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Who Uses Digital Lifestyle Interventions? The Relationship between Personality Traits and the Use of mHealth Apps

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Theoretical Background

Rising Global Health Challenges

Regular physical activity and a healthy balanced diet have numerous physical, mental, and emotional benefits (World Health Organization, 2020; World Health Organization, 2024a). For instance, it can help to prevent chronic diseases, promote healthy brain development, reduce anxiety and depression and enhance overall well-being (An et al., 2020; World Health Organization, 2024a). Yet almost a third of the adult population fails to be sufficiently physically active, with a rising trend if no actions will be taken against it (World Health Organization, 2024a). Additionally, according to the Global Nutrition Report (2022), we are in a current “global nutrition crisis”, with worldwide famines on one side, while obesity and diet-related diseases increase. Unhealthy diets and an inactive lifestyle strongly contribute to the risk for obesity and non-communicable diseases, such as cardio-vascular diseases, cancer, or type-2 diabetes (Piercy et al., 2018; World Health Organization, 2024a). Additionally, not only the individuals’ health, but also rising healthcare costs and limited professional health resources must be considered while discussing the consequences of unhealthy behaviors (Duijvestijn et al., 2023; Lantzsch, 2022; Wijayaratne et al., 2018).

Global increase in physical inactivity and malnutrition can be partly explained by a more sedentary lifestyle and the rise in the production of processed food in the modern world (World Health Organization, 2020; World Health Organization, 2024a). In this context, health literacy could play an important role, since it refers to the knowledge and competences of an individual to seek, understand and use health-related information and services (Sørensen et al., 2015; World Health Organization, 2024b). While income, educational and vocational attainment have been shown to be important determinants for positive health outcomes, health literacy is considered to have an even greater influence on the individual's health (Sørensen et al., 2015; World Health Organization, 2024b). While some of the factors that favor unhealthy lifestyles might be more difficult to address, such as the availability and affordability of high-quality foods or socioeconomical inequalities (Hruby & Hu, 2014; World Health Organization, 2020), promoting a higher health awareness and health literacy among the population could be easier to implement.

In addition, lack of time, motivation, and an inadequate understanding of the correct techniques were found to negatively impact consistent physical activity (Guthold et al., 2018). Similarly, prior research has indicated that obstacles to healthy eating included low motivation or lack of knowledge to prepare healthy meals (Wijayaratne, 2018). Higher levels of food literacy, encompassing the capabilities, resources and knowledge to select, prepare and consume foods to meet recommended dietary guidelines (Kolasa et al., 2001; Vaitkeviciute et al., 2015), can help to successfully overcome these barriers (Wijayaratne, 2018). However, the challenge remains on how to increase motivation and health literacy among the population.

Health Promotion and Mobile Health Applications

In recent years, literature has demonstrated that health applications (apps) hold a great potential to motivate people to adopt healthier lifestyles and increase health education (Burke et al., 2011; Cho, 2015; ESPON, 2019; Lieneck, 2024; Sarcona et al., 2017; Standen & Rothman, 2023;Wang et al., 2024; Yerraklava et al., 2019). Such apps are available in all kinds of forms and especially mobile health (mHealth) has gained more attention and popularity in the recent years (Standen & Rothman, 2023; WHO Global Observatory for eHealth, 2011). mHealth apps can be seen as the use of mobile devices, for instance smartphones, tablets and smartwatches, to provide help for achieving different health outcomes (Pires et al., 2020; Standen & Rothman, 2023; WHO Global Observatory for eHealth, 2011). Given that most people carry their smartphone with them throughout the day, mHealth apps enable health-related support and the recording of health-related data nearly anywhere and at any time (Pires et al., 2020).

