WHO IS THE SELF-TRACKER?
ESTABLISHING AN INITIAL INSTRUMENT TO HOLISTICALLY ASSESS SELF-TRACKING BEHAVIOURS

MSc Thesis
Human Factors and Engineering Psychology

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Abstract

The advancement of tracking technology has given users new ways to understand and rediscover themselves. Despite its widespread use in consumer goods and medical contexts, a better understanding of self-tracking is needed. The current study aimed to develop an initial instrument to assess the self-tracker in a comprehensive manner, taking into account both self-tracker characteristics as well as the subject of privacy. A thematic literature study was undertaken to identify the key topics associated with self-tracking behaviour, and a questionnaire was designed, piloted, and assessed on 132 participants. Following a thorough descriptive analysis, a confirmatory factor analysis (CFA) was conducted to assess the instrument's validity. The descriptive analysis showed that trackers desire control over both their bodies (i.e., self-optimisation) and their data (i.e., data ownership). Trackers, on the other hand, expect control without necessarily wanting to exercise it or understand the complexities necessary for efficient data management, rendering them vulnerable to data ownership loss. Further, the CFA resulted in a 6-factor model with 28 items, one of which was healthism. However, because the instrument lacked the necessary discriminant validity, future research should employ it with caution. This study serves as a first step toward a comprehensive understanding of self-tracking behaviour by offering a preliminary instrument.

Keywords: data ownership, self-tracking, instrument development

Dedication

This thesis is dedicated to my mother and brother.

Thank you for your constant love, support, and faith in me.

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Chapter 1: Introduction

> "We now have the technology to digitise a human being in the highest definition, in granular detail, and in ways that most people thought would not be possible." —Topol (2013)

How many hours of sleep did you get last night? Did you drink enough water? How many calories did you burn? Self-tracking, also known as *self-monitoring*, *lifelogging*, *personal informatics*, or, in its most extreme form, *life-hacking*, is the practice of recording every detail and minute of our habits and activities using digital technology. Self-tracking has gained popularity in recent years and has become a standard practice in health promotion and care. Health and fitness apps, for example, make up 3.5 % of all available applications globally in the Google Play Store (Statista, 2022a), with over 53,000 mobile health apps (Statista, 2021a). Moreover, large organisations like the World Health Organization see significant long-term benefits in applying digital health technology to individuals on the one hand and the health industry on the other (World Health Organization, 2021). Experts predict that digital health revenue will expand at a 10.59 % annual rate from 2022 to 2026 (Statista, 2022b), resulting in a predicted market volume of $224.20 billion by 2026.

Several reasons contribute to the growing popularity of digital health technology. First, fast technical progress has made the creation of digital health technology more affordable and accessible. Smartphone use, for example, has grown at a breakneck pace, with an estimated 6.65 billion users globally (Statista, 2021b). In comparison, the 2016 total was only 3.7 billion. Second, the cost of manufacturing sensors has decreased. Sensors can now be manufactured at lower costs and smaller sizes, making them more wearable and manageable. These factors contribute to intelligent sensor technology rapidly penetrating daily life, with business models embedding it into everyday products such as phones and watches (Ajana, 2017, 2020a). In addition to this new generation of intelligent microsensors (Van Hoof et al., 2004), we live in the age of big data. Data is gathered, analysed, compared, and processed at an unprecedented velocity and volume to provide new information and knowledge (Mai, 2016). The rapidly expanding *Internet of Things*[1] (IoT) ecosystem is expected to increase data collection and sharing even further as technologies become more intelligent, omnipresent, and autonomous (Filkins et al., 2016; Swan, 2012).

Complete digitisation and real-time processing are transforming people's interactions with the world, as well as how they perceive their bodies and health (Berry et al., 2020; Brătucu et al., 2020; Smahel et al., 2018). Indeed, since self-tracking technology provides unparalleled information and personalisation of one's health (Vitak et al., 2018), anyone can improve their health and well-being without the assistance of a professional. Consequently, modern smartphone applications and wearable sensor technologies inspire a new, hopeful idealism in which the person is no more a passive patient but *can* and hence *should* take an active role in their health (Kahana & Kahana, 2001; Sharon, 2016). In this way, self-tracking promotes a shift toward preventative, personalised healthcare (European Commission, 2014; Sharon, 2016), in which the individual and their data are central (Swan, 2012).

However, as digital health technology becomes more widely available and accessible, it introduces new privacy concerns and risks (Filkins et al., 2016). Studies contend that users lose control of their personal data, making privacy in the digital age challenging to retain (Brandtzaeg et al., 2019; Hutton et al., 2018; Suver & Kuwana, 2021). Indeed, when personal information becomes more integrated into a larger, more complex digital network, individuals lose control over what information they disclose and with whom they share it (Henkel et al., 2018). As a result, the lines between *datafication* and *dataveillance* are becoming increasingly blurred (Selinger, 2015), with ethical considerations increasingly including data management and control (Mai, 2016). According to Hutton et al. (2018), it is important to assess how self-tracking technologies may affect the privacy landscape, necessitating research that examines self-tracking comprehensively and systematically.

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[1] The general concept of linking real-world objects to the Internet using sensors and processors to enable intelligent interactions (Geng et al., 2015).

This study is part of the *Digitale Selbstvermessung selbstbestimmt gestalten* (TESTER) project. TESTER aims to provide a virtual privacy assistant that is tailored to the needs of its customers to help them safeguard their self-tracking data better. The current study serves as a preliminary evaluation of self-tracking activities to set the foundation for the project. Using a thorough research technique will give valuable insights that will aid in the development of the privacy assistant.

1.1. Problem Statement and Thesis Objectives

Digital self-measurement tools and services are gaining popularity in both consumer products (such iPhone pedometers, fitness trackers, or smartwatches) and medical applications. The massive volume of data acquired leads to opportunities for individuals, the healthcare system, and businesses. However, concerns have been raised about a lack of transparency and the ability to control one's own data. To have a better understanding of self-tracking, it is essential to examine it holistically. The current study aims to accomplish the following:

1. Offering a preliminary evaluation of self-tracking.
2. Offering a comprehensive analysis of self-tracking behaviour that takes into consideration motivations, personality traits, demographics, and privacy.
3. Creating an initial instrument that will serve as a foundation for TESTER and the literature at large.

1.2. Thesis Structure

The remainder of this thesis is structured as follows:

- Chapter 2 offers the theoretical foundation of the relevant literature for the current study, as well as a broad overview of self-tracking.
- Chapter 3 outlines the research methodology for the design of the questionnaire as well as the data analysis.

- Chapter 4 presents the results.
- Chapter 5 discusses, interpret and explain the results. It also discusses the implications and prospective future study directions for both the self-tracking research field and the TESTER project.
- Chapter 6 concludes the thesis.

Chapter 2: Theoretical Background

This chapter establishes the theoretical foundation for the study's objectives and the research questions that will be offered at its conclusion. First, we look at the history of self-tracking as well as how it is infused in the healthcare sector and how it links to healthism and individualised healthcare. Additionally, we examine the self-tracker's profile, including its characteristics, motivations, demographics, and personality traits. We also examine the privacy implications of self-tracking in the digital era, with an overview of evolving privacy concerns. The study concludes with an assessment of the privacy paradox as an unsuccessful attempt at privacy management.

2.1. The Rise of Self-Tracking

As intelligent tracking devices have become more widely available and improved, data collection has become more straightforward, precise, and entertaining. Wearable technology for health, in particular, has increased in popularity, taking self-monitoring to new heights by making self-tracking appealing for conserving, optimising, and *redesigning* our health. Because of the growing popularity of self-tracking in San Francisco, the two Wired magazine editors, Gary Wolf and Kevin Kelly, decided in 2007 that it deserved its own space. The two created a website where technology enthusiasts, hobbyists, and anybody interested in personal data and improvement could share their experiences, provide feedback, and discuss their findings (Lee, 2014).

The Quantified Self (QS) is a group of people who aim to take charge of their health and lives through self-quantification. Members believe that, unlike self-reflection, daily tracking indicates what we *do* rather than what we *assume* we do. Identifying behavioural patterns might thereby promote self-improvement and self-awareness in ways that introspection cannot. As Kelly (2007) stated, "unless anything can be measured, it cannot be improved." Hence, members actively and systematically use applications and monitoring devices to track various metrics, including sleep, blood pressure, sugar levels, exercise, and others. However, the QS is a practical health movement focused on developing a framework of actionable insights and behavioural change (Heyen, 2019). The aim is not so much the data as it is the established self-awareness and actions that result from those insights. That is, metrics analysis and pattern findings should encourage the adoption of a better, healthier lifestyle. This viewpoint holds that data is only relevant if it generates actionable insights and is acted upon; otherwise, the entire process becomes meaningless. This is a huge change since, thanks to enabling technology, the individual may now actively contribute to the betterment of their life, body, and health rather than acting as a passive actor.

2.2. A Digital Healthcare Revolution

2.2.1. Self-Tracking and Healthism

Sharon (2016) contend that monitoring practices fit perfectly into a new Western healthcare paradigm that encourages extreme individualism and healthism. Crawford (1980) coined the term *healthism* to define a lifestyle that places an excessive amount of emphasis on personal health in order to achieve happiness and well-being. In this way, healthism reduces health from a complex to a simple matter of individual responsibility (Cheek, 2008; Crawford, 1980; Lupton, 2013b), making health concerns and treatments a matter of personal effort. By promoting the idea that what can be measured can also be improved (Kersten - van Dijk et al., 2015), self-tracking technology has taken a healthy lifestyle even further into the area of personal choice and responsibility (Berry et al., 2020). Indeed, with self-tracking devices becoming more accessible and user-friendly, there is no excuse for not taking ownership of one's health. Individuals are encouraged to become their own *health entrepreneurs* (Sharon & Zandbergen, 2016), using cutting-edge technology to "eat smarter," "reset their sleep habits," "fine-tune their schedule," and "improve their life." As a result, health has been overly associated with performance and is no longer solely associated with the concept of "not being ill" (Cheek, 2008).

Health has become a choice (Brown, 2018), a decision to embrace a variety of healthy lifestyle choices and technologies (Cheek, 2008). Similarly, Greenhalgh (2004) noted that healthism is related to the consumer movement, with self-tracking gadgets being the best way to achieve health goals. Recent research on the influence of monitoring devices on body image perception indicate that self-tracking and healthism are closely intertwined (Berry et al., 2020; Kersten - van Dijk et al., 2015). However, despite the fact that studies only identify the association between the two (Lupton, 2013b), no research have been undertaken to date to investigate the relationship between healthism and self-tracking.

2.2.2. The Potential of Mobile Health

The healthcare sector faces significant challenges due to an ageing population, chronic illnesses, and budgetary pressure (European Commission, 2014). As the need for new models and solutions grows, policymakers and health economists agree that self-tracking technologies have the potential to ignite a new healthcare paradigm. For example, the European Commission released a Green Paper on mobile health (mHealth) in 2014, stating that mHealth may "serve as a basis for evidence-driven care practice and research activities, while facilitating patients' access to their health information anywhere and at any time," therefore it may be regarded as a "a supportive tool for the management and provision of healthcare" (European Commission, 2014). Particularly, self-tracking wearables and technology have the potential to revolutionise the way healthcare is provided, placing the individual at the centre of health-related activities (Swan, 2012) and moving away from one-size-fits-all treatment towards individualised, preventative care (Sharon, 2016).

This model may benefit both the individual and the overall healthcare system by providing better preventive patient-centred treatment while free up the healthcare capacity, improving the system efficiency and making it more sustainable in the long term (European Commission, 2014). Although there are still obstacles to be solved in order to promote the usage of mHealth applications (Zakerabasali et al., 2021), research have shown that doing so has benefits. For instance, Smuck et al. (2021) found that implementing a digital care program using wearables leads to better health outcomes than traditional care as doctors can more carefully monitor their patients and provide better treatment in a more timely and effective manner. Similarly, Ventola (2014) argued that improving clinical decision-making, accuracy, efficiency, and productivity are some of the most significant advantages of mHealth. In an article by Forbes, Walter de Brouwer stated (Nosta, 2013):

> "Before Google, information was power, now we all have it. Healthcare can benefit from the very same disruption. It is going to mutate, hacked by evolution and will become a more efficient version of itself. A version where the patient will be discovered as the most underused resource. The grand theory of diagnosis will welcome new players next to doctors: machines, algorithms, patient advocacy communities and the crowd. A Cambrian Revolution of medical devices and apps is the straw that will break the camel's back. For centuries we have been reading our health, now we will start writing it —changing it in real time. The conversion will be incredible— instead of watching over our health, our health will be watching us!"

2.2.3. Health as a New Morality

Despite the benefits of mHealth for both patients and the healthcare system, Sharon (2016) stated that rising individual health responsibility is "directing the management of health away from the state and onto the shoulders of individual citizens." Adopting a healthy lifestyle through self-tracking has gradually evolved from an empowering tool to a moral imperative in order to contribute to the long-term sustainability of the healthcare system (Ajana, 2017). In this way, digital health means that rather than the individual being in control of their health, digital health may become in control of the individual. Someone in poor health may now be held accountable by society for failing to take adequate responsibility for their own health (Brown, 2018), increasing the burden and cost to the public health system.

Similarly, Lupton (2017) noted that health promotion by self-monitoring may contribute to socioeconomic disadvantages and marginalisation. For example, sensitive information about a person's sexual preferences, medical issues, or simply body weight may lead to insurance refusal or societal stigma. It highlights the rather dangerous dynamic of *shaping and shaming*, in which self-tracking drives an individual to conform to the desired standard and is shamed for not doing so, either by the individual (i.e., self-shaming) or society (i.e., social shaming).

The strong moral component at work is what makes the combination of self-tracking and healthism potentially harmful on both an individual and collective level. Moralisation is a social process in which behaviours are good or bad based on whether they are morally acceptable. Brown (2018) went into detail on how public health promotion (in)directly moralises people's behaviour. On the one hand, there is a reinforcement of the association between health and personal responsibility, and on the other, there is a moralising discourse of health-related behaviours. As self-tracking facilitates health promotion, the impression that people *can* and thus *should* adopt healthy behaviours intensifies. Health is portrayed as a choice, and failing to pursue a healthy lifestyle or being in poor health results in moral judgment. According to Cheek (2008): "Health takes on new and different forms of discipline. We can now speak of being good or bad, or strong or weak in terms of our health behaviors, of making responsible or irresponsible choices."

2.2.4. Intermediate Conclusion

Self-tracking has a significant impact on both the individual and collective levels, promoting a new perspective on health and shaping our understanding of health care. In addition, self-tracking technologies become a perfect instrument to free up the healthcare system by offering healthcare centered on the individual and their data. This shift propels health to become more than just an ideal (Crawford, 1980), but a new morality based on human responsibility and guilt in the case of failure (Brown, 2018; Conrad, 2012). However, although both healthism and self-tracking establish a strong connection between health, individual performance, optimisation, and moral obligation (Ajana, 2017; Kristensen & Ruckenstein, 2018; Lupton, 2013a), there has been no research on the influence of healthism on self-tracking behaviour (Brown, 2018; Conrad, 2012).

2.3. Self-Tracker Characteristics

Gaining a deeper understanding of oneself through data is at the heart of the self-tracking movement (Heyen, 2019). Self-tracking is not just a habit for data and technology fetishists—it encompasses a diverse range of people with differing backgrounds, interests, motivations, and goals (Sharon & Zandbergen, 2016). Following a discussion on motivations, we explore how various demographics influence self-tracking behaviour before concluding with research on personality traits and self tracking.

In summary, we may infer from the descriptive analysis that trackers want to be in control of their bodies (i.e., self-optimisation) as their data (i.e., data ownership). This is reflected in what and why they track, as well as the specific privacy concerns trackers have (i.e., only the secondary use dimension) and the specific protective measures they are willing to take.

2.3.1. Motivations

The concept of a quantified self (QS) is ingrained in the broader Dataism paradigm, claims Nicholls (2016). Harari (2016) popularised the concept of *Dataism*, which is the conviction that data and analytics are the sole dependable sources of value and knowledge, with little regard for human experience. In this way, the QS is an extension of the Dataism paradigm, in which the self is reduced to a mathematical formula that enables one to become an ideal version of themselves. The iterative process of collecting, analysing, and interpreting self-tracking data has emerged as the key tool for obtaining objective and reliable facts. The ability to transcend the *numerical self* to a *qualified self* is therefore made desirable and feasible by data (Swan, 2013). Studies show a significant link between self-tracking and a desire for self-improvement (En & Pöll, 2016; Kristensen et al., 2015; Whooley et al., 2014) and a need for control (Ajana, 2017) through the use of gamification tactics such as leader boards and trophies (Lupton, 2014; Schmidt-Kraepelin et al., 2020). In other words, gamification features encourage individuals to be more engaged in the optimisation process by making monotonous physical activities more appealing (Gimpel et al., 2019; Zuckerman & Gal-Oz, 2014).

However, just sticking to metrics may eventually lead to alienation rather than empowerment, as trackers come to trust numbers more than their own bodies (Folkvord et al., 2021; Lupton, 2016). Hence, according to Sharon and Zandbergen (2016), characterising self-trackers as those driven solely by a desire for control and self-optimisation is a restricted framework for understanding the practice. Instead, self-tracking is an intentional activity for discovering meaning in everyday life. Choe et al. (2014) discovered, for example, that, in addition to improving one's health and other elements of one's life, the third motivation for QS members was to seek new life experiences. Similarly, Whooley et al. (2014) shown that self-trackers were driven either by curiosity or self-improvement. Additionally, Kristensen and Ruckenstein (2018) discovered how self-trackers reframe tracking devices as tools for "open-ended self-experimentation and self-discovery" once the first allure of self-objectification wears off and is perceived as restricting and limiting their experience.

Moreover, there is a significant social component to self-tracking as the majority of trackers consider themselves part of a group (Kristensen & Ruckenstein, 2018; Lee, 2014; Lupton, 2014). Self-trackers interact and share their experiences, fostering a sense of belonging and community (Ajana, 2020b). "Personal data are ideally suited to a social life of sharing. You might not always have something to say, but you always have a number to report," Wolf (2010) wrote in the New York Times Magazine.

There have also been research that have attempted to understand the main motivations behind self-tracking. For instance, according to Lupton (2016), the fundamental motivations for self-trackers include *self-optimisation* (e.g., work, body, and health), *desire for self-knowledge*, *curiosity*, *self-awareness*, *pleasure*, and *self-experimentation*. In the same line, Wieneke and Lehrer (2016) performed in-depth interviews to establish six psychological components (i.e., *distinguishing oneself*, *attractiveness*, *self-awareness*, *self-control*, *motivation*, and *self-improvement*) and eight corresponding values (i.e., *social belonging*, *social acceptability*, *contentment*, *exploration*, *success*, *health*, *self-improvement*, *quality of life*). Likewise, Gimpel et al. (2013) developed a five-factor framework with the underlying motives of *self-entertainment*, *self-association*, *self-design*, *self-discipline*, and *self-healing* (**Table 1**).

Table 1

Overview of Main Motivations

Gimpel et al. (2013)	Lupton (2016)	Wieneke & Lehrer (2016)
1. Self-entertainment	1. Self-improvement	1. Distinguishing oneself
2. Self-association	2. Desire for knowledge	2. Attractiveness
3. Self-design	3. Curiosity	3. Self-awareness
4. Self-discipline	4. Self-awareness	4. Self-control
5. Self-healing	5. Pleasure	5. Motivation
	6. Self-experimentation	6. Self-improvement

Note. An overview of the primary motivations for self-tracking.

Self-entertainment is the joy of self-tracking; self-trackers find it intriguing and fun to monitor themselves using tracking devices and play with the statistics. Second, *self-association* refers to community engagement and associated behaviours, such as presenting oneself in front of a group, comparing oneself to others, and accepting and providing feedback. Third, *self-design* is concerned with self-improvement and is strongly related to a sense of control. Fourth, *self-discipline* is about working toward a specific goal and receiving rewards. Finally, *self-healing* is the belief or expectation that self-tracking would aid in self-healing and, consequently, get healthier. It is also associated with scepticism and opposition to the healthcare system. Gimpel et al. (2013) found that the main motivations for self-tracking are self-design and self-healing, whereas Findeis et al. (2021) observed that self-design and self-discipline are the most important drivers.

2.3.2. Demographic Characteristics

Seniors are less likely to employ digital tracking devices for various reasons. To begin with, they see less value in them and, as a result, are less interested in incorporating monitoring into their lifestyle (Rupp et al., 2018). Poor design is another aspect that may dissuade older people from using monitoring devices. Self-tracking devices are typically designed to meet the expectations of younger self-trackers, resulting in designs that discourage older people from using self-tracking equipment. Classic design flaws are illegible lettering, difficulty putting up the equipment, and understanding the data analysis (Caldeira & Chen, 2019). In addition, older people have poorer levels of e-health literacy, which may act as a barrier to adopting monitoring devices.

