor, A., Parker, A. G., Levinger, P., & Levinger, I. (2021). The Evolution of Technology and Physical Inactivity: The Good, the Bad, and the Way Forward. *Frontiers in Public Health*, *9*, 655491. https://doi.org/10.3389/fpubh.2021.655491

World Health Organization. (n.d.). *Constitution of the World Health Organization*. https://www.who.int/about/governance/constitution

World Health Organization. (2022). *Global Status Report on Physical Activity 2022*. https://www.who.int/teams/health-promotion/physical-activity/global-status-report-on-physical-activity-2022

Zimdars, M. (2021). The Self-Surveillance Failures of Wearable Communication. *Journal of Communication Inquiry*, *45*(1), 24–44. https://doi.org/10.1177/0196859920977113

EXECUTIVE SUMMARY

Self-tracking technologies have gained tremendous popularity in recent years as tools to encourage healthier lifestyles. While prior empirical research has highlighted the benefits these technologies can offer, growing concerns have emerged regarding their potential negative psychological effects on users. This thesis therefore investigates the extent to which self-tracking technology usage affects psychological well-being, specifically focusing on body image concerns and self-esteem. More precisely, it examines the impact of specific self-tracking features, namely fitspiration content, behavior change techniques, and gamified and social design, on these outcomes. Through an experimental quantitative study (N = 186), participants were exposed to one of three self-tracking technology features or to a control condition to assess whether certain features are more likely to exacerbate negative psychological outcomes. Additionally, the moderating effects of usage intensity and usage motivation were explored to better understand how individual differences influence these outcomes. Findings revealed no significant differences in body image concerns or self-esteem levels across the different self-tracking technology features. In addition, the moderating role of usage motivation could not be confirmed. However, higher usage intensity was associated with greater body image concerns in certain feature conditions, suggesting that individual engagement patterns may play a critical role in shaping users' psychological responses. Based on these insights, this study outlines implications for managers, policymakers, and health insurers, acknowledges its key limitations, and proposes directions for future research.

KEYWORDS: self-tracking technologies, psychological well-being, body image concerns, self-esteem, usage intensity, usage motivation

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