In general, mHealth can be used to support health education and health management, but also in larger healthcare contexts, e.g., for digital health counselling with health professionals (Cho, 2015; ESPON, 2019). mHealth apps can be broadly categorized into medical apps and non-medical apps, which are also referred to as lifestyle apps (Keller & Ercsey, 2023; Pires et al., 2020). While medical apps are designed for specific patients with medical conditions and often focus on the diagnosis and management of diseases, lifestyle apps are intended for a more general use and to support healthy behaviors (Pires et al., 2020). These apps most commonly address areas such as diet and weight management, physical activity or mental health (Pires et al., 2020). In an analysis of literature references and available mHealth apps in app stores, Pires et al. (2020) identified nutrition and fitness apps as one of the most relevant categories among lifestyle apps. Nutrition and fitness apps often include many helpful features and integrated sensors which facilitate engaging in healthy behaviors, e.g., tracking functions to record calorie intake or physical activity, goal setting, exercise plans, recipes, educational content or motivational prompts (Pires et al., 2020). Findings have shown that lifestyle apps hold the potential to successfully improve personal health (Lieneck et al., 2024; Wang et al., 2024), such as increasing daily steps, reducing daily sitting time and improving overall fitness (Yerrakalva et al., 2019). In the context of nutrition, other findings indicated that diet and weight apps were associated with healthier eating behaviors and weight-loss (Burke et al., 2011; Sarcona et al., 2017).

In the last decade, there has been a notable rise in daily smartphone use (Gama & Laher, 2023) while the mHealth app market is consistently growing (Dittrich et al., 2023; Statista, 2024). This offers the chance to reach more people than ever before (Elavsky et al., 2017), especially when compared to traditional ways of health promotion. While traditional health interventions that do not use digital devices can be effective, mHealth offers certain advantages in terms of convenience, accessibility and costs (Albrecht, 2016; Amagai, 2022; ESPON, 2019; Gama & Laher, 2023; Lantzsch, 2022). Since mHealth apps can be used from anywhere, this can reduce time and distance barriers (Amagai, 2022), which are often reasons why people do not engage in physical activity (Guthold et al., 2018). Since mHealth apps are often considered low-cost (Gama & Laher, 2023; Marcolino, 2018), another advantage is financial affordability. Lowering barriers for health promoting behaviors is thus one the greatest advantages of mHealth (Amagai, 2022; ESPON, 2019; Gama & Laher, 2023; Lantzsch, 2022).

Additionally, mHealth apps and tracker are also able to assess health-related data, which is not only reliable due to its real-time assessment but can provide useful information for individuals and health practitioners when health concerns arise (Amagai, 2022). Another advantage might be that since mHealth apps can assess people's goals, needs and preferences while tracking real-time data, this allows individuals to receive more personalized feedback to reach their health goals (Aguiar et al., 2022; Amagai, 2022; Ghose et al., 2021).

With its potential to reach many people via their smartphones, mHealth could effectively support individual health and therefore minimize the risk of non-communicable diseases and obesity among the population. In the long run, the prevention of diseases could lead to a decrease in health care costs (Albrecht, 2016; Duijvestijn et al., 2023; ESPON, 2019). Especially when health resources are limited, mHealth could offer a low-threshold, accessible option and help reduce the burden on the health care system (Gama & Laher, 2023; Lantzsch, 2022).

However, despite the promising potential of mHealth apps and high download rates, many people do not actively use such offers or dropout within the short term (Amagai et al., 2022; Conway et al., 2015; Hershman, 2019; Krebs & Duncan, 2015; Lee et al., 2018). Lee et al. (2018) reported that users most frequently did not use a mHealth app shortly after the initial adoption and gradually disengaged in active use over time. However, research shows that positive health outcomes from mHealth use start to occur after a longer duration of use, with findings suggesting a timeframe of eight weeks to one year (Burke et al., 2011; Gómez-Cuesta et al., 2024; Yerrakalva et al., 2019; Whitehead & Seaton, 2016). This highlights the importance of sustained user engagement since with only a short period of time, it is less likely that mHealth apps will have a positive impact on users' health. While many studies investigate the benefits of mHealth apps and who uses them, still little is known about how to ensure active app use in the long run (Lee et al., 2018).

It is therefore crucial to gain a better understanding of not only what determines the initial adoption but also the sustained use of mHealth apps.