These findings are congruent with the concept of the *digital divide*, an imbalance in today's information society between white, middle-class Internet users and minority, lower-income non-users. Politicians and academics agree that socioeconomic status and ethnicity are significant factors, but a psychological factor linked to self-efficacy deficiencies is also crucial, according to Eastin and LaRose (2006). Self-efficacy, according to Bandura (1977), is the conviction that one can carry out an activity or accomplish a goal. Self-efficacious people are more inclined to persevere in the face of adversity. After numerous failures while using the Internet, people may become trapped in a self-helpless loop. This downward spiral hinders individuals from obtaining the necessary abilities to deal with such technologies.

The digital divide may be regarded as a *social divide*, with e-health and socioeconomic variables playing a significant role. A study by Bol et al. (2018) showed that younger, more educated people were more likely to use mobile health apps than older, less educated people. Similarly, Lupton (2016) wrote that self-trackers "are principally drawn from the ranks of younger, socio-economically privileged, health-conscious, and technologically oriented people." Thus, demographic factors including education, e-health literacy, and socioeconomic level seem to be key indicators of whether or not people would start and sustain a monitoring habit in the digital age.

2.3.3. Personality Traits

The Big Five Model by McCrae and Costa (2008) is the most widely accepted personality theory among psychologists today. It divides personality into five fundamental factors, abbreviated CANOE or OCEAN: *openness*, *conscientiousness*, *extraversion*, *agreeableness* and *neuroticism*. The study by Szalma and Taylor (2011) found an association between personality traits and how people interact with automation and complicated technology. Similarly, Franke et al. (2018) indicated that personality traits influence how people engage with new technologies in their daily lives. That is, personality traits affect how much individuals trust technology, how often they use it, and whether they are receptive to it or reluctant to actively engaging and embracing it.

Though Attig and Franke (2019) found no significant effect of personality traits on intrinsic motivations for tracker use, Rupp et al. (2018) found that personality traits influence the desire to use monitor devices due to perceived usability and motivational affordances such as autonomy (i.e., a desire to be in control), competence (i.e., a desire for a challenge), and relatedness (i.e., a desire to interact with others). The study found that extraverts in particular are more responsive to technology because they regard them as motivational and usable. It also found that higher degrees of agreeableness were associated with being open about technology systems, which the authors ascribe to their more trusting attitude of others (McCrae & Costa, 2008) and hence to technological devices in general. However, Jin et al. (2020) found that agreeableness and conscientiousness are crucial personality traits that influence tracking usage. Moreover, Maltseva and Lutz (2018) found that conscientiousness is a strong driver of self-quantification, while emotional stability has a negative effect, implying that "the more conscientious and less emotionally stable individuals are, the more frequently they engage in self-tracking" (Maltseva & Lutz, 2018). In a similar vein, Chatzigeorgakidis et al. (2016) reported an association between consciousness and self-tracking.

2.3.4. Intermediate Conclusion

Beginning with motivations, we examined the five-factor model developed by Gimpel et al. (2013), which characterises tracking in terms of five primary motivations. We also emphasised how younger, more educated people are more likely to embrace and continue self-tracking (Bol et al., 2018). Finally, we discussed the influence of personal qualities on self-tracking, which remains unclear if they have any effect at all (Attig & Franke, 2019), and if so, which dimensions are more associated with self-tracking usage.

We also discussed how self-tracking fits into the larger Dataism paradigm, which holds that data and its analysis establish truth and value (Harari, 2016, 2018). In light of the increasing complexity of technology and information, self-tracking can therefore be seen as a process that aids individuals in making sense of themselves and their lives. This viewpoint is congruent with the study by Sharon and Zandbergen (2016), in which the authors noted that the QS "is a network of people who seek to find new ways of navigating, finding agency in, and making sense of an increasingly datafied world."

2.4. Privacy and Control in the Digital Age

Though research suggests that self-tracking may have health advantages (Stiglbauer et al., 2019), it also suggests that there may be a darker side to the rising datafication movement (Brandtzaeg et al., 2019; He et al., 2014; Hutton et al., 2018; Suver & Kuwana, 2021). They discuss ethical issues relating to data collection and management (Mai, 2016), which may boil down to a question of control—the fine line between self-tracking and being tracked by others (Selinger, 2015). The sections that follow go into the background of privacy and privacy concerns, touch on the privacy paradox, and offer another perspective on the issue by framing it as a failed effort at privacy self-management, similar to Solove (2021).

2.4.1. Walking Data Generators

As big data becomes increasingly prevalent, human life has grown into a large-scale, automated data source (Mejias & Couldry, 2019). The process of converting human experience into digital information and subsequently producing (commercial) value is known as datafication (Mejias & Couldry, 2019). Big data fosters a new sort of information society in this way (Mai, 2016), necessitating a new understanding of privacy. Initially, privacy was associated with a physical space and the right to be alone (Warren & Brandeis, 1890). However, as information technology advanced, privacy became closely linked with a *personal information space* (George, 2018). Hence, we solely consider information privacy when we address privacy.

Westin (1968) defined privacy as "the claim of individuals, groups, or institutions to determine for themselves when, how, and to what extent information about them is communicated to others." Individuals, according to the author, should always retain ownership of their information, with the last say over how much and what information is disclosed. This control-centered perspective has become the standard in privacy research (Smith et al., 1996), laying the groundwork for today's understanding of privacy regulations (Rollenhagen, 2021). According to Mason (1986), one of the most challenging ethical issues of the information age will be balancing the use of personal information with the preservation of privacy. Indeed, the author anticipated that the increased use of information technology will result in four ethical dilemmas, abbreviated as PAPA: *privacy*, *accuracy*, *property*, and *accessibility* (**Table 2**). Two elements in particular would compromise privacy in the Information Age, including "the growth of information technology, with its enhanced capacity for surveillance, communication, computation, storage, and retrieval." Secondly, information will become "increasingly valuable to policy makers; they covet it even if acquiring it invades another's privacy."

Table 2

The PAPA Framework

Privacy	What information about one's self or one's associations must a person reveal to others, under what conditions and with what safeguards? What things can people keep to themselves and not be forced to reveal to others?
Accuracy	Who is responsible for the authenticity, fidelity and accuracy of information? Similarly, who is to be held accountable for errors in information and how is the injured party to be made whole?
Property	Who owns information? What are the just and fair prices for its exchange? Who owns the channels, especially the airways, through which information is transmitted? How should access to this scarce resource be allocated?
Accessibility	What information does a person or an organization have a right or privilege to obtain, under what conditions and with what safeguards?

Note. An outline of the main questions to consider in the Information Age according to Mason (1986).

In line with Mason (1986), Henkel et al. (2018) noted that personal data has become a part of an expanding digital network that comprises users, self-tracking devices, health promoters, and huge corporations. Individuals in the United States, Australia, and Germany, for example, are persuaded to share personal information with companies and health insurance providers in exchange for bonuses and incentives (Henkel et al., 2018). As a result, studies show a transition from the quantified self to a *quantified us* (Kersten-van Dijk & IJsselsteijn, 2016), in which personal information is no longer considered as private but as a communal good (Ajana, 2017; Angst, 2009). Collective knowledge and information transparency is regarded as beneficial to society as a whole. This is consistent with the observation by Becker (2019) that "when privacy is defined in terms of control over flows of information, an approach is required that surpasses the perspective of the individual."

Moreover, studies have reported a shift in attitudes and values toward privacy: some argue that privacy in the digital era is outdated (Johnson, 2017) or dead (Sahota, 2020). This idea usually originates from two angles. The first is that people believe it is pointless to protect their data (Kerry, 2022), also known as *privacy cynicism* (Hoffmann et al., 2016). Users assume privacy violations are inescapable, developing apathy and cynicism about online privacy. Morgan (2014) highlights this cynicism and sense of powerlessness in an opinion piece for Forbes:

> "I think we've clearly reached a point in today's world where privacy is pretty much a lost cause. Our information is already out there and regardless of how hard we scream that we want it back or want it to be secure, it's not going to happen... ever. If anything we are seeing a shift towards more openness, more transparency, and less privacy."

The second argument is based on the *I-have-nothing-to-hide* rationale (Santanen, 2019; Solove, 2011), which is that the desire for privacy shows that the individual in question has something to hide and hence must have done something wrong (Blundell, 2020). Privacy is important when negative information about a person must be kept private. Research by Ajana (2020b) on self-trackers' views on privacy, data sharing, and protection is a good example of both perspectives being demonstrated. The findings revealed that trackers believed their data was unsafe from the start, and as a result, the advantages of data reuse for research and knowledge creation exceeded privacy concerns. Participants also expressed a sense of *self-insignificance*, thinking their data was irrelevant and that they had nothing to conceal in any case.

This *sharing is caring* ethos has become an important component of online interactions (Lupton, 2021), which also suits the aims of the exploitative data economy. Indeed, digital technologies make data collection, usage, and distribution less expensive and faster (Duch-Brown et al., 2017), while the use of information technology reduces the visibility of privacy intrusions (Mason, 1986). Users, for example, lose control over what information they divulge because most services and networks employ automated data synchronisation (Henkel et al., 2018). The Commission (1977) stated:

> “The real danger is the gradual erosion of individual liberties through automation, integration, and interconnection of many small, separate record-keeping systems, each of which alone may seem innocuous, even benevolent, and wholly justifiable.”

Furthermore, most users lack sufficient understanding of data processing and management. Vitak et al. (2018) showed that 73 % of participants did not know if their tracking provider sold their data, 66 % who controlled their data, and 85 % how long the tracking companies stored their data. Similarly, Ajana (2020b) showed that 50 % of participants were unfamiliar with the data regulations of self-tracking devices and applications. According to Mcafee and Brynjolfsson (2012), this causes individuals to unwittingly become a real-time “walking data generator,” unaware of how much and what type of data they generate and what happens with their data.

To summarise, information digitisation ushers in a new era of a connected knowledge economy in which personal informatics becomes a collective good, underlining the ethical dilemma of protecting one’s individual right to privacy versus promoting the overall common good (Angst, 2009; Toesland, 2021). Users begin to question if data should be kept private at all (Ajana, 2020b), whether from a standpoint of privacy cyncism (Hoffmann et al., 2016), self-insignificance (Ajana, 2020b), or the I-have-nothing-to-hide rationale (Solove, 2011). Besides that, there is a combination of corporations’ lack of transparency and the general user’s lack of privacy awareness (Ajana, 2020b; Vitak et al., 2018). Overall, this puts pressure on the core principle of information privacy (Mason, 1986; Smith et al., 2011; Westin, 1968), which maintain that people should retain ultimate control over their personal data. Though there are reasons to be optimistic about big data processes, such as better informed, strategic population-level decision-making (Sousa et al., 2019), privacy concerns are on the rise.

2.4.2. Privacy Concerns

As highlighted by the controversies and the exposure of questionable data processing practises (Krasnova et al., 2009), privacy is one of the most pressing issues of the Information Age (Mason, 1986). Smith et al. (1996) is the first reference in the literature to create and validate a scale for assessing privacy concerns. The *Concern for Information Privacy* (CFIP) (**Table 3**) investigates the impact of organisation's information policies and practices on customers' privacy concerns, and has been acknowledged by Stewart and Segars (2002) as a viable tool for analysing consumers' concerns in traditional marketing. The 15-item framework conceptualises privacy concerns in four fundamental dimensions: *collection*, *errors*, *unauthorised secondary use*, and *improper access*.

First, *collection* relates to people's concerns that a bunch of personal information about their actions, interests, personalities, and other factors is being acquired and stored. Second, *errors* is related to the concern that organisations do not adequately guard against inaccurate personal data and the consequences of such errors. Third, *unauthorised secondary use* describes the use of personal data for additional purposes without the author's consent. Finally, *improper access* raises the issue of who inside the organisation should have access to personal data.

Table 3

Overview of the Concern for Information Privacy (CFIP)

Collection	Errors	Unauthorised Secondary Use	Improper Access
Customers' concern about the acquisition and storage of large quantities of personal data.	Customers' concern about companies' failure to protect against data errors and the consequences of such errors.	Customers' concern that their information is being reused without their permission.	Customers' concern that anyone within the organisation may have unauthorised access to personal data.

Note. An overview of Smith et al. (1996)'s framework.

However, the Internet's growing popularity has given rise to new types of privacy concerns (Jakovljević, 2011). Unlike conventional marketing, the Internet allows for more dynamic, two-way engagement (Fawkes & Gregory, 2000), prompting the need for a theoretical framework tailored to privacy issues in the Internet setting. To investigate internet users' privacy concerns, Malhotra et al. (2004) proposed the *Internet Users' Information Privacy Concerns* (IUIPC) scale (**Table 4**). The theoretical framework is founded on the social contract theory, which asserts that acquiring personal information by an organisation is only fair if the consumer retains control and is informed about its usage (Malhotra et al., 2004). Internet users' privacy concerns are divided into three categories: *data collection*, *data control*, and *awareness of privacy practices*.

First, the authors contend that data collection, whether legal or illicit, is already a source of privacy concerns. This concern intersects with the collection dimension by Smith et al. (1996), in which the internet user is concerned about the quantity of personal information gathered and possessed by others. This relates to the second concern of users, which is the ability to exercise control over their data by deciding how it is used, accessed, modified, or deleted. Finally, user awareness of privacy practices relates to how concerned users are about the knowledge they have regarding data handling.

Table 4

Overview of the Internet Users' Information Privacy Concerns (IUIPC)

Data Collection	Data Control	Awareness of Privacy Practices
Internet users' concern about the acquisition and storage of large quantities of personal data.	Internet users' concern about their ability to control their data.	Internet users' concern about their understanding of how their data is handled and processed.

Note. An overview of Malhotra et al. (2004)'s framework, a scale tailored for the Internet setting.

However, over 90 % of the worldwide internet population uses a mobile device to access the internet, with mobile internet traffic accounting for 55 % of total web traffic (Ceci, 2022). Mobile users create more personal data on a continuous and automatic basis since they may connect to networks and services at any time and from any place. Therefore, Xu et al. (2012) highlighted that privacy concerns necessitate a new scale, fitted to the constantly growing usage of mobile network technology. The authors presented the *Mobile Users' Information Privacy Concerns* (MUIPC) (**Table 5**) framework to capture mobile users' privacy concerns across three dimensions: *perceived surveillance*, *intrusion*, and *secondary use of personal information*.

Mobile devices may capture significantly more sensitive data in large quantities than computers could. *Perceived surveillance* is how mobile users perceive that their personal information is being collected, stored, and used by a third party. As a result, perceived surveillance focuses on ongoing monitoring rather than the invasive eye of another person (Becker, 2019). Solove (2006) defined surveillance as "the observation, listening to, or recording of an individual's activities."

Perceived intrusion is the perception of a potentially harmful invasion into one's personal information space. The main idea behind intrusion is that it harms and inconveniences mobile users. According to (Solove, 2006), "it disrupts the victim's everyday activities, affects her routines, destroys her isolation, and frequently makes her feel uncomfortable and uneasy." The usage of malware is used as an example by Xu et al. (2012), who notes that "users may resits mobile apps for the fear that the malicious apps may interrupt their activities through the unwanted presence."

Additionally, the breach feels more threatening in a mobile environment due to the sensitive nature of the exposed data. However, Barth et al. (2019) points out that the impact of privacy intrusion are not felt directly since invasion of someone's personal space in the online world is less tangible than in the offline world.

Smith et al. (1996) defined *secondary use of personal information* as the "concern that information is collected from individuals for one purpose but is used for another, secondary purpose without authorisation the individuals." The Cambridge Analytica scandal is one example of how personal data belonging to millions of Facebook users was gathered without their knowledge and consent and primarily used for political advertising (Wong, 2019). Secondary use creates '"a sense of powerlessness and vulnerability" (Solove, 2006) because customers have a limited grasp of the conditions under which their personal information is obtained, sold, or processed.

Table 5

Overview of the Mobile Users' Information Privacy Concerns (MUIPC)

Perceived Surveillance	**Perceived Intrusion**	**Secondary Use**
Mobile users' perception that their personal information is always being observed, acquired, stored, and exploited by a third party.	Mobile users' perception that their personal information space is compromised.	Mobile users' concern that personal information obtained for one purpose may be used for another without their consent.

Note. An overview of Xu et al. (2012)'s framework, a scale tailored for the mobile setting.

Given the proliferation of monitoring devices, it is not surprising that the acquisition of personal information by wearable gadgets and tracking applications has become a new focus for addressing privacy concerns (Dearborn, 2014). The authors of Klasnja et al. (2009) reported that trackers' privacy concerns differed depending on what was being recorded, where participants worked and resided, and therefore where data would be obtained, and how much value participants believed the data would provide. In contrast, Gorm and Shklovski (2016) found that trackers were indifferent about disclosing their health data. Similarly, Pinchot and Cellante (2021) used the MUIPC on self-trackers and concluded that the majority of participants rated neutral on the MUIPC scale. Given the variety of findings, it appears that there is still a need to further assess and understand privacy concerns among self-trackers, as well as if these concerns impact their tracking activities.

Concluding, privacy issues evolve in response to the context in which data is collected and handled (**Table 6**). Because of the changing nature of information generation in the mobile setting, Xu et al. (2012) created the MUIPC, a scale tailored to mobile users. Given that self-tracking applications and devices record continually and automatically as mobile devices, the MUIPC may be appropriate for measuring privacy concerns among self-trackers.

Table 6

A Summary of the Three Privacy Concerns Scales

	CFIP	IUIPC	MUIPC
Study	Smith et al. (1996)	Malhotra et al. (2004)	Xu et al. (2012)
Items	15-item scale	10-item scale	9-item scale
Setting	Conventional marketing	Internet users	Mobile users
Goal	Assessing individuals' concerns regarding organisational privacy practices.	Assessing Internet users' concerns regarding their information privacy.	Assessing mobile users' concerns regarding their information privacy.
Focus	Organisational responsibility for the proper management of customer information.	Individuals' subjective perceptions of fairness in the context of information privacy.	Individuals' beliefs that they have the right to own their personal information.
Dimensions	1. Collection 2. Errors 3. Unauthorised Secondary Use 4. Improper Access	1. Data Collection 2. Data Control 3. Awareness Privacy Practices	1. Perceived Surveillance 2. Perceived Intrusion 3. Secondary Use of Personal Information

Note. An overview of the three different privacy concern scales.

2.4.3. Rethinking the Privacy Paradox

Although users express increasing concerns about their privacy, they do not take the required precautions to protect themselves and even continue to interact with technology in ways that jeopardise it (for a literature overview, see Kokolakis (2017)). For example, users reveal highly personal information on social media but make little attempt to protect their data by actively deleting cookies. Similarly, when presented with the opportunity to read the terms and conditions, most users accept them without reading them carefully or at all. This is known as the *privacy paradox*, which is the finding that users' strong privacy concerns do not correspond to their actions. This paradox is prominent in privacy research because it may imply how privacy should be governed (Solove, 2021). Therefore, numerous theories have been presented to explain this gap, such as the privacy calculus hypothesis (Culnan & Armstrong, 1999), a lack of understanding (Vitak et al., 2018), privacy cynicism (Hargittai & Marwick, 2016; Hoffmann et al., 2016), or the trust paradox (Lutz & Strathoff, 2014) (for a more in-depth discussion, see Gerber et al. (2018). In other words, the dominating strategy was to investigate the causes of this disparity, with the implicit idea that people's behaviour could be realigned with their attitudes. The mismatch is deemed irrational (Barth & De Jong, 2017), which is consistent with the long-held belief that users should be able to make reasonable and independent privacy decisions (Smith et al., 1996).

However, aside from the privacy landscape, there are several comparable paradoxes, such as having a monthly gym membership but not going, or knowing the dangers of smoking but not quitting. This misalignment of actions and attitudes is a well-known concept in social psychology, with the theory of cognitive dissonance, i.e., the mental conflict that occurs when a person's behaviour patterns and beliefs do not accord (Festinger, 1962), implying that the privacy paradox is not a new observation in human behaviour. In addition, the study by Solove (2021) contends that presuming evidence of a privacy paradox when privacy concerns and behaviour do not coincide is flawed logic. While attitudes are more value-focused and may last outside of context, behaviour is very context-dependent since it involves decision-making and risk assessment. As a result, there is no such thing as a contradiction because the two concepts do not have to be aligned.

According to Solove (2013), people's failure to safeguard their privacy is a natural result of privacy legislation relying too heavily on *privacy self-management*. Privacy self-management is based on the notion that users *can* and *should* make autonomous, rational privacy decisions in order to safeguard their data (Solove, 2013). This idea is based on the conventional individual-centered approach to information privacy (Mai, 2016), which emphasises personal responsibility and control over information (Smith et al., 1996). However, this model faces issues (Lehtiniemi & Kortesniemi, 2017). For example, individuals' online decision-making is constrained, a phenomenon known to behavioural scientists as *bounded rationality* (Simon, 1990). In addition, research questions whether it is still viable and reasonable to expect individuals to have complete control in an ever-changing digital environment where data management has become highly complicated (Chakravorti, 2020; de Boer et al., 2021; Solove, 2021). Matz (2021) stated:

> "Current regulations drop people in the middle of a raging technology sea and bless them with the right to control their personal data. Instead of forcing the tech industry to make systemic changes that would create a safer and more amenable ecosystem, we put the burden of safeguarding personal data on consumers."