Characterization of mHealth User Groups

Due to its potential for broad-based health promotion and minimizing health care costs, many European countries are currently trying to increase the acceptance of digital health promotion and the number of mHealth app users (Directorate-General for Health and Food Safety, 2012; ESPON, 2019). Therefore, the European Union has been developing strategies to enhance the effectiveness and user-friendliness of digital health services (Directorate-General for Health and Food Safety, 2012; ESPON, 2019). Studies demonstrate that users have varying preferences for presented content and motivational features, depending on their individual goals and needs (Belmon et al., 2015; Kaptein, 2015; Khwaja et al., 2021; Orji et al. 2013; Ryan & Xenos, 2010). This is important to consider since these differences influence the perceived use, acceptance and enjoyment of an app as well as the intention to use it (Alshawmar et al., 2022; Burtăverde et al., 2019; Halko & Kientz, 2010; Nunes et al., 2018). To increase mHealth app user rates, an initial step could be to identify different groups of users and non-users and characterize their characteristics. This would provide app developers and policymakers with valuable insights about different preferences and needs (De Heredia et al., 2018), as well as motivational processes underlying the adoption of mHealth apps (König et al., 2018).

Various factors were found to influence the likelihood of adopting mHealth apps, for instance, sociodemographic characteristics (Elavsky et al., 2017; Klenk et al., 2017; König et al., 2018; Krebs & Duncan, 2015) health-related variables (Dennison et al., 2013; König et al., 2018) or psychological or cognitive aspects (Aziz et al., 2023; Cho et al., 2015; Elavsky et al., 2017; Su et al., 2020). Research indicates that mHealth app users are generally above average educated, have higher incomes and live in more urban areas (Krebs & Duncan, 2015; Purcell, 2016). Moreover, findings have shown that frequent users of mHealth apps tend to show higher levels of health consciousness, a stronger orientation towards health information, and higher eHealth literacy (Cho et al., 2014).

However, prior research has often generalized findings of mHealth users for different app categories (Cho, 2015; Krebs & Duncan, 2015), although user characteristics might vary depending on the health-related content of the app: For instance, while the overall use of mHealth apps appears to be uncorrelated with gender (Krebs & Duncan, 2015), users of nutrition and weight management apps tend to be female (Elavsky et al., 2017). Since women tend to be more driven by motives such as appearance and health when engaging in physical activity (Egli et al., 2011; Molanorouzi et al., 2015), they might be more inclined to use nutrition apps as they often support these motives. Men, on the other hand, were found to be more motivated by strength, competition and challenge in physical activities (Egli et al., 2011; Molanorouzi et al., 2015),which are less commonly addressed by nutrition apps. This aligns with findings indicating that physical activity interventions which used gamification strategies targeting these motives were especially effective for young adult males (Arteaga et al., 2012).

Therefore, to obtain an accurate characterization of users and non-users it appears crucial to distinguish between different health domains of mHealth interventions. Since findings show that fitness and nutrition apps appear to be the most popular health-related lifestyle apps (Pires et al., 2020), the present study focused on the investigation and characterization of users and non-users of these two app categories.

Finally, while it is necessary to gain a better understanding about the reasons why people engage with mHealth apps in the first place, it is equally important to understand why some have stopped using a mHealth app (König et al., 2018; Lee et al., 2018). Findings indicate that the motives for initial adoption and disengagement with technologies could differ. For instance, while the initial engagement could be driven by perceived compatibility, long-term engagement might be more dependent of the perceived benefits of a certain technology (Lee et al., 2018). Therefore, to address the issue of low engagement rates after initial adoption, it is important to additionally investigate whether individuals differ at different motivational stages of mHealth app use.

Stage Models of Behavior

Previous mHealth research has often binary categorized people into active users and non-active non-users. However, the investigation of non-users might require more detailed information as their motivation and reasons to not use an app could differ (König et al., 2018; Lee et al., 2018). For example, non-users may differ in terms of whether they have never used mHealth apps before or whether they have used them in the past but no longer do so (König et al., 2018). Considering different types of non-users is therefore necessary to gain a better understanding of target groups and adapt apps accordingly (König et al., 2018; Lee et al., 2018).

In health psychology, stage models of behavior change offer a helpful approach when it comes to understanding how to encourage people to live healthier (Lippke & Ziegelmann, 2005; Schwarzer, 2008). According to these models, individuals move through qualitatively distinct stages in the process of adopting a new behavior (Lippke & Ziegelmann, 2005; Sniehotta & Aunger, 2010). Those stages are characterized by different levels of awareness and consideration for the adoption of healthier lifestyle choices (Lippke & Ziegelmann, 2005; Schwarzer, 2008). People in different stages therefore have different cognitions and thoughts about a certain behavior and related obstacles (Lippke & Ziegelmann, 2005; Sniehotta & Aunger, 2010), which implies that different approaches are needed to support behavior change (Sniehotta & Aunger, 2010).

Initially, traditional social cognition models of behavior change were used in health psychology to gain a better understanding about behavior change mechanisms (Sniehotta & Aunger, 2010). Yet, most of those theoretical models focused on only a few psychological variables, such as self-efficacy or outcome expectations, suggesting that a new behavior can be adopted when those single variables change (Sniehotta & Aunger, 2010). Stage models on the other hand, such as the Transtheoretical Model of Health Behavior Change (TTM; Prochaska & Velicer, 1997) or the Precaution Adoption Process Model (PAPM; Weinstein & Sandman, 1992), consider different tasks and cognitions at each stage as important. Those need to be addressed to transit from one stage to another to achieve the desired behavior (Lippke & Ziegelmann, 2005; Sniehotta & Aunger, 2010). For example, Individuals who are undecided whether they want to engage in a certain behavior might be more encouraged by further information about the consequences of their behavior, whereas those who have already decided to act are more likely to benefit from concrete suggestions on how to start the behavior (Sniehotta & Aunger, 2010). On the other hand, those who decided not to engage in a certain behavior have already formed an opinion and might be more resistant to persuasion (Weinstein & Sandman, 1992; Weinstein et al., 2008). As interventions might be less successful within that group, it could be more effective to focus on other types of non-users (König et al., 2018).

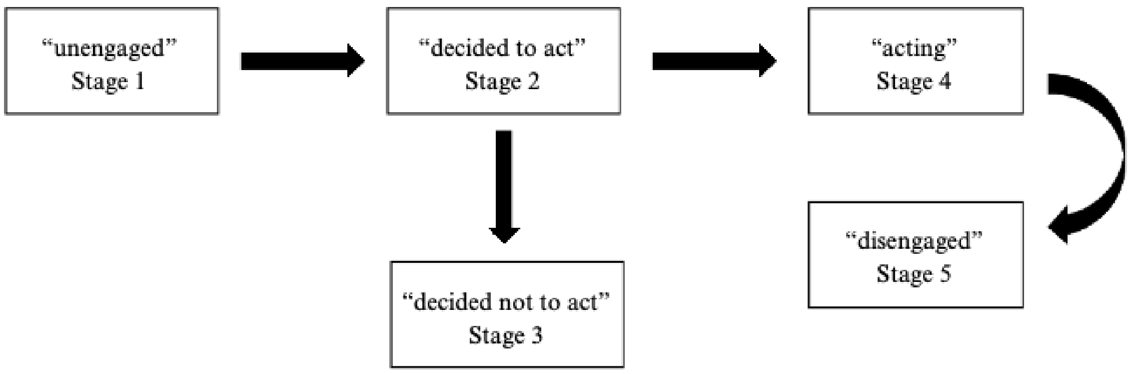
The PAPM describes decision-making processes of each stage during the adoption of behavior change (Sniehotta & Aunger, 2010; Weinstein & Sandman, 1992). The model claims that individuals transit through qualitatively different motivational stages when adopting a behavior. Those stages range from being “unaware,” “unengaged”, “undecided”,

"decided not to act", "decided to act", "acting", to finally "maintaining" the behavior (Weinstein et al., 2008). Further, as the model provides information about stage-specific barriers, interventions can be tailored accordingly, increasing the likelihood of behavioral change (Prochaska, 2018; Schwarzer et al., 2010; Weinstein & Sandman, 1992, Weinstein et al., 2008).