In short, self-management of personal data cannot be the main focus of long-term and viable privacy legislation for three reasons. First, the large volume of created data makes even the most knowledgeable users struggle to keep up with (de Boer et al., 2021). Second, there has not yet been created in the data ecosystem the appropriate environment that offers basic protection (Matz, 2021). Third, and linked to the second issue, providing customers with new privacy rights has not changed the fact that their data is still subject to surveillance, collecting, and datafication (Mai, 2016). In other words, relying just on the individual no longer makes sense in a modern information society since it oversimplifies the complexities of privacy. According to Kerry (2022), it is a "losing game for both the individual and privacy legislation," since the consequences of datafication reach beyond the individual's control (Mejias & Couldry, 2019).

Solove (2021) proposes a new paradigm in which personal responsibility is no longer the sole source of data protection and privacy policies need to begin to shift in a new direction, with legislation focusing on broader structures beyond the person by regulating how information should be handled. Similarly, De Mooy (2017) stated that forward-thinking policy regulations are required, leaving behind "outdated interpretations of individual control, and instead focus on creating mechanisms that offer individuals authority, practical impact assessments and robust accountability in such a way as to build public trust and engagement." Chakravorti (2020), for example, argues that we should foster digital agency by providing individuals with the required management tools so that they may take ownership of their own data in the same manner that we have a digital bank account.

2.4.4. Intermediate Conclusion

Tracking technologies pose new and unique challenges to individual privacy, especially when privacy breaches become less apparent and users are not sufficiently aware of privacy legislation and risks. Research on privacy concerns related to self-tracking data, however, remains inconclusive and poorly understood. In addition, the core notion of information privacy (i.e., control) in the digital world is under threat as users fail to take the necessary precautions to protect themselves. A new approach to privacy is required, one in which individual self-management is not the primary focus but may be encouraged by better structure in the data ecosystem on the one hand and tools promoting digital agency on the other.

2.5. Research Questions

Based on the theoretical foundation and the study's initial aims, we had various research questions that might be classed as descriptive or relational (**Table 7**).

Table 7

Research Questions

Number	Question	Type
1	What are the overall demographics of the self-tracking sample?	Descriptive
2	How many individuals from the sample track, how intensely, for how long, and with what tools?	Descriptive
3	Do trackers have specific reasons to self-track? Do non-trackers have specific reasons for not tracking?	Descriptive
4	Are trackers willing to share their data? If so, what type of self-tracking data are they sharing and with whom?	Descriptive
5	Are trackers concerned about their privacy?	Descriptive
6	Do trackers have confidence in their tracking service providers?	Descriptive
7	Are self-trackers knowledgeable about data processing and handling?	Descriptive
8	What are self-trackers' attitudes and preferences towards (improved) data protection?	Descriptive
9	Do self-trackers face any challenges in protecting their data?	Descriptive
10	What factors (e.g., healthism, motives, privacy concerns, confidence, attitudes, value, vanity, and Big 5 personality characteristics) are valuable in explaining self-tracking behaviour?	Relational

Note. An overview of the research questions, with the type of question given in the column "Type."

Chapter 3: Methodology

Based on the study objectives, theoretical framework, and predefined research questions, this chapter discusses the research methodology, instruments, and analysis. This section describes how the questionnaire was developed, the items that were included, and highlights the general procedure and standards.

3.1. The Development Process

We wanted to reach a large number of people while collecting data fast and efficiently. We decided to develop our own questionnaire using LimeSurvey, an online survey platform. We created a survey that included a range of factors, including motivation, privacy, personality traits, and demographics. We did so while limiting the questionnaire to under 15 minutes to keep it as brief as possible. We went over the questionnaire numerous times to make sure that all of the questions were relevant, that they were easy to follow, and that the interface was straightforward to use. Before the items were modified and improved, the questionnaire was piloted with a small sample of participants (N= 10). The final survey includes 26 items organised as follows: *(1) self-tracking characteristics*, *(2) motivations*, *(3) privacy*, *(4) personality traits*, *(5) demographics*.

Questions for each section were all on one page, allowing participants to see how far they had advanced on the progress bar after completing one part. This was done to encourage respondents to finish the questionnaire. Because the privacy section was the most complex and time-consuming, we divided it into four smaller sections. See **Appendix A** for the entire questionnaire.

3.2. The Questionnaire

We will go through each section in further detail, describing which questions were asked as well as the reasoning and research behind them. As there are many details, we have summarised them in a table to make it simpler to digest in **Table 8** at the conclusion of this section.

3.2.1. Self-Tracking Characteristics

The first part of questionnaire examined at the person's general profile. Participants who indicated they were not tracking were given different questions with the primary goal of determining why.

3.2.1.1. Intensity and Frequency. We took over the tracking categories from Gimpel et al. (2013) and asked respondents what they track (e.g., body, well-being, nutrition, etc.), how long (e.g., under 1 month, 1-3 months, under 6 months, etc.) and how intensely (e.g., sporadically, daily, weekly, etc.).

3.2.1.2. Sharing Activities. We asked if they shared their data, and if so, with whom they shared their self-tracking data and what information they were willing to share with others. We wanted to see if trackers were comfortable sharing their data and if data sensitivity was a consideration. Participants responded a 5-point Likert scale, with 1 being *strongly disagree* and 5 *strongly agree*.

3.2.1.3. Healthism. Despite the potentially significant link between the two notions, no study has been undertaken on the relationship between healthism and self-tracking behaviours. We developed our own items to assess the relationship between healthism and self-tracking. We relied on Anisimova (2016), a study on the influence of healthism in the purchase of organic foods. We modified these items in the context of self-tracking, adding new items where we wanted to particularly study how participants link health with responsibility (e.g., "I feel responsible for my own health") and how self-tracking may be a tool to assist them do so (e.g., "Self-tracking allows me to take control of my own health"). The items were evaluated on a 5-point Likert scale, with 1 being *strongly disagree* and 5 *strongly agree*.

3.2.1.4. Non-Tracker. Those who were not self-tracking were asked questions to determine whether they had any specific reasons (e.g., "It's too much effort," "It frustrates me"). We also wanted to know if they had tried self-tracking before, what their experiences were, and if they would consider starting or continuing the practice in the future. The items were evaluated on a 5-point Likert scale, with 1 being *strongly disagree* and 5 *strongly agree*.

3.2.2. Motivations

We employed the framework created by Gimpel et al. (2013) to investigate the motivations of self-tracking behaviour. Self-tracking is characterised by five underlying motivations in this 19-item framework: *self-entertainment*, *self-association*, *self-design*, *self-discipline*, and *self-entertainment*. The items were rated on a 5-point Likert scale, with 1 representing *strongly disagree* and 5 representing *strongly agree*.

3.2.3. Privacy

Because the privacy part of the questionnaire was the most extensive, we chose to divide the items into four subsections: *(1) privacy concerns*, *(2) confidence and knowledge data management*, *(3) privacy value, attitudes and barriers*, *(4) privacy preferences*.

3.2.3.1. Privacy Concerns. We used the 9-item MUICPC scale developed by Xu et al. (2012) to investigate privacy concerns among self-trackers. We chose to modify the items to make them more precise and suitable to the setting of self-tracking, while retaining the three dimensions of *perceived surveillance*, *perceived intrusion*, and *secondary use of information*. “I feel that as a result of my using mobile apps, others know more about me than I am comfortable with,” for example, is changed to “I am concerned about people knowing more about me than I am comfortable with because of the use of self-tracking devices and services.” The items were rated on a 5-point Likert scale, with 1 representing *strongly disagree* and 5 representing *strongly agree*.

3.2.3.2. Confidence and Knowledge Data Handling. We developed four items to assess the topics of data collection ("I am aware that tracking companies and services are collecting and using my personal information for other purposes"), retention ("I am aware of how long tracking companies story my self-tracking data"), ownership ("I am aware of who has access to my self-tracking data"), and selling ("I am aware if my self-tracking data has been shared without my permission"). This is due to the fact that these are the most discussed issues in studies when it comes to data management knowledge among self-trackers (Ajana, 2020b; Vitak et al., 2018). In addition, we included three items to assess the user’s confidence in monitoring companies (e.g., “I have confidence that my tracking service provider will not disclose any of my personal information”). The items were rated on a 5-point Likert scale, with 1 representing *strongly disagree* and 5 representing *strongly agree*.

3.2.3.3. Privacy Value, Attitudes and Barriers. We assessed how trackers valued their data (e.g., “I believe my tracking data is valuable enough to be used against me”). Furthermore, we wanted to know if self-trackers face any difficulties in adequately safeguarding their data, such as time (e.g., "I value my privacy, but I don’t have the time to be concerned about it.") or skills (e.g., "I have the necessary technical skills and knowledge to adequately secure my data."). In addition, we enquired about their overall attitudes towards privacy (e.g., “Ì believe privacy concerns are overrated”). The items were rated on a 5-point Likert scale, with 1 representing *strongly disagree* and 5 representing *strongly agree*.

3.2.3.4. Privacy Preferences. We asked if they would be willing to learn more about privacy regulations (e.g., “Would you be willing to spend some time learning more about self-tracking privacy policies?”), refrain from engaging in certain behaviours (e.g., “Would you stop sharing your information with online platforms and friends if it meant your privacy would be more protected?”), or even pay for a service that manages their data in the background. The items were rated on a 5-point Likert scale, with 1 representing *strongly disagree* and 5 representing *strongly agree*.

3.2.4. Personality Traits

We used the Big Five Inventory-10 (BFI-10) (Gosling et al., 2003), a condensed version of the original 44-inventory by Goldberg (1993). To test for vanity, we included elements from the vanity scale by Netemeyer et al. (1995). However, we only chose items from the vanity scale that we considered were relevant to self-tracking: *physical concerns* (i.e., items concerning how the participant appears) and *achievement concerns* (i.e., items concerning how others recognise the person’s accomplishments).

3.2.5. Demographics

Demographic information like gender, age, educational level, marital status, and gross monthly income were collected.

Table 8

The Questionnaire

Section	Topic	Literature
Self-tracking characteristics	Object of tracking	Gimpel et al. (2013)
	Sharing activities, self-tracking tools, intensity, frequency, etc.	Own devised items
	Healthism	Based on healthism items Anisimova (2016)
Motivations	Motivations	19-item framework by Gimpel et al. (2013)
Privacy	Privacy concerns	Based on 9-item MUICPC scale by Xu et al. (2012)
	Confidence and knowledge data handling	Own devised items & based on Vitak et al. (2018)
	Values, attitudes and barriers	Own devised items
	Privacy preferences	Own devised items
Personality traits	Big 5 dimensions	Big Five Inventory-10 by Gosling et al. (2003)
	Vanity	Selected items from Netemeyer et al. (1995)
Demographics	Gender, age, education level, marital status, monthly income	Own devised items

Note. A summary of the questionnaire sections, topics addressed, and literature used.

3.3. Study Procedure

Participants were told that their participation in the study was entirely voluntary and that they could withdraw at any time. The questionnaire was administered online and took around 15 minutes to complete, and participants received no compensation for their time.

3.4. Inclusion and Exclusion Criteria

There were no specific requirements for participation; both trackers and non-trackers were eligible to participate. Likewise, no exclusion criteria were established other than the requirement that they complete the entire questionnaire.

3.5. Participants

We obtained a total of 132 individuals who completed the questionnaire. The tracking ratio in the sample was roughly equal, with 46.97 % self-trackers (*N* = 62) and 53.03 % non-trackers (*N* = 70). There were 52.27 % females (*N*= 69), 45.46 % men (*N* = 60), and 2.27 % other (*N* = 3).

3.6. Data Analysis

We conducted a descriptive analysis to gain a full overview of self-tracking. Confirmatory factor analysis seemed to be the logical next step in determining the model's goodness-of-fit to the data because the items had a solid conceptual foundation. Cronbach alpha (α) was used to evaluate the instrument's internal consistency.

3.6.1. Descriptive Analysis

Descriptive analysis of self-tracking has been performed using R Studio (version 2021.09.01) for statistical analysis (RStudio Team, 2020).

3.6.2. Confirmatory Factor Analysis

CFA was performed using the lavaan package (version 0.6-9) to evaluate the instrument's validity (Rosseel, 2012). Maximum Likelihood Robust Method was used to estimate all models as the data was not normally distributed. This approach is a more accurate adjusted measure of fit for non-normal data than the conventional ML statistic (Satorra & Bentler, 2001). Several model fit measures were used to assess the model's goodness-of-fit: the Comparative Fit Index (CFI), the Root Mean Square Error of Approximation (RMSEA), the Standardized Root Mean Square Residual (SRMR), the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC).

CFI values greater than .90 indicate a good fit to the data, while values larger than .95 highly supporting (Hu & Bentler, 1999). The RMSEA compares the model to a perfect baseline model, with values less than .05 considered a good fit. The SRMR measures the difference between the observed and expected correlation, with values less than .07 indicating a good fit (Hu & Bentler, 1999; Pavlov et al., 2021). The AIC measures the performance of the model being evaluated in contrast to the other model. The model with the lowest AIC score is thought to be the best fit. The BIC is used to pick the best-fitting model, with lower BIC values indicating a better model fit (Vrieze, 2012). Finally, to measure item quality, the factor loadings of each item were evaluated using the general rule that factor loadings of >.60 and an R2 of >.40 are considered acceptable (Othman et al., 2014).

3.6.3. Reliability Analysis

Reliability analysis was performed to evaluate the quality of the items. The item-total correlation (i.e., r.drop) was calculated with values <.30 indicating that the item does not correlate with the entire scale (Yusoff et al., 2010). Cronbach's alpha was used to assess the instrument's internal consistency using the Psych package (Revelle, 2022). Cronbach alpha values of $\geq$.70 suggest satisfactory internal consistency (Taber, 2018).

3.6.4. Regression Analysis

Logistic regression analysis was done to determine how well the instrument explains self-tracking (i.e., does someone track, yes or no).

Chapter 4: Results

4.1. Descriptive Analysis

4.1.1. Demographics

The sample included 132 people, with 69 females (52.27 %), 60 men (45.46 %), and 3 (2.27 %) identifying as other. The age distribution was slighted to the left, with 21.21 % under the age of 20, 33.33 % between the ages of 21 and 30, 25 % between the ages of 31 and 40, 8.33 % between the ages of 41 and 50, 6.06 % between the ages of 51 and 60, and 5.30 % older than 61. The group was well-educated, with 50.00 % holding a master's degree and 10.61 % a Ph.D. Individuals were in a relationship (26.52 %), married (30.30 %), or single (34.09 %). Participants had various economic backgrounds (**Table 16** in Appendix B).

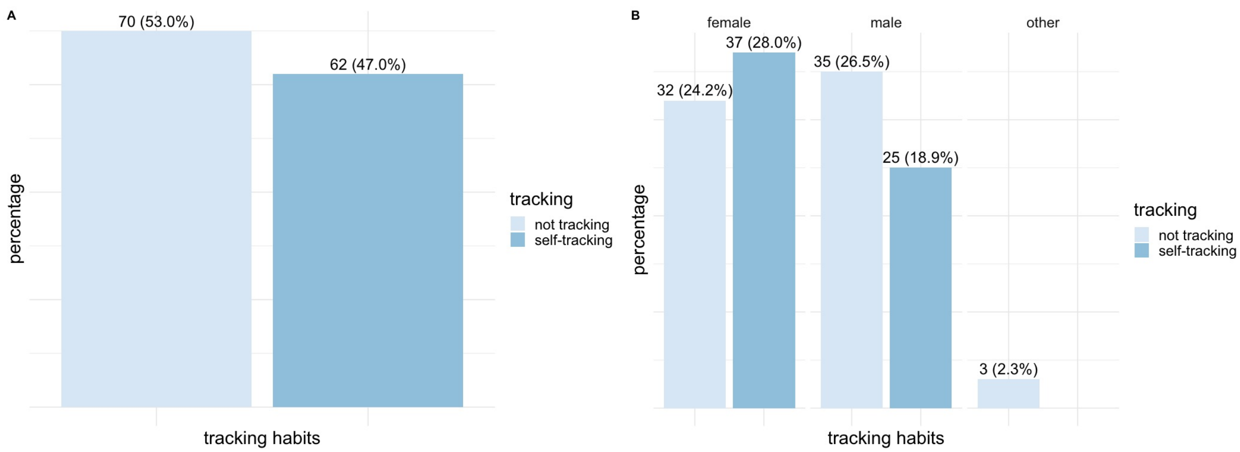
4.1.2. Tracking Ratio

There were 70 non-tracking individuals (53 %) and 62 self-trackers (47 %), with 37 women (28 %) self-tracking and 25 males (18.9 %) (**Figure 1**). The bulk of self-trackers were aged 21 to 30 (**Figure 13** in Appendix B) and held a master's degree (**Figure 14** in Appendix B).

50 % of non-trackers indicated they had tried tracking before, 45.71 % said they had never tried it, and 4.29 % indicated they had tried it multiple times. Those who had previously attempted self-monitoring had a neutral (55.26 %) to positive (21.05 %) experience and were undecided (34.21 %) to agreeing (31.58 %) on whether they would consider resuming a tracking habit in the future. Non-trackers with no previous experience were undecided (28.12 %) and disagreed to strongly disagreed ($\sim$65.62 %) that they would start a tracking habit in the future (**Figure 15** in Appendix B).

Figure 1

Gender and Tracking Ratio



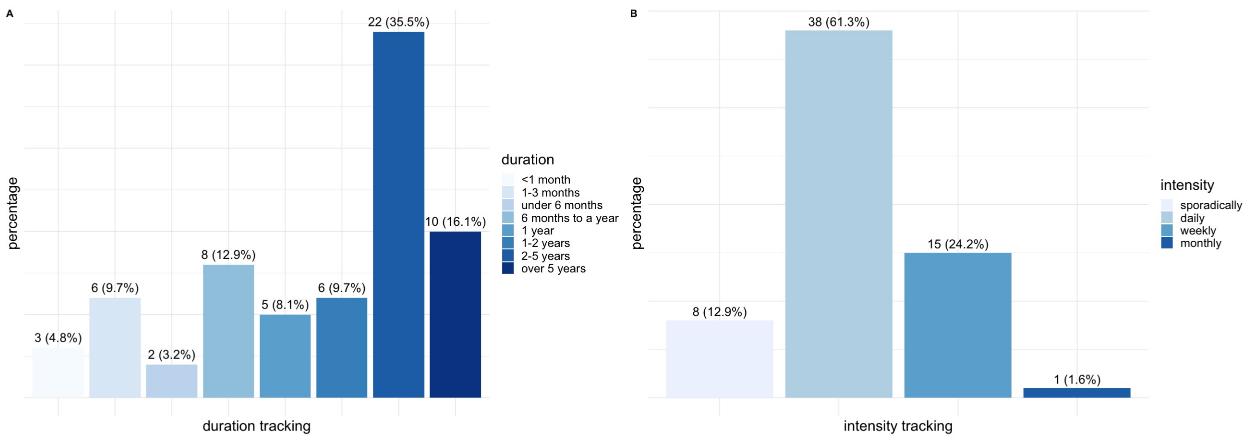
Note. Figure A depicts the tracking ratio. Figure B depicts the tracking ratio in relation to age.

4.1.3. Duration and Intensity

Self-trackers tracked for less than one month (4.84 %), 1-3 months (9.68 %), under six months (3.23 %), six months to a year (12.90 %), one year (8.06 %), and two years (9.68 %). There were trackers that indicated a tracking term of 2 to 5 years (35.48 %) and longer (16.13 %). The bulk of trackers (61.29 %) tracked on a daily basis (**Figure 2**).