Research suggests that using stage models to tailor interventions to specific stages can enhance the recruitment and retention of individuals and their progress in behavior change (Prochaska, 2018). Based on stage models from health psychology, and the PAPM in particular, König et al. (2018) developed a stage model approach for the adoption process of mHealth apps. They identified five different stages for the adoption of fitness and nutrition apps (see Figure 1).

Figure 1

Behavioral Stages of Fitness and Nutrition App Adoption



Note. Stage model approach for fitness and nutrition app adoption based on König, L. M., Sproesser, G., Schupp, H. T., & Renner, B. (2018). Describing the process of adopting nutrition and fitness apps: Behavior Stage Model approach. *JMIR Mhealth and Uhealth*, *6*(3), e55. https://doi.org/10.2196/mhealth.8261

These stages in the model include 1) individuals who have never thought about using mHealth apps (“unengaged”), 2) those who intend to use mHealth apps in the future (“decided to act”), 3) those who have decided against using mHealth apps (“decided not to act”), 4) those who are currently using mHealth apps (“acting”), and 5) those who have stopped to use mHealth apps (“disengaged”). Especially to better understand the long-term use of mHealth apps, König et al. (2018) highlight the importance of the fifth stage: comparing “disengaged” with “acting” individuals could provide valuable information about the motivational reasons for discontinued behavior. While it might be that the achievement of a goal led to disengagement, research shows that it’s more likely that people have given up on their goals (Murnane, 2015) and therefore stopped using an app. Additionally, certain feature related tasks might be too time consuming and therefore the reason for disengaged behavior, for example tracking food intake (Krebs & Duncan, 2015). To design interventions that stop people from the transition to the “disengaged” stage, detailed information about that group and different approaches would be needed to convince them to use mHealth apps in the long-term (König et al., 2018).

Once, a person’s or group’s stage of fitness and nutrition app adoption has been identified, valuable information can be obtained by characterizing the people of each stage. Based on that information, more effective interventions can be developed by tailoring them to each group’s preferences and needs (Weinstein et al., 2008; König et al., 2018).

Personality Traits and Personalization of mHealth Services

Current research suggests that the personalization of mHealth apps could be relevant to achieve a higher adoption rate and sustained mHealth use (Avanesova et al., 2022; Kim et al., 2020; Zanker et al., 2019). Additionally, higher engagement with digital services and more successful health outcomes were observed when mHealth interventions were personalized (Madeira et al., 2018; Zanker et al., 2019).

In the context of technology, personalization refers to changes in functionality, user interface and in the presented content of a digital device to enhance personal relevance to the user (Blom, 2004; Fan & Poole, 2006). Given that people seem to be more likely to adopt apps which are associated with their interests, demographics and personality traits (Ryan & Xenos, 2011; Xu et al., 2016), digital health interventions should be designed in such a way that they match these characteristics. Previous studies have demonstrated that a person’s personality is associated with preferences for digital services (Joshi & Das, 2023; Xu et al., 2016), app features (Alqahtani et al. 2020; Khwaja et al., 2021), digital behavior change techniques (Belmon et al., 2015), as well as the perceived usefulness of digital health services and the intention to use them (Alshawmar et al., 2023; Nunes et al., 2018). Therefore, a comprehensive understanding of differences in personality might be a promising approach for a better personalization of mHealth apps (Alshawmar et al., 2022; Avanesova et al., 2022; Aziz et al., 2023; Khwaja et al., 2021) and their advertisement (Bregenzer et al., 2017).

In psychology, personality can be described as a structure of characteristic patterns of qualities and needs, including thoughts and feelings, that remain relatively constant across time and situations (Connor-Smith & Flachsbart, 2007), age groups and culture (McCrae et al., 1998). It has also been shown that personality traits indicate behavioral tendencies in different situations (Paunonen, 2003; Sherman et al., 2015). Currently, the five-factor model, also called the Big Five, seems to be the most accepted model in psychology for describing personality (Costa & McCrae, 2008). The Big Five describe human personality by using the five major personality traits Neuroticism, Extraversion, Openness, Agreeableness and Conscientiousness (Costa & McCrae, 2008). Personality traits can be assessed and measured for each person (Vinciarelli & Mohammadi, 2014), with individuals differing in the strength of their characteristics (Goldberg, 1992).

In the context of behavioral stages of fitness and nutrition app adoption, it is assumed that people in different stages might differ in their reasons for non-use and need distinct approaches to transit from one stage to another (König et al., 2018). As mentioned before, those who became "disengaged" might have struggled with certain app features (Krebs & Duncan, 2015) and therefore stopped using an app, while "unengaged" individuals might lack information about mHealth benefits to become interested in them. Further, those who have already "decided to act" might require specific suggestions and support on how to put their plans into action (Sniehotta & Aunger, 2010). Understanding differences in personality could improve these approaches by tailoring information about mHealth app benefits, support strategies or app features based on personality related tendencies.

Although findings suggest that information about personality traits hold great potential for the personalization of mHealth services, research on the exact relationship between personality and mHealth app users and non-users is limited (Alshawmar et al., 2022; Bregenzer et al., 2017; Khwaja et al., 2021; Su et al., 2020). Additionally, to the best of my knowledge, no study to date has investigated users and different types of non-users and their relationship to the Big Five in the context of fitness and nutrition app adoption. However, based on findings on the relationship between the Big Five and the use of technologies, mHealth apps and health-related behavior, possible tendencies of the Big Five in the adoption process of fitness and nutrition apps are discussed below.

The Big Five and Adoption of Fitness and Nutrition Apps

Extraversion

Extraversion is typically defined by characteristics such as being social, affectionate, fun-loving and talkative (McCrae & Costa, 1987). Extraverts often seek excitement (Müller, 2023) and value social connections, both in-person and online (Ross et al., 2009). This algins with research indicating that Extraversion was shown to be positively correlated with the use of apps that enable communication (Peltonen et al., 2020). Further, Extraversion was associated with the willingness to share personal information online (Both, 2021) and a preference for social features such as commenting, messaging and posting on social media (Ryan & Xenos, 2010). However, some findings suggest that extraverts prefer to socialize offline and use online tools as an extension of their social life (Ross et al., 2009), while low levels of Extraversion, also referred to as Introversion, might be linked to a higher enjoyment for online tools (Nopiana et al., 2022) and a preference for online communication over traditional forms of interaction (Chittaranjan et al., 2011). For instance, introverts reported higher satisfaction with remote forms of physiotherapy (Cieślik et al., 2023) and online learning compared to face-to-face education during the COVID-19 epidemic (Hayat et al., 2023).

A study on persuasive strategies in mHealth apps showed that high levels of Extraversion correlated negatively with perceived enjoyment, usefulness and the intention to use a physical activity app (Halko & Kientz, 2010). Since extraverted people tend to have strong social networks, the researchers suggested they may not feel the need to use technologies to achieve their health goals. Contrary, Alshawmar et al. (2022) found that extraverts showed higher levels of perceived usefulness of fitness apps, which might be due to social features which are commonly incorporated in fitness apps, such as leaderboards, team-based challenges, or sharing progress. Additionally, extraverted people show higher levels of physical activity, which might be explained by their need for stimulating experiences (Eysenck et al., 1982; Müller, 2023; Wilson & Rhodes, 2021) and a higher pain tolerance, which could be beneficial for the participation in physical activities (Eysenck et al., 1982). Based on these findings, one could argue that extraverted individuals might be more inclined to use fitness apps, especially when they include social features.