Figure 2

Tracking Duration and Intensity



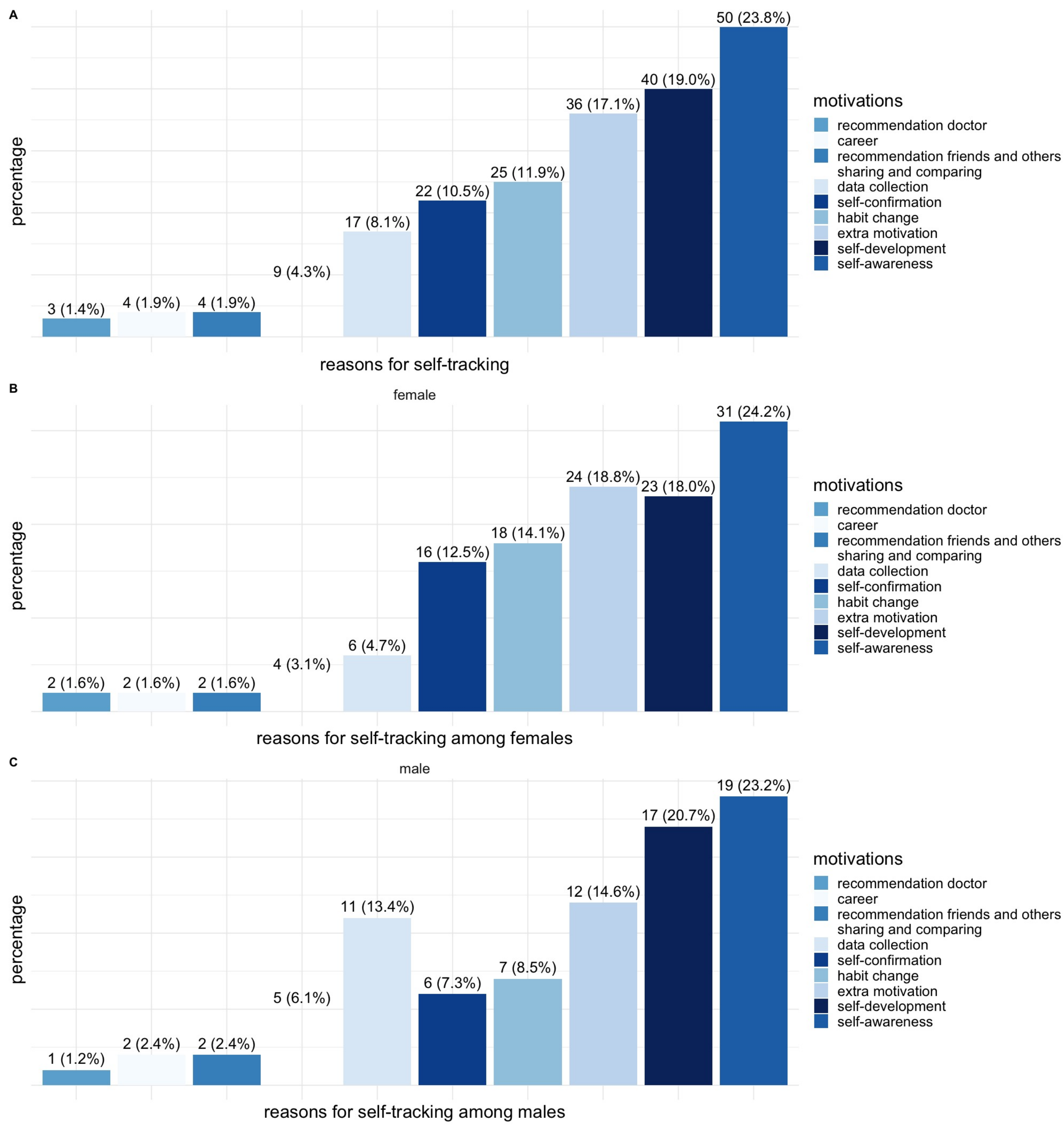
Note. Figure A depicts how long self-trackers track themselves, Figure B how intense.

4.1.4. Reasons (not) to Track

Lack of motivation (17.45 %), disinterest in self-tracking (13.68 %), and feeling pressured by it (10.38 %) were the three main reasons for not self-tracking (**Table 17** in Appendix B). 50 % of self-tracking participants did not self-track to cope with a medical condition, compared to 32.26 % who did (17.74 % indicated they did not wish to answer the question). Instead, the primary motives were self-awareness (23.81 %), self-development (19.05 %), and extra motivation (17.14 %). The top three motivations were identical for both sexes, but habit change (14.1 %) and self-confirmation (12.5 %) were additional motivations for females while data collection for males (**Figure 3**).

Figure 3

Reasons and Gender



Note. Figure A depicts the reasons for tracking among the self-trackers, while Figure B represents female trackers and Figure C male trackers.

4.1.5. Tracking Categories and Tools

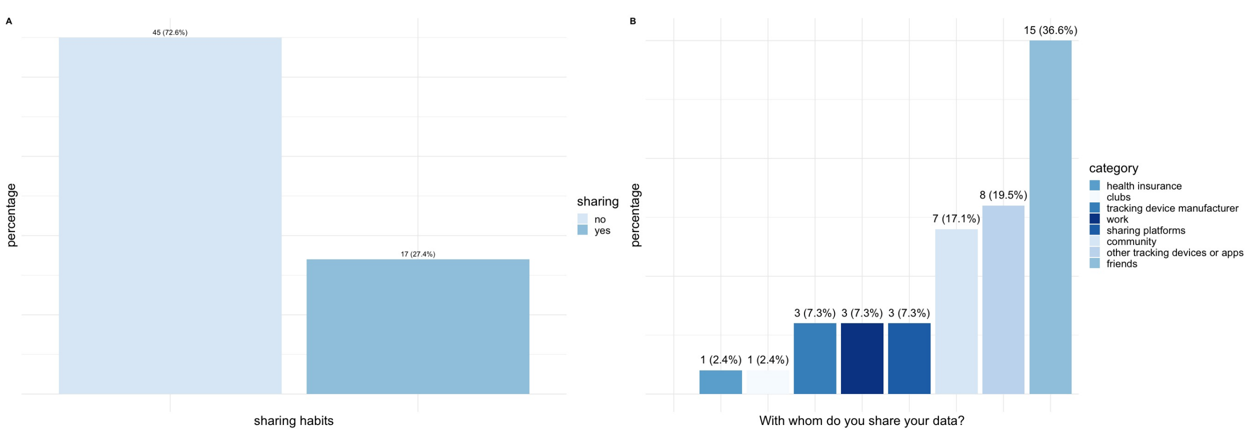
Trackers mostly tracked physical activity (29.89 %), body measures (22.41 %), and general well-being (14.94 %). They used smartphones (36.36 %), wearable devices such as smartwatches (31.40 %), and mobile applications (25.62 %). Trackers also used medical devices, however they were in the minority (6.61 %) (**Figure 16** in Appendix B).

4.1.6. Sharing Activities

72.58 % did not share their self-tracking data. Of the 27.42 % who did share their data, they shared it with friends (36.59 %), other self-tracking devices and applications (19.51 %), and a (online) community (17.07 %) (**Figure 4**). In addition, trackers were divided on sharing health and nutrition information, with about an equal number strongly opposing sharing and others approving. Trackers were most willing to disclose information about their progress, such as the number of steps taken and metrics linked to exercise and workouts, but not body weight and mood (**Figure 17** in Appendix B).

Figure 4

Sharing Behaviour



Note. Figure illustrating who self-trackers are willing to share their tracking data with.

4.1.7. Privacy Concerns

Nearly an equal number strongly disagreed (16.13 %), disagreed (19.35 %), stayed undecided (20.97 %), agreed (20.97 %), and strongly agreed (20.97 %) when asked whether they are concerned about devices tracking their location. Similar mixed results were seen for devices collecting personal data. When asked if they were concerned about their actions being tracked, ∼46.77 % disagreed to strongly disagreed, 25.81 % were undecided, and ∼27.42 % agreed to strongly agreed.

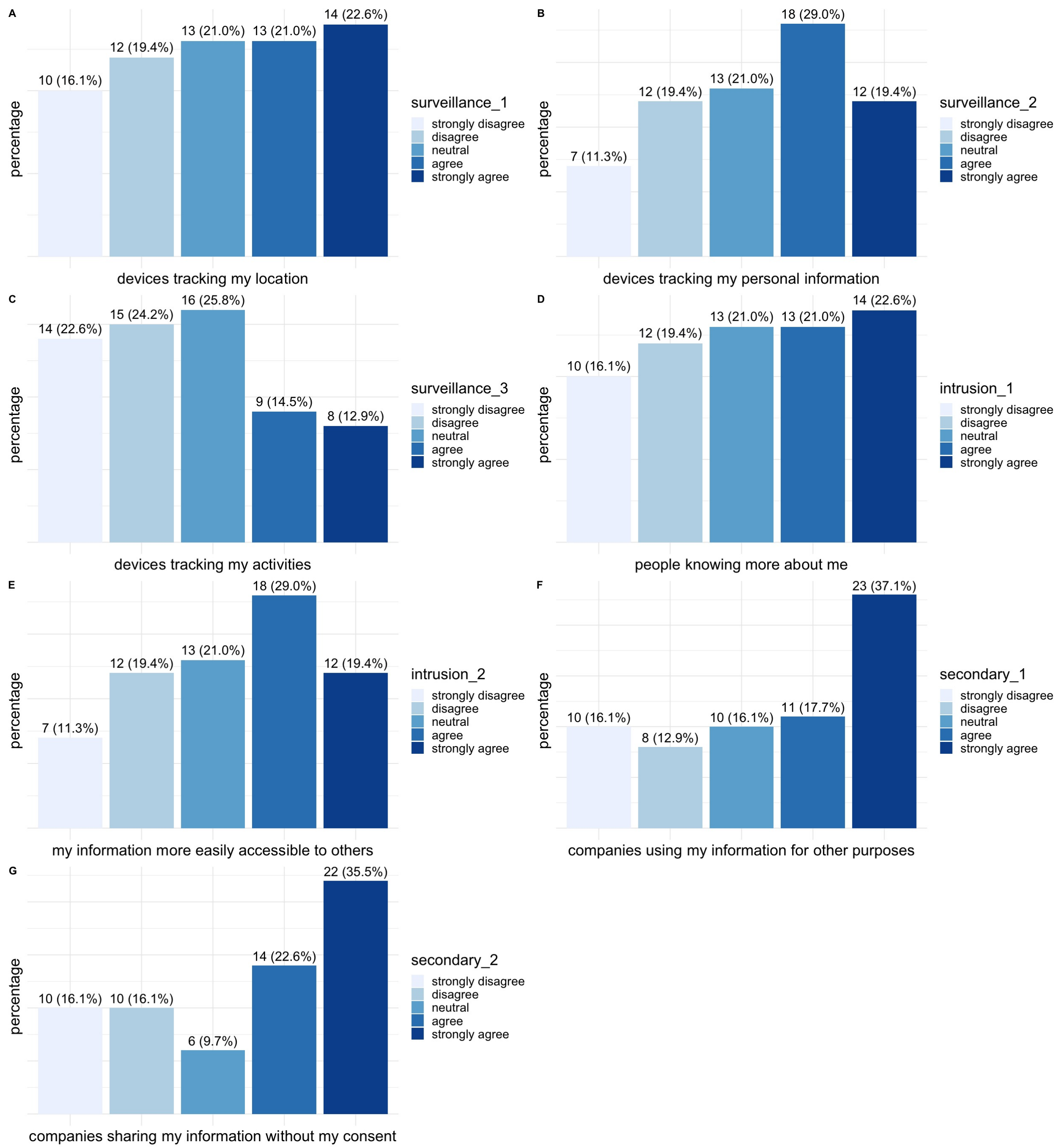
Similarly, the results for both intrusion dimension items (i.e., "I am concerned about the use of self-tracking services making my personal information more easily accessible to others" and "I am concerned about self-tracking technologies using my personal information for other purposes") were mixed. However, there was a clear tendency for the secondary use items. ∼54.84 agreed to strongly agreed to be concerned about companies exploiting their information for other purposes and ∼58.06 % agreed to strongly agreed to be concerned about companies sharing their information with third parties without permission (**Figure 5**).

4.1.8. Confidence in Tracking Providers

Self-trackers were undecided about whether they trust their tracking providers to not disclose their information, keep their data private, and not exploit their data. Responses for the three items ranged from disagreeing to undecided to agreeing (**Figure 18** in Appendix B).

Figure 5

Privacy Concerns Among Self-trackers



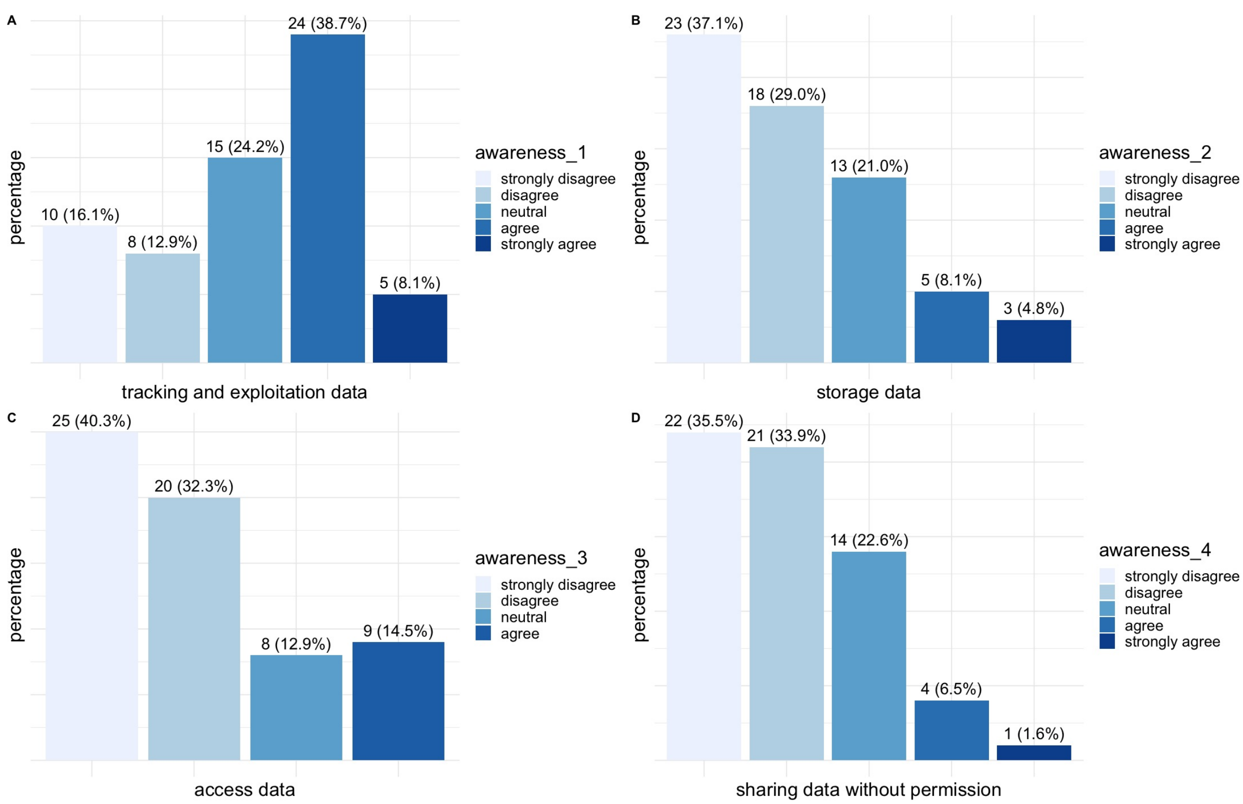
Note. Figure A depicts the concern about self-tracking devices recording the location of the self-tracker, Figure B acquiring personal information, and Figure C monitoring activities. Figure D represents the concern that people know more about them as a result of the use of such devices and services. Figure E shows the concern their personal information is more easily accessible to others. Figure F depicts self-tracking companies exploiting their users' personal information and Figure G the concern of tracking companies selling their data to third parties without permission.

4.1.9. Knowledge Data Handling

∼66.13 % disagreed to strongly disagreed, 20.97 % remained undecided, ∼12.09 % agreed to strongly agreed on whether they know how long their data is stored. Similar patterns emerged when people were asked who could access their data and whether or not their data is shared without their permission (see Figure 6). 38.71 % of trackers agreed (24.19 % were undecided and 12.90 % disagreed) to be aware of the collection and exploitation of their personal data by tracking devices and services (**Figure 6**).

Figure 6

Self-Trackers' Knowledge Data Handling



Note. Figure A shows the awareness of the use and exploitation of their personal data; Figure B how long their data is retained, Figure C who has access to their data and Figure D if their data has been shared without their permission.

4.1.10. Privacy Attitudes, Values and Barriers

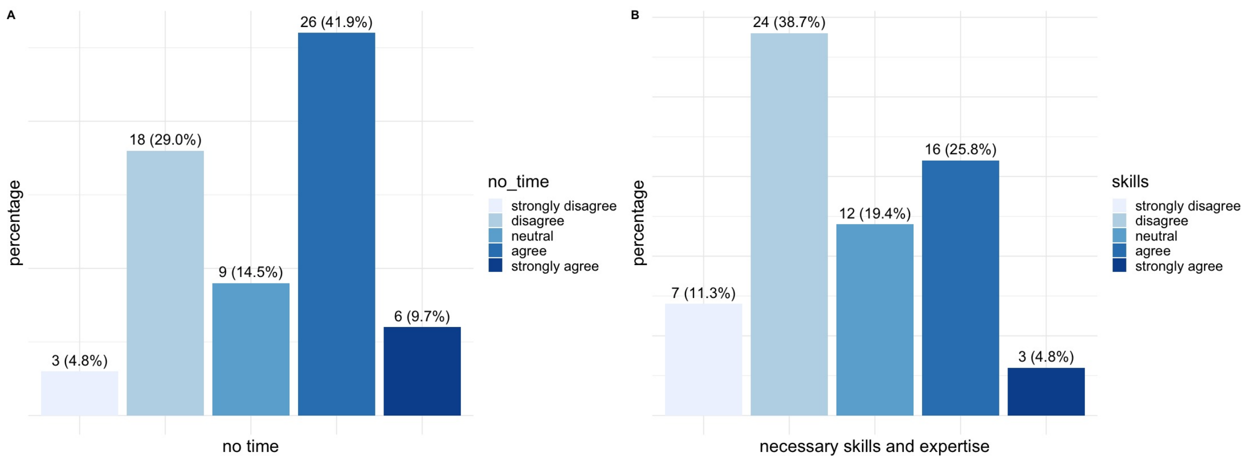
Self-trackers agreed to strongly agreed with ∼74.20 % that self-tracking data should be kept private, and disagreed to strongly disagreed with ∼69.36 % that privacy concerns are overrated. 40.32 percent were undecided and ∼37.10 % disagreed to strongly disagreed that it was their responsibility to ensure the security of their data. When asked if they feel self-tracking corporations violate their privacy by gathering their personal information, ∼53.22 % disagreed to strongly disagreed and ∼24.20 % remained undecided (**Figure 19** in Appendix B).

Trackers disagreed to strongly disagreed with ∼46.77 %, agreed to strongly agreed with ∼29.03 %, and were undecided with 24.19 % on whether their data was valuable enough to be used against them. They did, however, agreed to strongly agreed with ∼48.39 % that companies exploiting their information would have an influence on them, compared to ∼27.42 % who disagreed to highly disagreed and 24.19 % who were undecided (**Figure 20** in Appendix B).

∼51.62 % agreed to strongly agreed that they do not have the time to be concerned about their privacy (compared to ∼33.87 % disagreeing to strongly disagreeing and 14.52 % undecided). ∼50.00 % disagreed to strongly disagreed that they have the necessary technological skills and expertise to adequately preserve their data (compared to ∼30.65 % agreeing to strongly agreeing and 19.35 % undecided) (**Figure 7**).

Figure 7

Self-Trackers' Privacy Barriers



Note. Note. Figure A displays if self-trackers do not have time to be concerned about their privacy, Figure B depicts if they think they have the requisite technical skills and knowledge to adequately safeguard their data.