On the other hand, extraverts also demonstrate a greater preference for group or supervised sports activities (Wilson & Rhodes, 2021), a higher motivation to attend fitness centers (Lin et al., 2007), and derive motivation from social interaction and competition (Allen & Laborde, 2014; Rhodes & Smith, 2006), while introverts tend to be more socially isolated and enjoy participating in individual activities (Wilson & Rhodes, 2021; Xu et al., 2016). This seems plausible given that introverts were shown to be more likely to experience negative affect in highly stimulating situations (Wilson & Rhodes, 2021). Therefore, fitness apps could equally appeal to introverted individuals, as those apps might facilitate engaging in physical activity while avoiding places or situations that could be perceived as overstimulating.

In terms of nutrition, a review of personality traits and healthy eating habits found that extraverted individuals show a higher consumption of sweet and savory foods, meat and soft drinks in several interdisciplinary studies (Tsartsapakis & Zafeiroudi, 2024). This is consistent with findings suggesting that higher levels of Extraversion are linked to the consumption of less healthy foods (Keller & Siegrist, 2015) and obesity (Pristyna et al., 2022). As extraverted people tend to be sociable, this might be connected to consuming meals in social settings more frequently, which often includes foods that are less recommended by dietary guidelines (Keller & Siegrist, 2015). These tendencies towards a less healthy diet, could make extraverted individuals a potential target group for nutrition apps. However, as nutrition apps often involve more structured and monotonous tasks, such as tracking food intake, they may not provide the kind of external stimulation that extraverts typically seek (Chittaranjan et al., 2013; Peltonen et al., 2020). Su et al. (2020) discovered that extraverted patients with diabetes were less likely to continuously use an mHealth app for self-management strategies, despite the app's social features. Additionally, extraverted individuals were shown to prefer direct social support in problem solving and as a coping strategy (Connor-Smith & Flachsbart, 2007), although this preference could be moderated by age: Chang et al. (2023) found that elderly Chinese adults high in Extraversion were more prone to adopt mHealth apps, as especially with age, online tools might enable them to enhance their social interaction and discuss health-related concerns more easily. However, the paper by Chang et al. (2023) has only been published as a preprint and should therefore be considered with caution.

As previous research has not yet been able to establish a definitive link between extraversion and the use of nutrition apps, it still remains unclear whether extroverts are more likely to adopt nutrition apps or not. Based on evidence that associates Extraversion with lower adherence to healthy eating habits (Keller & Siegrist, 2015; Pristyna et al., 2022; Tsartsapakis & Zafeiroudi, 2024) and a preference for face-to-face interaction and support (Cieślik et al., 2023; Hayat et al., 2023; Ross et al., 2009; Su et al., 2020), extraverted individuals may be less motivated to consistently engage with nutrition apps.

Neuroticism

Neuroticism, also referred to as emotional instability, is characterized by experiencing heightened levels of anxiety, depression and anger (McCrae & Costa, 1987). Highly neurotic individuals also tend to be more self-conscious and feel embarrassed (McCrae & Costa, 1987). As highly neurotic individuals are prone to experiencing negative emotions (McCrae & Costa, 1987), it appears plausible that Neuroticism is often associated with higher interest in using apps for stress-related support (Borghouts et al., 2021) and the use of mental health apps (Aziz et al., 2023). Longitudinal research indicates that Neuroticism has not only a negative influence on subjective well-being, but also on physical health (Friedman et al., 2010). Yet, research has yielded mixed results in examining whether neurotic individuals are more likely to use mHealth apps related to physical health (Alshawmar et al., 2022; Aziz et al., 2023; Bregenzer et al., 2017).

In general, studies have found that Neuroticism is associated with lower levels of physical activity (Müller, 2023; Rhodes & Smith, 2006; Stieger et al. 2020) which could be explained by the fact that neurotic individuals naturally show stronger responsiveness to intense stimuli (Rhodes & Smith, 2006; Wilson & Dishman, 2014). As these feelings could be induced by high intensity exercises, physical activity could be therefore perceived as stressful and uncomfortable (Rhodes & Smith, 2006; Wilson & Dishman, 2014). This could explain why highly neurotic individuals were found to prefer low-intensity or sedentary activities (Müller, 2023), which is supported by another study that has shown that high Neuroticism and low Conscientiousness were linked to a more sedentary lifestyle (Allen et al., 2016). Neurotic individuals also tend to avoid competitive situations and social interactions, which can negatively impact their engagement in physical activity (Eysenck et al., 1982) and eventually the adoption of fitness apps.