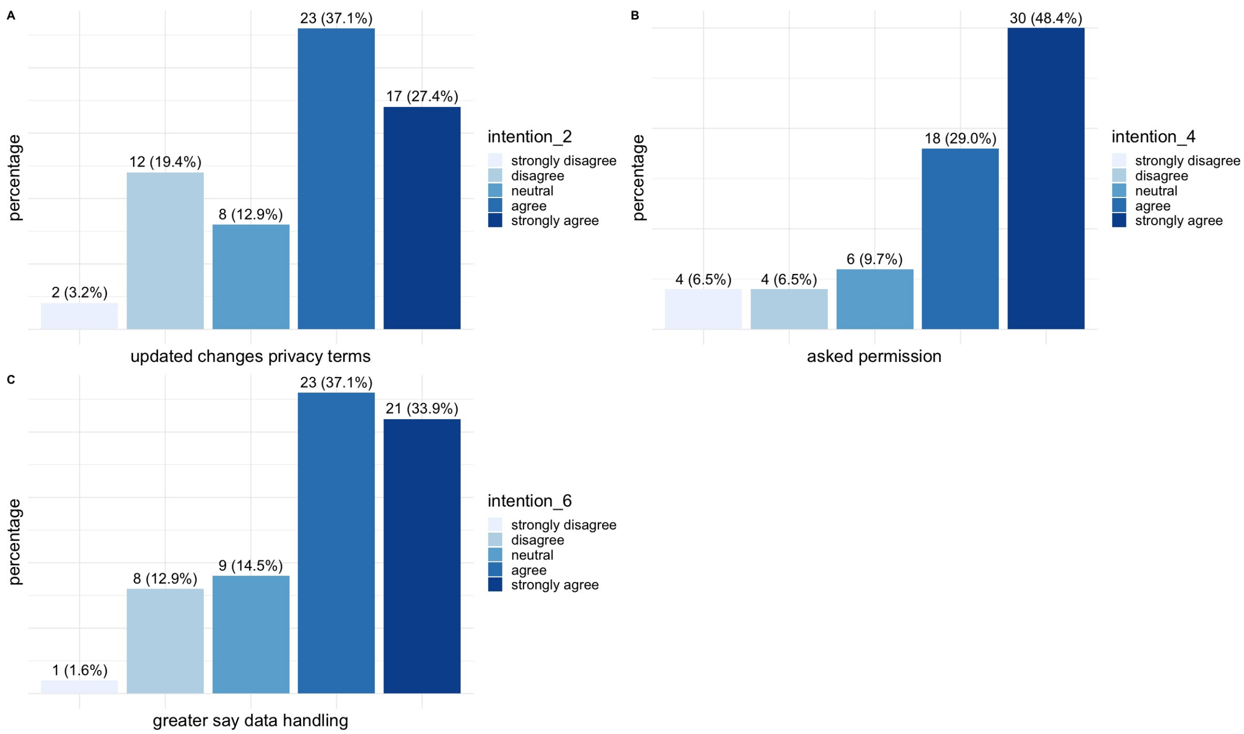
4.1.11. Privacy Preferences

Trackers reported an interest in learning more about privacy regulations, data processing and storage, and how to better protect their data. Responses were divided as to whether they would effectively spend time learning more about privacy policies. They stated that they would use other applications or self-tracking devices if they believed their privacy would be better secured, but were split on whether they would quit sharing if that would better protect their data (**Figure 21** in Appendix B).

∼77.97 % agreed to strongly agreed that if a self-tracking company wants to use their personal information for other purposes, they should be informed or asked permission. Similarly, ∼77.42 % agreed to strongly agreed that they want more say in how companies manage their personal data and that they should be notified of changes to their privacy terms and conditions (∼64.52 %, **Figure 8**). Users were split on whether they would pay an annual membership or delegate responsibility for protecting their privacy to a service (**Figure 22** in Appendix B).

Figure 8

Self-Trackers' Privacy Preferences



Note. Figure A depicts the responses to the question of whether they want to be updated on any changes to the privacy terms and conditions of their self-tracking tools, Figure B if they want to be notified or asked for permission every time a self-tracking company wants to use their personal information for other purposes, and Figure C if they want to have a greater say in how companies handle their personal information.

4.2. Confirmatory Factor Analysis

4.2.1. Model 1

CFA was undertaken to establish the optimal goodness-of-fit model. Model 1 (**Figure 9**) consisted of 14 factors: *healthism*, *entertainment*, *association*, *design*, *discipline*, *healing*, *surveillance*, *intrusion*, *secondary use*, *confidence*, *attitudes*, *value*, *physical vanity*, *achievement vanity*. The dimensions of the Big 5 could not be taken into consideration right from the start as it is recommended to have at least three items per factor (**Table 18** and **Table 19** in Appendix C).

Model 1 did not show an acceptable fit to the data (CFI=.850, RMSEA=.081, SRMR=.061, AIC=20394.307, BIC=20294.271). The CFI value was unacceptable since it was below the threshold of .90 (Hu & Bentler, 1999). The RMSEA value was unacceptable since it exceeded the threshold of .05. The SRMR value was acceptable as it was below the required level of .07 (Hu & Bentler, 1999; Pavlov et al., 2021) (**Table 9**).

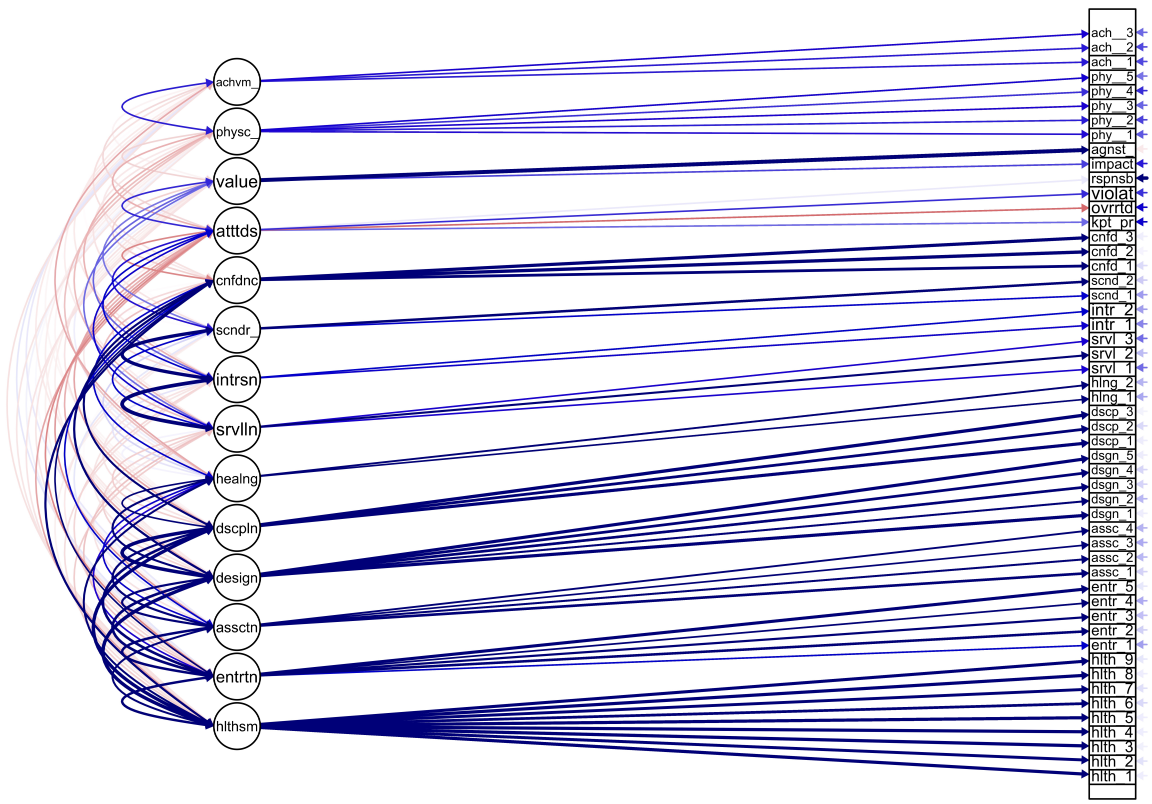
Table 9

Fit Indices Model 1

Model	Df	p	CFI	RMSEA	SRMR	AIC	BIC
Model 1	1658	.001	.850	.081	.061	20394.307	20294.271

Figure 9

CFA Model 1



Note. Model 1's structure graph, with higher factor loading presented in darker blue. Similarly, the stronger the covariances between the latent variables, the darker blue the arrows connecting them.

4.2.2. Model 2

The fit of Model 1 could be improved by deleting the variables *Attitudes 1*, *Attitudes 2*, *Attitudes 4*, *Value 1*, *Physical concern 4*. The criteria for removal were that acceptable factor loadings for each item should be >.60 and an R2 of >.40 (Othman et al., 2014). Model 2 (**Figure 10**) showed an improved fit (CFI=.933, RMSEA=.072, SRMR=.040, AIC=13765.588, BIC=13705.342). The CFI value was acceptable since it surpassed the .90 cutoff. The RMSEA value, however, was still unsatisfactory because it was more than the .05 threshold (**Table 10**).

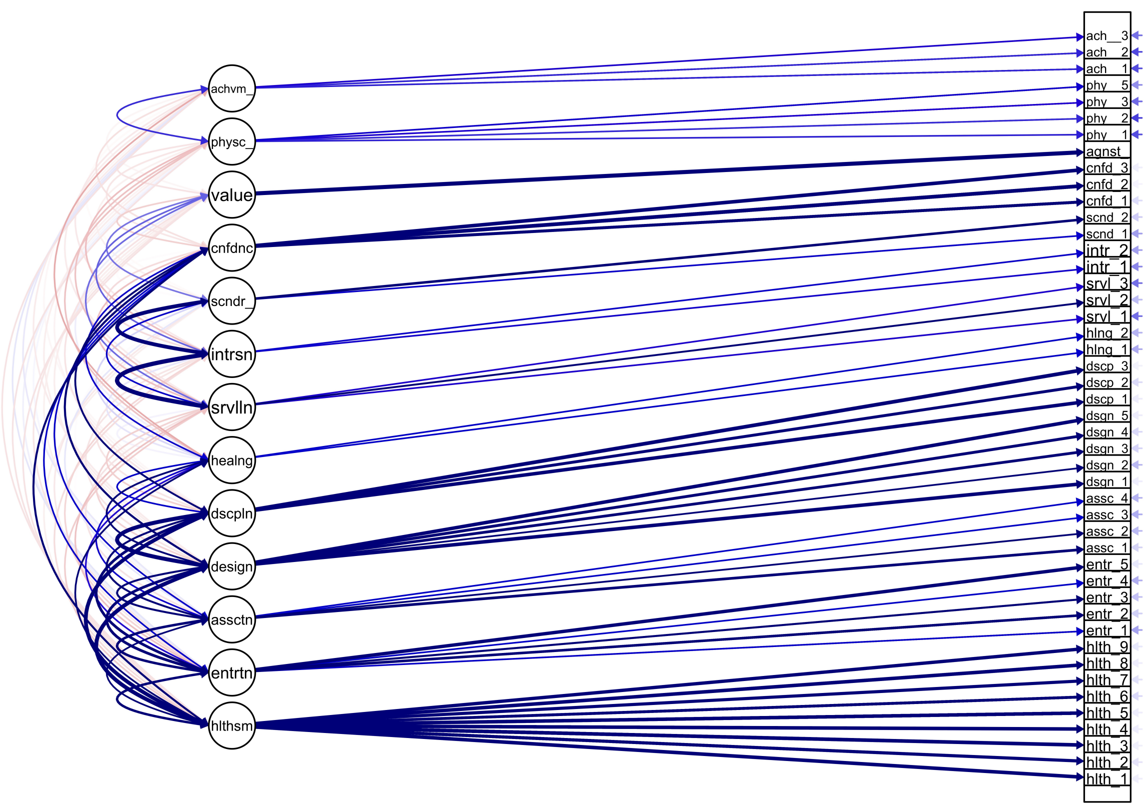
Table 10

Fit Indices Model 2

Model	Df	p	CFI	RMSEA	SRMR	AIC	BIC
Model 1	1658	.001	.850	.081	.061	20394.307	20294.271
Model 2	933	.001	.933	.073	.040	13765.588	13705.342

Figure 10

CFA Model 2



Note. Model 2's structure graph, with higher factor loading presented in darker blue. Similarly, the stronger the covariances between the latent variables, the darker blue the arrows connecting them.

4.2.3. Model 3

The best model overall was one that included only the six factors: *healthism*, *entertainment*, *association*, *discipline*, *design*, and *healing* (CFI=.969, RMSEA=.050, SRMR=.022, AIC=7394.339, BIC=7366.597). Model 3 (**Figure 11**) had lower AIC and BIC values compared to Models 2 and 1, indicating that it is the best in terms of goodness of fit (**Table 11**). The inclusion of the remaining latent variables had no improving effect on the indices. All of the factors loadings were greater than .85 (**Table 20** in Appendix C).

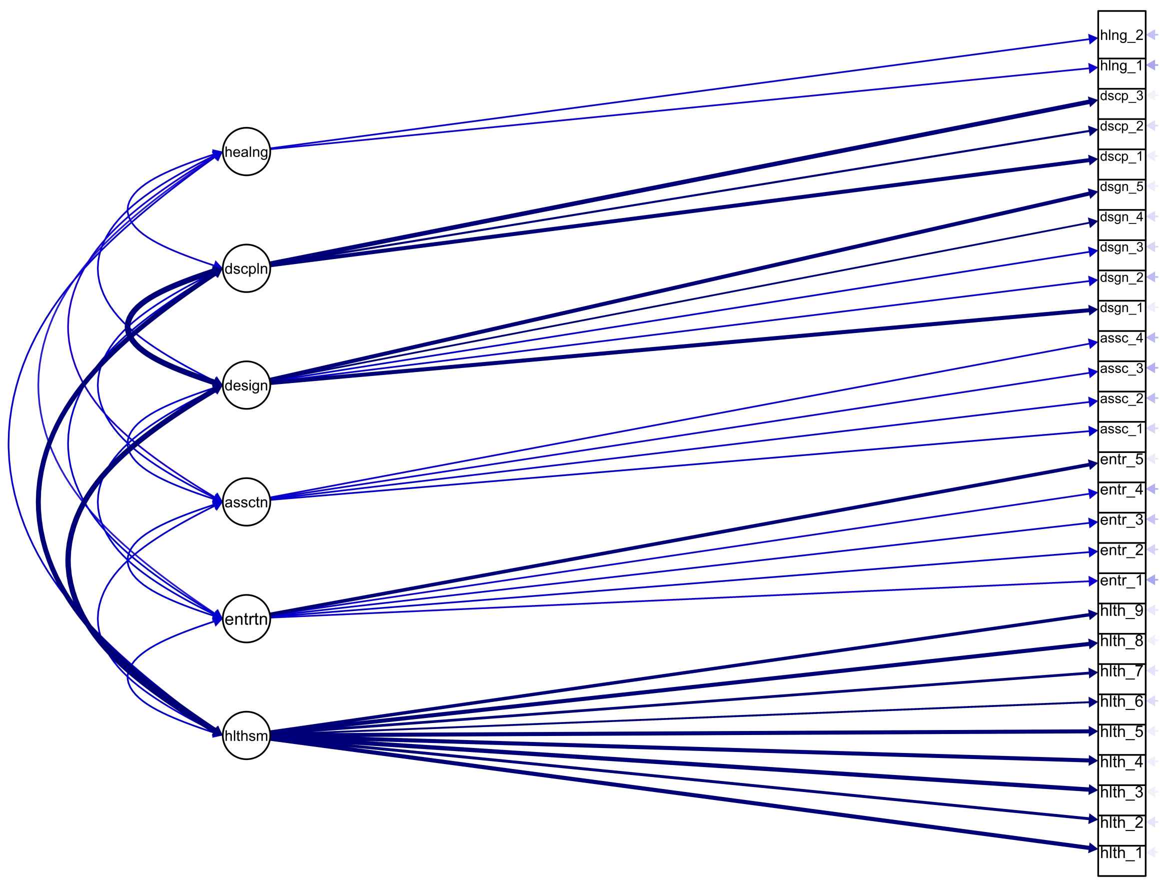
Table 11

Fit Indices Model 3

Model	Df	p	CFI	RMSEA	SRMR	AIC	BIC
Model 1	1658	.001	.850	.081	.061	20394.307	20294.271
Model 2	912	.001	.928	.064	.040	13765.588	13705.342
Model 3	335	.001	.969	.050	.022	7394.339	7366.594

Figure 11

CFA Model 3



Note. Model 3's structure graph, with higher factor loading presented in darker blue. Similarly, the stronger the covariances between the latent variables, the darker blue the arrows connecting them.

4.3. Reliability Analysis

Reliability analysis was conducted to assess the quality of the questionnaire items. The value of r.drop represents the total correlation of the scale in the absence of a given item. If the value is low (.30), this item does not correspond to the overall scale. All of the r.drop values were good (**Table 12**). Next, the Cronbach's alpha value for the 28-item questionnaire was determined. Results showed a high-reliability value of α = .99, indicating that the scale has strong internal consistency (**Table 21** in Appendix C).

Table 12

Item Total Correlations

Item	r.drop
Healthism_1	0.97
Healthism_2	0.95
Healthism_3	0.96
Healthism_4	0.96
Healthism_5	0.96
Healthism_6	0.94
Healthism_7	0.95
Healthism_8	0.97
Healthism_9	0.95
Entertainment_1	0.84
Entertainment_2	0.88
Entertainment_3	0.86
Entertainment_4	0.86
Entertainment_5	0.92
Association_1	0.88
Association_2	0.81
Association_3	0.82
Association_4	0.84
Design_1	0.97
Design_2	0.89
Design_3	0.94
Design_4	0.94
Design_5	0.97
Discipline_1	0.96
Discipline_2	0.94
Discipline_3	0.97
Healing_1	0.75
Healing_2	0.80

4.4. Regression Analysis

Regression analysis was performed with the factors *healthism*, *self-entertainment*, *self-association*, *self-design*, *self-discipline* and *self-healing* regressed upon *tracking*. There was no significant effect of healthism (β=.308, p=.441, 95 % CI [-.476, 1.091], Std.All=.617) on tracking. Similarly, there was no significant effect of entertainment (β=-.284, p=.874, 95 % CI [-3.806, 3.238], Std.All=-.570), association (β=.178, p=.850, 95 % CI [-1.675, 2.031], Std.All=.358), design (β=1.442, p=.737, 95 % CI [-6.970, 9.855], Std.All=2.890), discipline (β=-.889, p=.704, 95 % CI [-5.476, 3.699], Std.All=-1.781) and healing (β=-.298, p=.826, 95 % CI [-2.961, 2.365], Std.All=-.597).

Table 13

Covariance Matrix

	Healthism	Entertainment	Association	Design	Discipline	Healing
Healthism	1					
Entertainment	0.927	1				
Association	0.895	0.930	1			
Design	0.992	0.940	0.908	1		
Discipline	0.987	0.940	0.907	0.996	1	
Healing	0.898	0.736	0.823	0.901	0.873	1

The non-significant results may be explained by the absence of discriminant validity in this model. Indeed, the covariances were quite high, making distinguishing the unique contribution of the variables to a factor difficult and suggesting multi-collinearity (**Table 13**). The six variables might be components of a single latent variable that explains self-tracking behaviour. The next step was to establish a CFA model in which all variables were allocated to a single factor, *g*.

4.4.1. Model 4: Single-Factor Model

A single-factor CFA model is the most fundamental model since it implies that the covariance across items could be explained by a single common factor. Model 4 (**Figure 12**) was created to test if a single-factor model could explain the covariance structure by grouping *healthism*, *self-entertainment*, *self-association*, *self-design*, *self-discipline* and *self-healing* under one latent variable g (**Table 21** in Appendix C). The model's fit indices were CFI=.920, RMSEA=.113, SRMR=.035, AIC=7772.508, and BIC=7748.970 (**Table 14**). The factor loadings were all $\geq$.80 (**Table 22** in Appendix C).

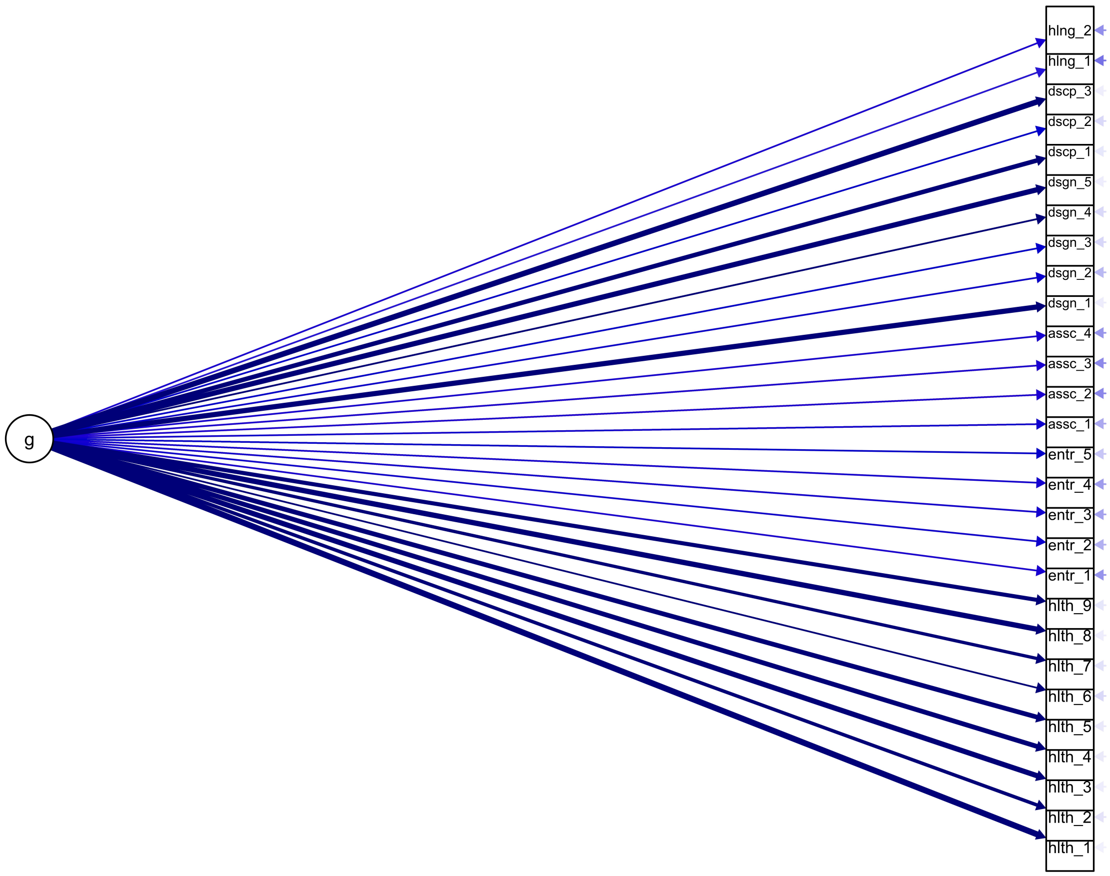
Table 14

Fit Indices Model 4

Model	Df	p	CFI	RMSEA	SRMR	AIC	BIC
Model 1	1658	.001	.850	.081	.061	20394.307	20294.271
Model 2	912	.001	.928	.064	.040	13765.588	13705.342
Model 3	335	.001	.969	.050	.022	7394.339	7366.594
Model 4	350	.001	.920	.113	.035	7772.508	7748.970

Figure 12

CFA Model 4



Note. Model 4's structure graph, with higher factor loading presented in darker blue.

4.4.2. Single-Factor Regression

Single-factor regression analysis was performed with the factor *g* regressed upon *tracking*. The effect of the common factor *g* on *tracking* was significant (β=.492, *p*=.001*** , 95 % CI [.487, .497], Std.All=.985). These findings point in one of two directions: either tracking is the predictor, or there might be a third variable. In line with the second possibility, we did another regression with the factors *g* and the demographic variables *gender*, *age*, *education*, *marital status*, and *income* regressed onto *tracking*.

Education and g both had a significant effect on self-tracking. However, gender, age, marital status, and income had no influence on whether or not respondents self-tracked (**Table 15**).

Table 15

Regression Analysis

	Estimate	P(>|z|)	ci.lower	ci.upper	Std.all
Tracking $\sim$					
g	0.489	0.001***	0.482	0.496	0.985
Gender	-0.007	0.581	-0.034	0.019	-0.008
Age	-0.008	0.316	-0.023	0.007	-0.021
Education	0.024	0.018*	0.004	0.043	0.056
Marital status	0.009	0.206	-0.005	0.023	0.026
Income	-0.007	0.118	-0.017	0.002	-0.032

Note. $*p$<.05; $**p$<.01; $***p$<.001;

Chapter 5: Discussion

5.1. Descriptive Analysis

We aimed to acquire a comprehensive image of the self-tracker by examining both the general profile and the subject of privacy. We had questions about their demographics, what they tracked, how long and intensely they tracked, and why they tracked themselves. We also asked them about their privacy concerns, preferences, attitudes, and values.

Self-trackers were primarily driven by a desire to enhance their body, physique, and well-being. These findings are consistent with the literature, which indicates a strong connection between self-tracking and self-optimisation (En & Pöll, 2016; Kristensen et al., 2015; Whooley et al., 2014). As Sharon (2016) indicated, people are becoming their own health entrepreneurs, proactively involved in and dedicated to the care of their own bodies. In contrast to what the study by Sharon and Zandbergen (2016) suggested, trackers did not show much indication of self-experience and expression.

The majority of trackers did not share their data with others, and even if they did, they were careful not to expose any sensitive information. This contradicts previous research that found a strong social component to self-tracking (Gimpel et al., 2013; Lee, 2014), and highlights the importance of data sensitivity. Trackers were more likely to reveal information about their progress, exercises, and activities, but less likely to reveal information about their mood or body weight. However, attitudes about sharing health information were divided. This is an intriguing finding since it corresponds to the observation that health information is rapidly becoming a collective benefit in an open, connected knowledge economy (Angst, 2009; Henkel et al., 2018; Toesland, 2021).

Regarding privacy concerns, the results for the perceived surveillance and intrusion dimensions were mixed. This is consistent with prior research by Gorm and Shklovski (2016) and Pinchot and Cellante (2021), which found that trackers are neutral to indifferent to their data. However, there was more consensus on the secondary use dimension, which encompasses the exploitation and sharing of self-tracking data with third parties without permission. This might be explained by the fact that, as Solove (2006) points out, secondary usage creates a sense of helplessness and vulnerability among users due to consumers' lack of awareness about data handling and management. Indeed, our findings demonstrated that trackers had no clue how long their data was stored, who had access to it, or if it was shared without their knowledge. In line with this, ∼50.00 % disagreed to strongly disagreed that they have the technological skills and expertise to adequately preserve their data.

Trackers expressed a want to learn more about privacy regulations, data processing and storage, and how to better safeguard their data. In addition, trackers agreed with ∼64.52 % that they wanted to be notified of changes to their tools' privacy terms and conditions, and ∼77.97 % agreed that they want more say in how corporations manage their personal data. These findings suggest that trackers associate privacy with having control over one's personal information. This is not surprising given that data ownership has long been the central component of information privacy (Mason, 1986; Westin, 1968).

Trackers, on the other hand, expressed reservations about entrusting their data privacy to a (paid) service. Similarly, they expressed reservations about spending actual time learning about privacy regulations and other privacy issues. These findings suggest that people are not interested in handing over control or devoting effort to data privacy. The latter finding suggests evidence for the privacy paradox. Users do track with the desire to be in control of their data, yet their behaviour and lack of understanding make them susceptible to data ownership loss.

5.2. Confirmatory Factor Analysis

CFA was used to evaluate the instrument's validity. The model with the best fit comprised 28 items classified into six categories: *health*, *entertainment*, *association*, *discipline*, *design*, and *healing*. This model, however, displayed strong covariance patterns among the factors, indicating that the instrument has low discriminant validity and so is unable to reflect the different constructs. According to the data, the covariances across items might be explained by a single underlying construct.

This is supported by the regression analysis, which showed that the model with the six factors regressed upon tracking does not provide significant results, but does so when grouped under one latent variable g.

The instrument lacks the validity to accurately measure what it is designed to measure and perform as intended. This is, however, a viable route to pursue further. One conclusion is that privacy concerns, attitudes, and values do not appear to play a role in understanding monitoring behaviour. One explanation for this finding is the cognitive dissonance avoidance theory. Festinger (1962) stated that if a person's views, attitudes, or behaviours conflict, the individual would alter them to alleviate mental distress and restore equilibrium. One strategy to overcome dissonance is to minimise the significance of current beliefs, thus reducing the impact of the conflicting cognition. A smoker may convince themselves that it is preferable to have a short life while smoking rather than a miserable long life without enjoyment. While this is an oversimplified example, it may explain why the data revealed low to mixed privacy concerns and attitudes among self-trackers, and why these factors were not essential in the model, since trackers may have minimised the relevance of their privacy concerns.

Another potential conclusion to draw is that, because the instrument only measures one latent variable, the true predictor might be tracking itself. Rather than focusing on the characteristics of self-trackers to better understand the habit, the findings suggest that tracking behaviour itself may modify and affect one's goals, beliefs, and behaviour. This might be a topic for discussion and research in the future, such as through an experimental or longitudinal study design.

5.3. Strengths and Limitations

Self-tracking has become widespread, and it is critical that research improves its understanding of self-tracking usage by assessing it holistically. One of the current study's strengths is that it applies a comprehensive approach to self-tracking behaviour by assessing a variety of factors. To the best of our knowledge, this is the first study to look at self-tracking from such a wide viewpoint. We gained some valuable results regarding individuals' motivations, obstacles in preserving their data, preferences toward (better) data protection, willingness to share data, and knowledge of data processing as well as trackers' concerns about data privacy.

Another point of strength is the contribution to the field as a whole by developing an initial instrument. Like the previous point, this is necessary for a better understanding of self-tracking. Though the instrument's validity is not where it should be, it has provided several points worth studying further.

The final study's strength is that it is the first to analyse the influence of healthism on self-tracking. We not only created items to assess healthism, but we also determined that the effect of healthism appears to be worth further examination since it is related to motivations such as entertainment, association, design, discipline, and healing. Moreover, we showed that these motivations and healthism may be grouped under a common variable, which could be an interesting foundation for future research.

The first limitation include selection bias, since we aimed to include as much factors as possible while still include the components that we considered relevant for the overall TESTER project. Of course, this is a biased and it would have been interesting to investigate how other criteria, such as perfectionism, influence self-tracking behaviour. Prioritisation is required, however, especially if one of the purposes of the questionnaire was to provide a broad overview of self-tracking behaviours in only a few minutes.

Another limitation, relating to the preceding point, is that we have disclosed the subject of self-tracking to the participants, resulting in potential priming effects, social and cognitive dissonance biases. In this sense, it would have been better to address privacy in a different context other than self-tracking. We could, for example, have posed privacy-related questions about shopping or GPS navigation systems in automobiles, both of which are connected to monitoring but not expressly to themselves. This might be an important point in terms of cognitive dissonance and priming effects.

Final limitation are minor flaws such as not being able to include the personality characteristics in the model since we had not anticipated more items were required for the confirmatory factor analysis.

5.4. Implications and Future Research Directions

First, further study is needed to analyse the impact of self-tracking behaviour on users' attitudes, motives, and privacy concerns. To assess the influence of self-tracking over a longer length of time, an experimental design or a longitudinal research could be appropriate. In the same vein, and assuming that there is a common factor that encompasses healthism, self-entertainment, self-association, self-design, self-discipline, and self-healing, it is worthwhile to investigate further and theorise on what this factor might be.

Further, given the high reliability of our newly devised healthism items, it would be interesting to do additional research to validate the items and investigate the relationship between healthism and self-tracking. The latter would be valuable because both notions have previously been discussed in the literature, with no in-depth examination.

Finally, self-trackers regard data ownership as an essential aspect of information privacy. Therefore, it is critical for the development of the privacy assistant to strike the proper balance between advising users to better safeguard their data and maintaining their sense of control over their data. This may be accomplished explicitly by allowing users to define their preferences and settings, such as receiving notifications when their companies wish to utilise their data for other purposes. This can also be provided implicitly, for example, by including a learning section in the application where trackers can get explanations on various privacy issues in a concise and entertaining manner. Learning about data management and processing can make users feel more self-efficient, giving them the feeling they are capable and in control of their data.

Chapter 6: Conclusion

The current study is the first step toward a more thorough understanding of self-tracking by examining several aspects such as self-trackers' characteristics, motivations, privacy, personality traits, and demographics. The findings resulted in four key takeaways.

First, the results indicated a strong association between healthism and the five motivations identified by Gimpel et al. (2013), implying that healthism may play a role in the understanding of self-tracking. Furthermore, it is possible that all of these factors are related to a common factor, which is a worthwhile avenue to explore further.

Second, having physical and data control is vital to the self-tracker. Self-trackers voluntarily track themselves to get control over their own bodies and health. Similarly, trackers demand control over their data, which is reflected in their privacy concerns as well as their privacy protection preferences.

Third, and linked to the second point, while trackers are their own health entrepreneurs, the results showed that they struggle to be their own data entrepreneurs. On the one hand, trackers want ownership of their data to achieve (better) data protection. As on the other hand, trackers expect control without necessarily wanting to exercise it or understand the complexities required for effective data management; they simply want it. Because of the gap between their desire for control and actual behaviour, self-trackers are prone to losing control of their data. It shows that the control-centered approach to privacy is still the norm, yet demanding control without executing it is unsustainable.

Fourth, while the results indicated promising future directions, the instrument lacks the requisite validity. As a result, data should be taken with caution, and further study is required to improve the instrument.

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Appendix

Appendix A

Part 1: Self-tracking Characteristics

1. Are you currently self-tracking? Please choose one of the following answers.

   O Yes [directed to further questions]

   O No [directed to questions for non-trackers]

2. What self-tracking tools do you use? Please check all of the boxes that apply. [*Options are randomised*]

   O Wearable devices (e.g., activity or chest trackers, smartwatch)

   O Medical devices (e.g., heart rate monitors, blood oxygen level monitors or blood pressure monitors)

   O Smartphone

   O Mobile applications

3. Why are you self-tracking? Please check all of the boxes that apply. [*Options are randomised*]

   O Recommendation friends or others

   O Data collection

   O Self-awareness

   O Habit change

   O Extra motivation

   O Recommendation doctor

   O Sharing and comparing data with others

   O Self-development

   O Self-confirmation

   O Career

4. How long how you been self-tracking? Please choose one of the following answers.

   O Under 1 month

   O 1-3 months

   O Under 6 months

   O 6 months to a year

   O 1 year

   O 1-2 year

   O 2-5 year

   O Over 5 year

5. How often have you been self-tracking? Please choose one of the following answers.

   O Sporadically

   O Daily

   O Weekly

   O Monthly

   O Yearly

6. How often do you self-track?

   O Sporadically

   O Daily

   O Weekly

   O Yearly

7. Are you using your fitness tracker to help improve a health or medical problem you are facing? Please choose one of the following answers.

   O Yes

   O No

   O No answer

8. Are you sharing your self-tracking data with others?

O Yes [receives questions 9 and 10 as well]

O No [directed to question 11]

9. Who are you sharing your self-tracking results with? Please check all of the boxes that apply. [*Options are randomised*]

   O Health professional

   O Other self-tracker devices or tracking apps

   O Sharing platforms (e.g., blogs, YouTube, Instagram, Twitter, Facebook, TikTok)

   O (Online) community (e.g., a running or meditation community)

   O Work

   O Friends

   O Clubs (e.g., sport clubs)

   O Tracking device manufacturer

   O Health insurance

10. Please read the following statements and indicate your level of agreement. [*Options are randomised, rated on 5-point Likert scale*]

    "I am willing to share my self-tracking information about..."

    • Progress (e.g., amount of steps, weight lifting)

    • Body weight

    • Nutrition

    • Exercise/workouts

    • Mood

    • Health information (e.g., heart rate, blood pressure, etc.)

11. Please read the following statements and indicate your level of agreement. [*Options are randomised, rated on 5-point Likert scale*]

    • I would encourage others to use self-tracking.

- I try to keep a healthy work life balance.
- I feel responsible for my own health.
- Self-tracking allows me to take control of my own health.
- I consider myself very health-conscious.
- I find the practice of self-tracking valuable.
- Self-tracking enhance my health.
- Self-tracking helps me to live a healthy lifestyle.
- Self-tracking has health-promoting effects.

12. Why are you not presently self-tracking? Please check all of the boxes that apply. [*Options are randomised*]

    O I am not interested in self-tracking

    O Self-tracking make me anxious

    O When a goal is not met, self-tracking makes me feel guilty

    O I get a sense of pressure from self-tracking

    O Self-tracking bores me

    O Self-tracking is not valuable to me

    O I am not motivated to do it

    O I am concerned about my privacy

    O Self-tracking makes me feel obsessed

    O I do not have the time

    O I am having trouble using its gadgets and applications

    O Self-tracking frustrates me

    O It is too much effort

13. Have you tried self-tracking before?

    O Yes [directed question 14]

    O No [directed question 15]

O Multiple times [directed question 14]

14. Please read the following statements and indicate your level of agreement. [*Rated on 5-point Likert scale*]
    - I had a positive experience with self-tracking.
    - I would consider resuming a tracking habit in the future.

15. Please read the following statements and indicate your level of agreement. [*Rated on 5-point Likert scale*]
    - I would consider starting a self-tracking habit in the future.

Part 2: Motivations

16. Please read the following statements and indicate your level of agreement. [*Options are randomised, rated on 5-point Likert scale*]

    "I am self-tracking because..."

    - I want to present myself to others.
    - it motives me to keep on working for a goal.
    - I want to compare my results to others.
    - I want to help/inspire others.
    - I try to manipulate certain aspects in my life.
    - it helps me to optimise the way I'm living.
    - I am interested in how certain things in (my) life interact.
    - I want to be independent from traditional medical treatments.
    - I enjoy forgetting about time while doing so.
    - I like playing around with my smartphone/technical device etc.
    - I enjoy getting lost totally in self-tracking activities.
    - it is fun and entertaining.

- I enjoy being my own master.
- I don’t trust the healthcare system/classic therapies.
- I like playing around with numbers/statistics etc.
- it allows me to reward myself.
- it facilitates my self-discipline.
- I want to control what I’m doing with my life.
- the way I’m doing it is interesting for others/might help.

Part 3: Privacy

17. Please read the following statements and indicate your level of agreement. [*Options are randomised, rated on 5-point Likert scale*]

    “I am concerned...”

    - about the use of self-tracking services making my personal information more easily accessible to others.
    - about self-tracking applications monitoring my activity.
    - about my self-tracking device recording my location.
    - about self-tracking services sharing my personal information with third parties without my consent.
    - about people knowing more about me than I am comfortable with because of the use of self-tracking devices and services.
    - about self-tracking technologies using my personal information for other purposes.
    - about my self-tracking device or applications gathering personal information about me.

18. Please read the following statements and indicate your level of agreement. [*Options are randomised, rated on 5-point Likert scale*]

    - I am confident that my tracking service provider (e.g., Fitbit, Apple, Garmin) will not misuse my data.

• I know if my self-tracking data has been shared without my permission.

• I am aware that tracking technologies and services are collecting and using my personal information for other purposes.

• I know who has access to my self-tracking data.

• I am confident that my tracking service provider (e.g., Fitbit, Apple, Garmin) will keep my data secure.

• I am confident that my tracking service provider (e.g., Fitbit, Apple, Garmin) will not disclose any of my personal information.

• I am aware of how long tracking companies store my self-tracking data.

19. Please read the following statements and indicate your level of agreement. [*Options are randomised, rated on 5-point Likert scale*]

• I consider it to be my responsibility to guarantee that my self-tracking data is secure.

• I value my privacy, but I don't have the time to be concerned about it.

• I believe my tracking data is valuable enough to be used against me.

• I believe privacy concerns are overrated.

• I believe that self-tracking data should be kept private.

• I believe that self-tracking companies violate my privacy by gathering personal information about me.

• I have the necessary digital skills and knowledge to effectively secure my data.

• I believe it would have an influence on me if tracking companies exploited my information.

20. Please indicate whether or not the following statements apply to you. [*Options are randomised, rated on 5-point Likert scale*]

"Would you..."

• stop sharing your information with online platforms and friends if it meant your privacy would be more protected?

• like to have a greater say in how companies handle your personal information?

• want to be notified or asked for permission every time a self-tracking company wants to use your personal information for other purposes?

• be willing to spend some time learning more about self-tracking privacy policies?

• like to be updated on any changes to the privacy terms and conditions of your self-tracking tools?

• be willing to delegate authority to a service that safeguards your privacy on your behalf?

• consider using other applications or self-tracking technologies if you believed your privacy would be better protected?

• like to learn more about how you may start securing your data more effectively?

• be willing to pay an annual membership to a service that handles your data for you while protecting your privacy?

• be interested in learning more about how your data is handled and stored?

• want to learn more about the privacy regulations of self-tracking technologies and companies?

Part 4: Personality Traits

21. Please read the following statements and indicate your level of agreement. [*Options are randomised, rated on 5-point Likert scale*]

    • I want others to look up to me because of my accomplishments.

    • Looking my best is worth the effort.

    • I feel comfortable in my own body.

    • I am open to new experiences and complex.

    • Achieving greater success than my peers is important to me.

    • I am disorganised and careless.

    • I am reserved and quiet.

- The way I look is extremely important to me.
- I would feel embarrassed if I was around people and did not look my best.
- I am critical and quarrelsome.
- I am conventional and creative.
- I am extroverted and enthusiastic.
- I am very concerned about my appearance.
- I am dependable and self-disciplined.
- It is important that I always look good.
- I am anxious and easily upset.
- I want my achievements to be recognised by others.
- I am calm and emotionally stable.
- I am sympathetic and warm.

Part 5: Demographics

22. What gender do you identify as? Please choose one of the following answers.

    O Male

    O Female

    O Other (please specify)

23. What is your current age? Please choose one of the following answers.

    O <20

    O 21-30

    O 31-40

    O 41-50

    O 51-60

    O >61

24. What is the highest level of education you have completed? Please choose one of the fol-

lowing answers.

O Primary school or equivalent

O Secondary school or equivalent

O Bachelor's degree or equivalent

O Masters degree or equivalent

O Ph.D. or higher

O Other (please specify)

25. What is your marital status? Please choose one of the following answers.

O Single

O In a relationship

O Engaged

O Married

O It's complicated

O Separated

O Divorced

O Widowed

26. What is your gross monthly income? Please choose one of the following answers.

O Less than €1000

O €1000-€2000

O €2000-€3000

O €3000-€4000

O €4000-€5000

O More than 5000

O No answer

Appendix B

Table 16

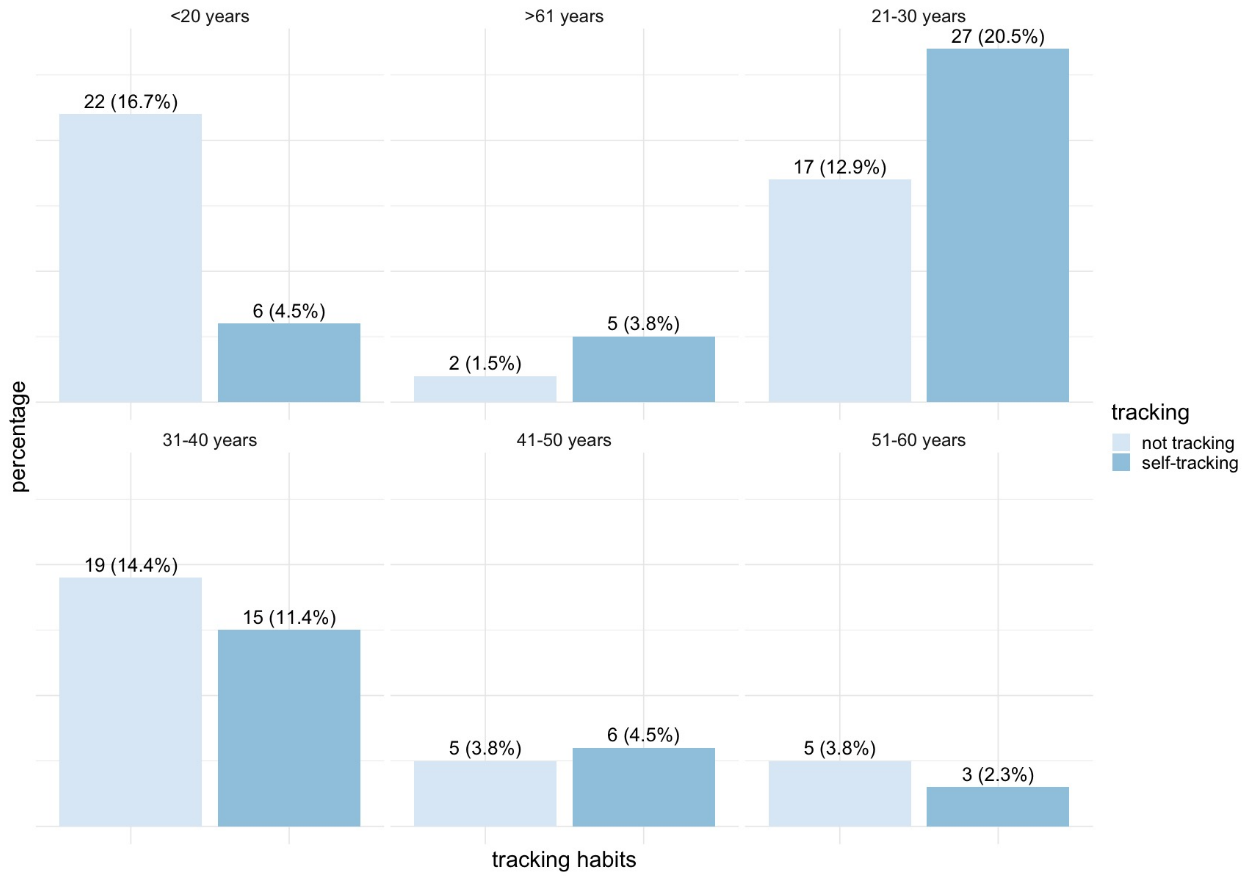
Demographic Characteristics

Gender	Female	69	52.27
	Male	60	45.46
	Other	3	2.27
Age	<20	28	21.21
	21-30	44	33.33
	31-40	34	25.76
	41-50	11	8.33
	51-60	8	6.06
	>61	7	5.30
Highest level of education	Primary school or equivalent	13	9.84
	Secondary school or equivalent	22	16.67
	Bachelor's degree or equivalent	17	12.88
	Master's degree or equivalent	66	50.00
	Ph.D. or higher	14	10.61
Marital status	Single	45	34.09
	In a relationship	35	26.52
	Engaged	3	2.27
	Married	40	30.30
	It is complicated	7	5.30
	Separated	0	0.00
	Divorced	2	1.52
	Widowed	0	0.00
Gross monthly income	No answer	28	21.21
	Less than €1000	20	15.15
	€1000-€2000	12	9.09
	€2000-€3000	20	15.15
	€3000-€4000	14	10.61
	€4000-€5000	19	14.39
	More than €5000	19	14.39

Note. A summary of the demographics.

Figure 13

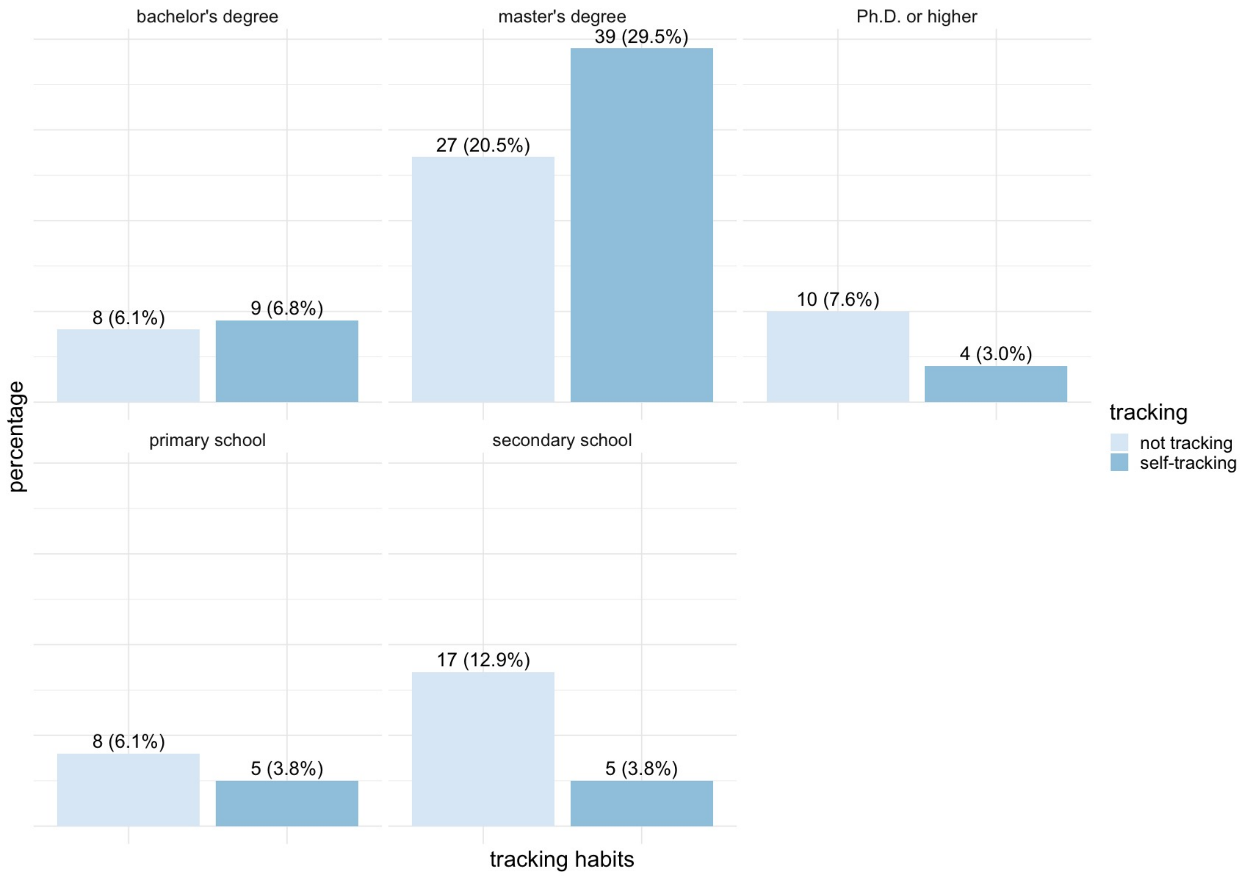
Age and Tracking Ratio



Note. Figure displaying the tracking ratio in relation to age.

Figure 14

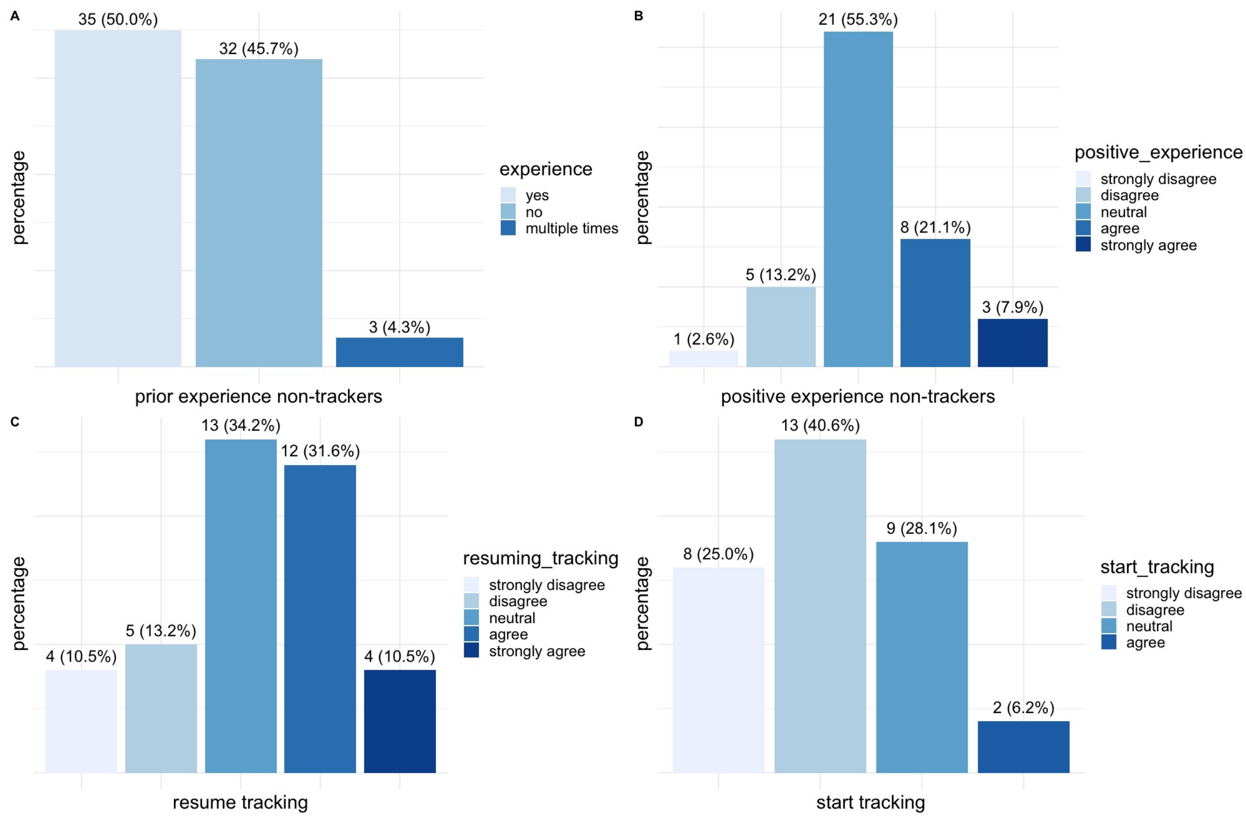
Education and Tracking Ratio



Note. Figure displaying the tracking ratio in relation to education.

Figure 15

Prior Experience Non-Trackers



Note. Figure A displays the rate of prior experience among non-trackers. Figure B shows how positive non-trackers regarded their prior self-tracking experience. Figure C indicates the rate at which non-trackers with prior experience consider restarting a monitoring habit in the future. Figure D depicts the rate at which non-trackers with no prior experience are considering starting a tracking habit in the future.

Table 17

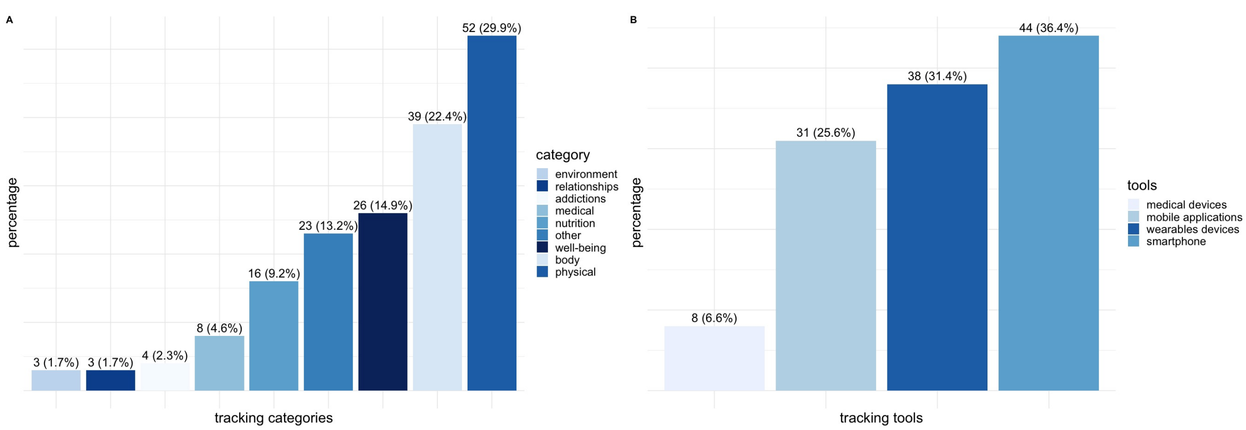
Reasons Not to Self-Track

	Count	%
I am not motivated to do it	37	17.45
I am not interested in self-tracking	29	13.68
I get a sense of pressure from self-tracking	22	10.38
I am concerned about my privacy	19	8.96
It is too much effort	17	8.02
Self-tracking is not valuable to me	17	8.02
I do not have the time	16	7.55
Self-tracking makes me feel obsessed	15	7.08
When a goal is not met, self-tracking makes me feel guilty	12	5.66
Self-tracking bores me	11	5.19
Self-tracking make me anxious	6	2.83
Self-tracking frustrates me	6	2.83
I am having trouble using its gadgets and applications	5	2.36

Note. A summary of the reasons given by non-trackers for not self-tracking.

Figure 16

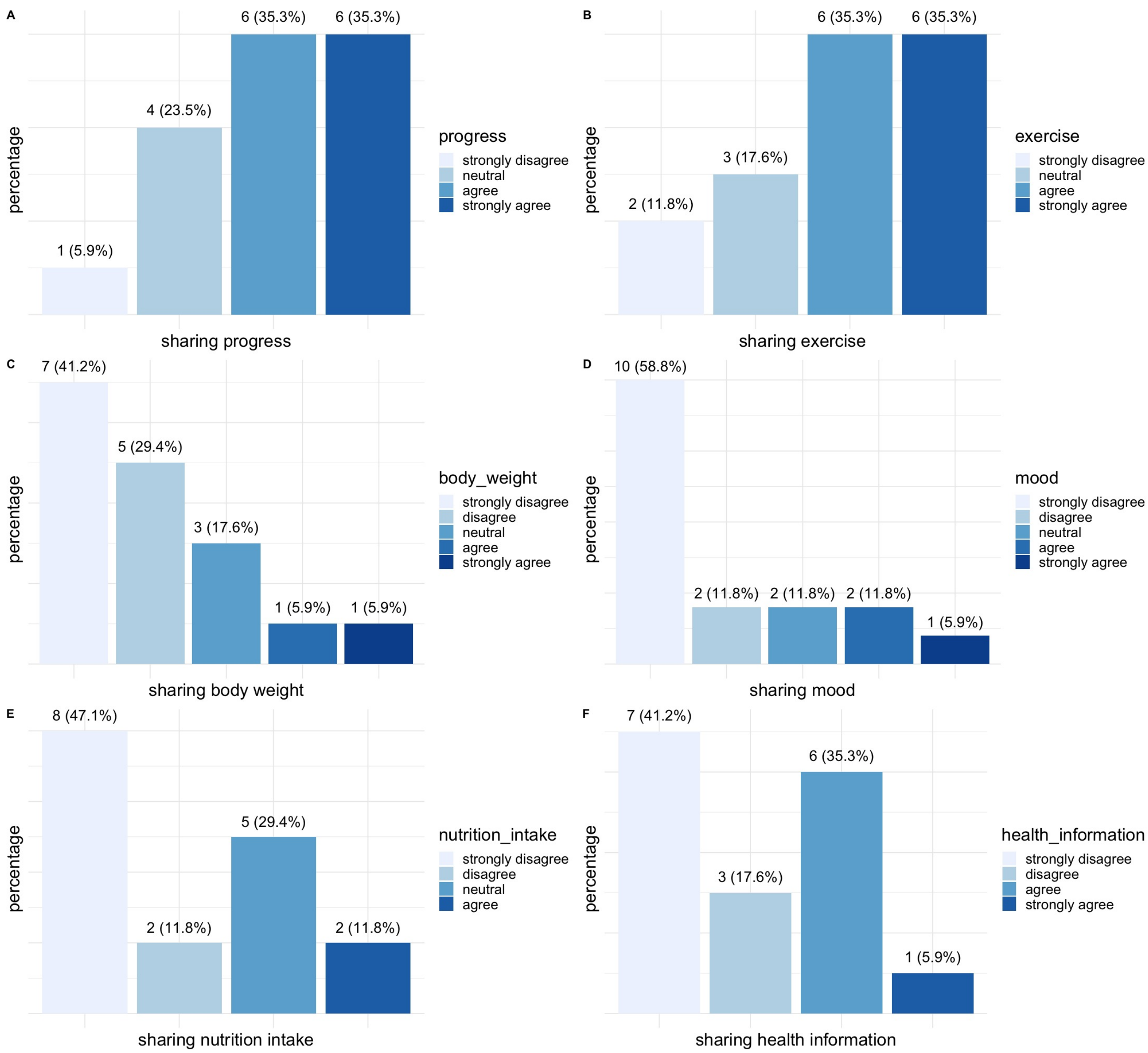
Tracking Categories and Tools



Note. Figure A displays the different tracking categories, Figure B the different tools trackers used to monitor themselves.

Figure 17

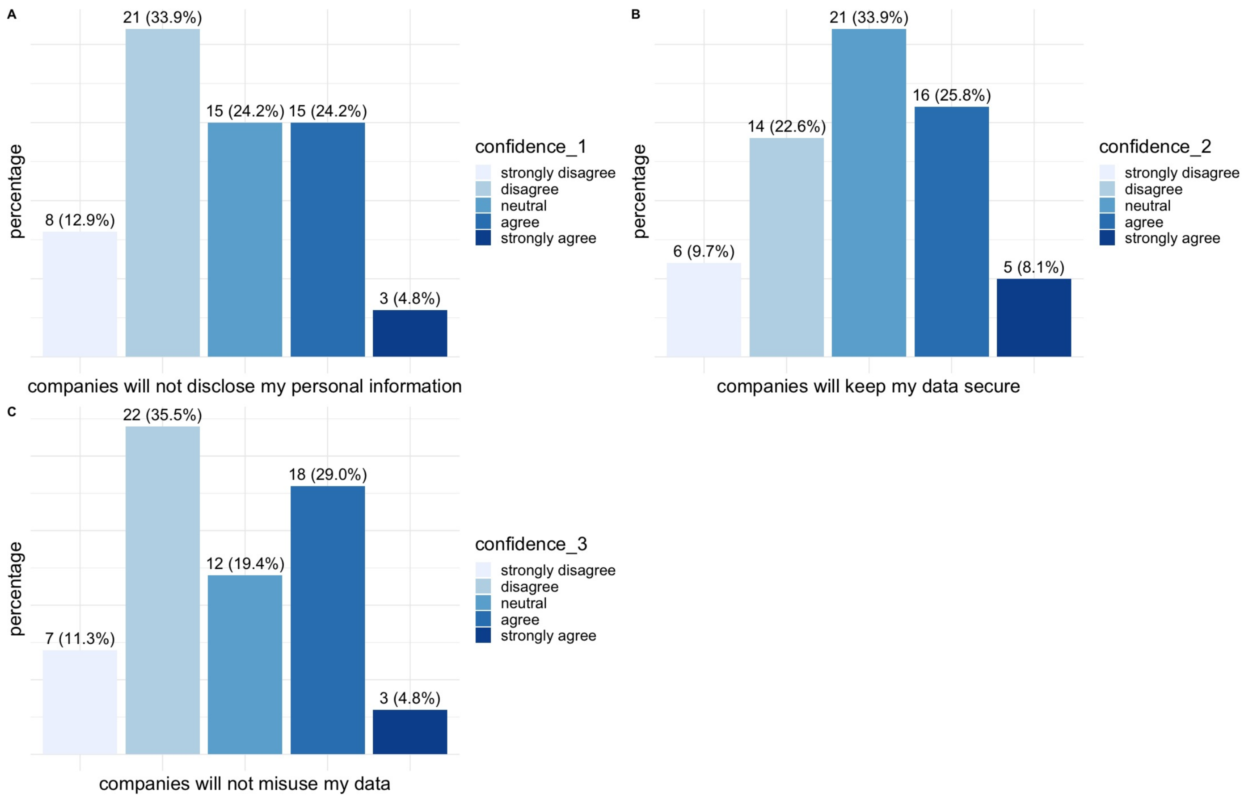
Sharing and Sensitivity Tracking Data



Note. These graphs depict respondents' willingness to share their self-tracking data with others. Figure A shows this for progress data, Figure B for exercise, Figure C for body weight, Figure D for mood, Figure E for nutrition consumption, and Figure F for health information.

Figure 18

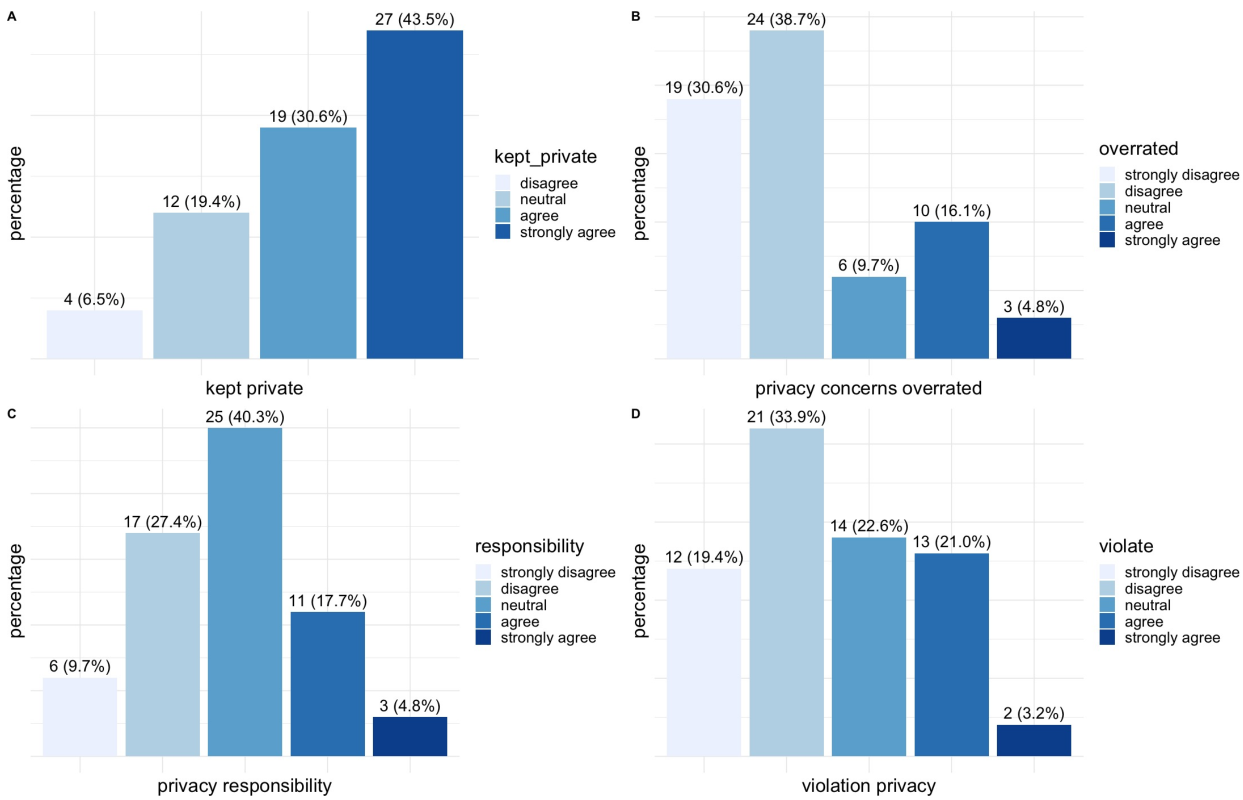
Confidence in Tracking Corporations and Services



Note. Figure A displays the responses of self-trackers to the question of how confident they are that their tracking service provider will not disclose any of their personal information. Figure B demonstrates self-tracking users' confidence in self-tracking services to keep their data safe. Figure C demonstrates self-trackers' confidence in their tracking service provider not misusing their data.

Figure 19

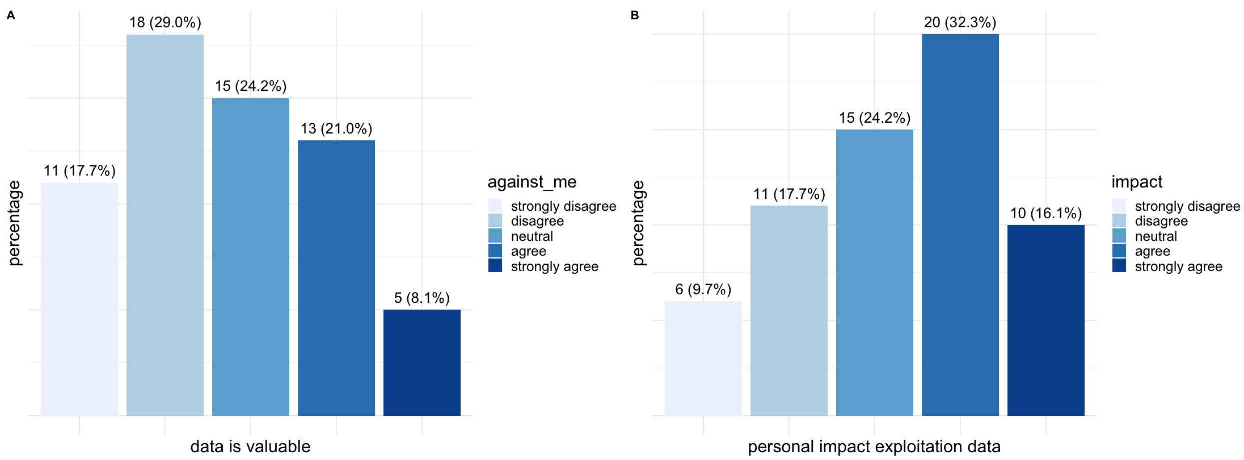
Self-Trackers' Privacy Attitudes



Note. Figure A shows the responses to the statement that self-tracking data should be kept private, Figure B whether privacy concerns are overrated, Figure C if they believe it is their responsibility to keep tracking data secure, and Figure D that they think tracking companies' collection of personal information is a violation of their privacy.

Figure 20

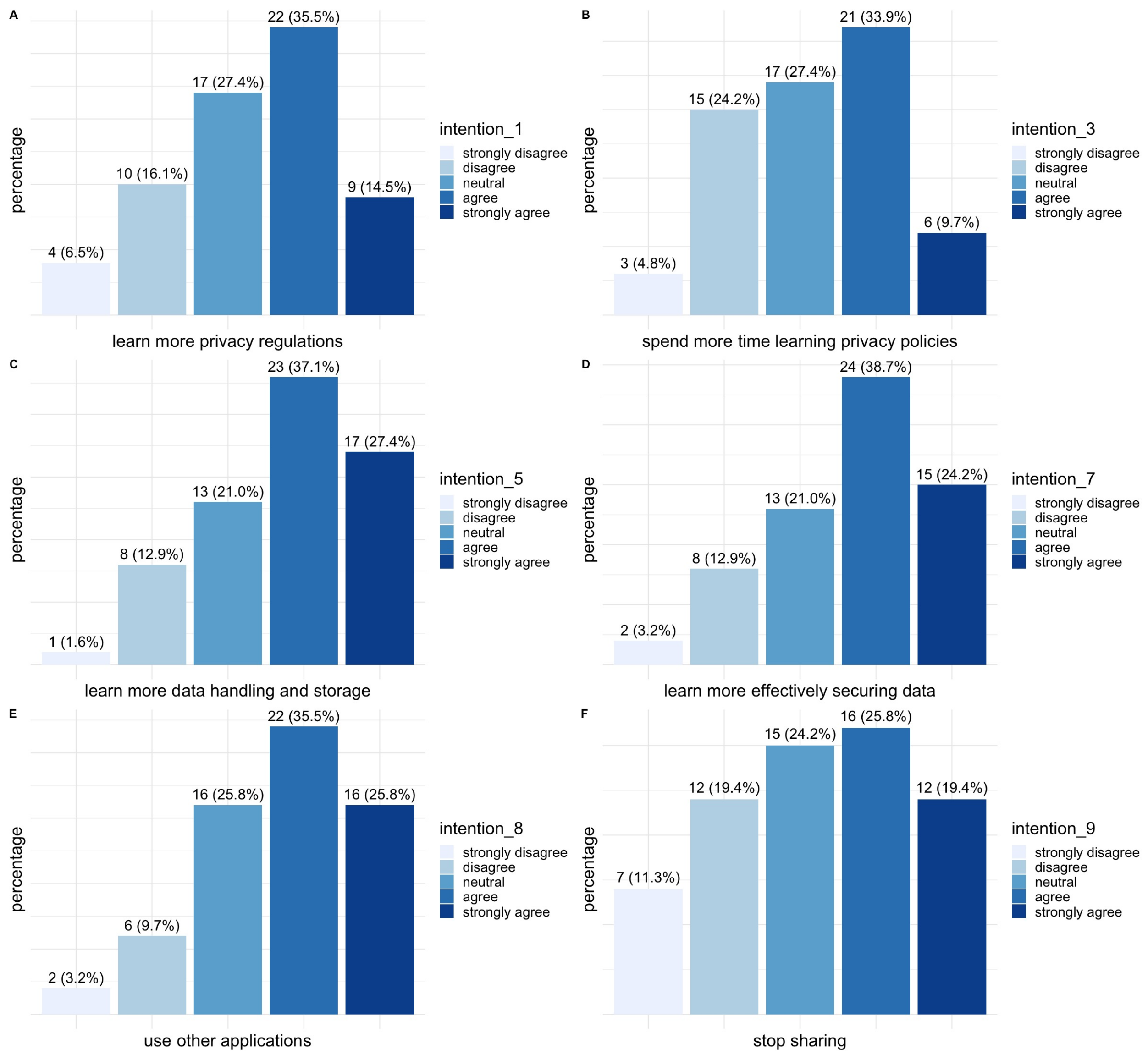
Self-Trackers' Privacy Value



Note. Figure A depicts the replies to the issue of whether self-trackers believe their data is valuable enough to be used against them, and Figure B if it would impact them if tracking companies used their information.

Figure 21

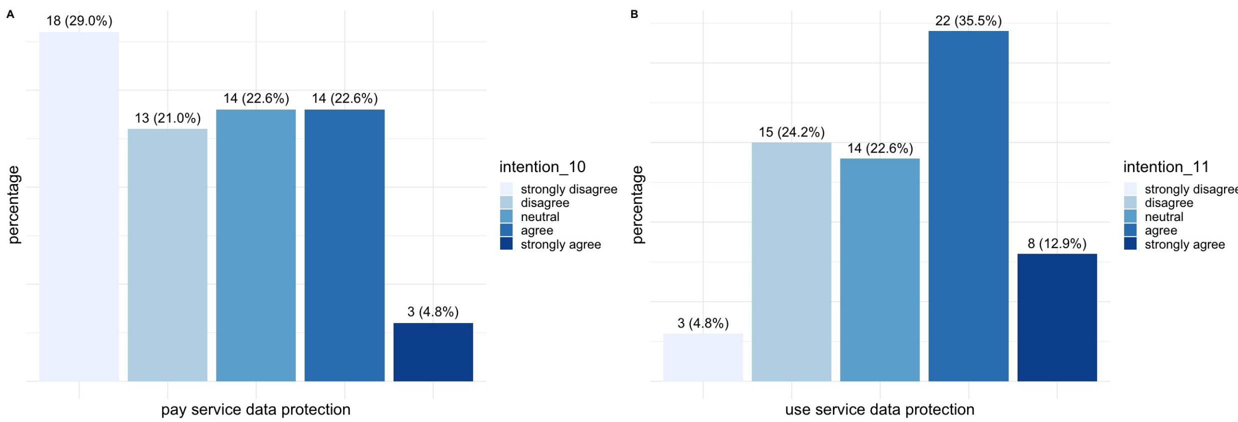
Self-Trackers' Privacy Preferences



Note. Figure A depicts the responses if trackers want to learn more about self-tracking privacy regulations and companies, Figure B if they are willing to spend some time learning more about self-tracking privacy policies, Figure C if they want to learn more about how their data is handled and stored, and Figure D if they want to learn more about how they can begin more effectively securing their data. Figure E shows whether they would consider using other applications or self-tracking technologies if they believed their privacy would be better protected, and Figure F shows whether they would stop sharing their information with online platforms and friends if they believed their privacy would be better protected.

Figure 22

Self-Trackers' Privacy Preferences



Note. Figure A depicts the replies to the question of whether trackers would be prepared to pay an annual membership fee to a service that handles data protection for them, Figure B if they would be willing to delegate responsibility to a service to protect their privacy on their behalf.

Appendix C

Table 18

Items Model 1 (Part 1)

Latent Variable	Number Item	Item Description
Healthism	Healthism_1	I find the practice of self-tracking valuable.
	Healthism_2	I would encourage others to use self-tracking.
	Healthism_3	Self-tracking has health-promoting effects.
	Healthism_4	Self-tracking helps me to live a healthy lifestyle.
	Healthism_5	Self-tracking enhance my health.
	Healthism_6	I consider myself very health-conscious.
	Healthism_7	I try to keep a healthy work life balance.
	Healthism_8	I feel responsible for my own health.
	Healthism_9	Self-tracking allows me to take control of my own health.
Self-entertainment	Entertainment_1	I'm self-tracking because I enjoy getting lost totally in self-tracking activities.
	Entertainment_2	I'm self-tracking because I like playing around with numbers/statistics etc.
	Entertainment_3	I'm self-tracking because I like playing around with my smartphone/technical device etc.
	Entertainment_4	I'm self-tracking because I enjoy forgetting about time while doing so.
	Entertainment_5	I'm self-tracking because it is fun and entertaining.
Self-association	Association_1	I'm self-tracking because I want to help/inspire others.
	Association_2	I'm self-tracking because the way I'm doing it is interesting for others/might help others.
	Association_3	I'm self-tracking because I want to compare my results to others.
	Association_4	I'm self-tracking because I want to present myself to others.
Self-design	Design_1	I'm self-tracking because I want to control what I'm doing with my life.
	Design_2	I'm self-tracking because I try to manipulate certain aspects in my life.
	Design_3	I'm self-tracking because I enjoy being my own master.
	Design_4	I'm self-tracking because I'm interested in how certain things in (my) life interact.
	Design_5	I'm self-tracking because it helps me to optimize the way I'm living.
Self-discipline	Discipline_1	I'm self-tracking because it motivates me to keep on working for a goal.
	Discipline_2	I'm self-tracking because it allows me to reward myself.
	Discipline_3	I'm self-tracking because it facilitates my self-discipline.
Self-healing	Healing_1	I'm self-tracking because I don't trust in the healthcare system/classic therapies.
	Healing_2	I'm self-tracking I want to be independent from traditional medical treatments.
Surveillance	Surveillance_1	I am concerned about my self-tracking device recording my location.
	Surveillance_2	I am concerned about my self-tracking device or applications gathering personal information about me.
	Surveillance_3	I am concerned about self-tracking applications monitoring my activity.

Table 19

Items Model 1 (Part 2)

Latent Variable	Number Item	Item Description
Intrusion	Intrusion_1	I am concerned about people knowing more about me than I am comfortable with because of the use of self-tracking devices and services.
	Intrusion_2	I am concerned about the use of self-tracking services making my personal information more easily accessible to others.
Secondary use	Secondary_1	I am concerned about self-tracking technologies using my personal information for other purposes.
	Secondary_2	I am concerned about self-tracking services sharing my personal information with third parties without my consent.
Confidence	Confidence_1	I am confident that my tracking service provider (e.g., Fitbit, Apple, Garmin) will not disclose any of my personal information.
	Confidence_2	I am confident that my tracking service provider (e.g., Fitbit, Apple, Garmin) will keep my data secure.
	Confidence_3	I am confident that my tracking service provider (e.g., Fitbit, Apple, Garmin) will not misuse my data.
Attitudes	Attitudes_1	I believe that self-tracking data should be kept private.
	Attitudes_2	I believe privacy concerns are overrated.
	Attitudes_3	I consider it to be my responsibility to guarantee that my self-tracking data is secure.
	Attitudes_4	I believe that self-tracking companies violate my privacy by gathering personal information about me.
Value	Value_1	I believe my tracking data is valuable enough to be used against me.
	Value_2	I believe it would have an influence on me if tracking companies exploited my information.
Physical Vanity	Physical_vanity_1	The way I look is extremely important to me.
	Physical_vanity_2	I am very concerned about my appearance.
	Physical_vanity_3	I would feel embarrassed if I was around people and did not look my best.
	Physical_vanity_4	Looking my best is worth the effort.
	Physical_vanity_5	It is important that I always look good.
Achievement Vanity	Achievement_vanity_1	I want others to look up to me because of my accomplishments.
	Achievement_vanity_2	Achieving greater success than my peers is important to me.
	Achievement_vanity_3	I want my achievements to be recognised by others.

Table 20

Standardised Factor Loadings

Item	Healthism	Entertainment	Association	Design	Discipline	Healing
Healthism_1	0.977					
Healthism_2	0.961					
Healthism_3	0.979					
Healthism_4	0.975					
Healthism_5	0.975					
Healthism_6	0.948					
Healthism_7	0.958					
Healthism_8	0.975					
Healthism_9	0.966					
Entertainment_1		0.858				
Entertainment_2		0.934				
Entertainment_3		0.909				
Entertainment_4		0.878				
Entertainment_5		0.969				
Association_1			0.938			
Association_2			0.899			
Association_3			0.877			
Association_4			0.889			
Design_1				0.975		
Design_2				0.896		
Design_3				0.942		
Design_4				0.946		
Design_5				0.974		
Discipline_1					0.974	
Discipline_2					0.950	
Discipline_3					0.981	
Healing_1						0.859
Healing_2						0.904

Table 21

Items Instrument

Factor	Item number	Item
Healthism	1	I find the practice of self-tracking valuable.
	2	I would encourage others to use self-tracking.
	3	Self-tracking has health-promoting effects.
	4	Self-tracking helps me to live a healthy lifestyle.
	5	Self-tracking enhance my health.
	6	I consider myself very health-conscious.
	7	I try to keep a healthy work life balance.
	8	I feel responsible for my own health.
	9	Self-tracking allows me to take control of my own health.
Self-entertainment	10	I'm self-tracking because I enjoy getting lost totally in self-tracking activities.
	11	I'm self-tracking because I like playing around with numbers/statistics etc.
	12	I'm self-tracking because I like playing around with my smartphone/technical device etc.
	13	I'm self-tracking because I enjoy forgetting about time while doing so.
	14	I'm self-tracking because it is fun and entertaining.
Self-association	15	I'm self-tracking because I want to help/inspire others.
	16	I'm self-tracking because the way I'm doing it is interesting for others/might help others.
	17	I'm self-tracking because I want to compare my results to others.
	18	I'm self-tracking because I want to present myself to others.
Self-design	19	I'm self-tracking because I want to control what I'm doing with my life.
	20	I'm self-tracking because I try to manipulate certain aspects in my life.
	21	I'm self-tracking because I enjoy being my own master.
	22	I'm self-tracking because I'm interested in how certain things in (my) life interact.
	23	I'm self-tracking because it helps me to optimize the way I'm living.
Self-discipline	24	I'm self-tracking because it motivates me to keep on working for a goal.
	25	I'm self-tracking because it allows me to reward myself.
	26	I'm self-tracking because it facilitates my self-discipline.
Self-healing	27	I'm self-tracking because I don't trust in the healthcare system/classic therapies.
	28	I'm self-tracking I want to be independent from traditional medical treatments.

Note. These items were tested with a five-point Likert scale from 1 being *Strongly Disagree* to 5 being *Strongly Agree*

Table 22

Factor Loadings Single-Factor Model

Item	Healthism	Entertainment	Association	Design	Discipline	Healing
~*g*						
Healthism_1	0.980					
Healthism_2	0.958					
Healthism_3	0.973					
Healthism_4	0.969					
Healthism_5	0.969					
Healthism_6	0.943					
Healthism_7	0.956					
Healthism_8	0.974					
Healthism_9	0.963					
Entertainment_1		0.825				
Entertainment_2		0.877				
Entertainment_3		0.849				
Entertainment_4		0.841				
Entertainment_5		0.913				
Association_1			0.864			
Association_2			0.797			
Association_3			0.804			
Association_4			0.826			
Design_1				0.973		
Design_2				0.890		
Design_3				0.941		
Design_4				0.943		
Design_5				0.973		
Discipline_1					0.967	
Discipline_2					0.943	
Discipline_3					0.976	
Healing_1						0.752
Healing_2						0.815