Further findings indicate that neurotic people tend to be more demotivated when confronted with negative feedback on difficult or frustrating tasks (Swift & Peterson, 2018), which might be due to their higher sensitivity to criticism (Robinson et al., 2010) and lower self-esteem (Eysenck et al., 1982). As feedback is a common feature of mHealth apps (Standen & Rothman, 2023), this could additionally discourage neurotic individuals from using mHealth apps. On the other hand, other studies have found that Neuroticism was positively related with the perceived usefulness of fitness apps (Alshawmar et al., 2022) and, when combined with high levels of Conscientiousness, with higher levels of healthy physical activity (Stieger et al, 2020). A study that identified user archetypes for physical health apps, revealed that individuals with high levels of Neuroticism and Conscientiousness were the most frequent users, launching these apps up to nearly three times per day (Aziz et al., 2023). These findings are consistent with other research, which has shown that individuals with high levels of Conscientiousness and Neuroticism tend to be associated with better health outcomes (Stieger et al., 2020). This may be due to the tendency of highly neurotic individuals to worry and be concerned about their health (Weston & Jackson, 2014) and the tendency of conscientious individuals to engage in health-promoting behaviors when health concerns arise (Aziz et al., 2023; Stieger et al., 2020). Thus, conscientious neurotics may be better at transforming their health concerns into beneficial behaviors (Stieger et al., 2020) and might be more inclined to use fitness apps.

In the context of nutrition, Neuroticism is linked with a poorer-quality diet (Keller & Siegrist, 2015; Pristyna et al., 2022; Tiainen et al., 2013). Studies indicate that neurotic individuals are more susceptible to emotional eating and tend to consume high-calorie, sweet, and savory foods (Keller & Siegrist, 2015; Pristyna et al., 2022), especially when experiencing stress or negative emotions (Groesz et al., 2012). While Neuroticism was associated with restrained eating, which could indicate healthy eating behaviors, research suggests that neurotic individuals may follow restrictive diets for different, potentially less health-oriented reasons (Heaven et al., 2001). Indeed, neurotic individuals have been shown to engage in problematic health behaviors such as extreme dieting (Groesz et al., 2012; Lahey, 2009) or overeating (Lurz et al., 2024), possibly as a way of emotional coping (Ward & Hay, 2014). Supporting this, findings indicated that neurotic individuals have shown greater intention in using a support app for stress-overeating (Lurz et al., 2024). However, no significant effect of neuroticism was found on the continued use of a self-management app for diabetes (Su et al., 2020). This might be partially explained by the fact that neurotic individuals were shown to negatively evaluate app features such as self-monitoring and feedback (Belmon et al., 2015), which are commonly used in mHealth interventions.

This suggests that neurotic individuals could be more likely to use nutrition apps when they address stress-related eating behaviors. On the other hand, they could find long-term use challenging due to negative emotions triggered by certain app features.

Agreeableness

People who score high on Agreeableness tend to be more trusting, empathetic and more likely to help others (Alshawmar et al., 2022; Xu et al., 2016). They are also more tolerant and forgiving, which makes them more inclined to perceive new technologies as useful (Devaraj et al., 2008). Additionally, research suggests that agreeable individuals are more likely to use technologies that promote cooperation and collaborative tasks (Deveraj et al., 2008).

In terms of physical activity, previous research only indicated a weak or negligible relationship between Agreeableness and engagement in physical activity (Müller, 2023; Rhodes & Smith, 2006; Strickhouser et al. 2017; Wilson & Dishman, 2014). This trend complements findings that Agreeableness was not associated with the perceived usefulness of fitness apps (Alshawmar et al., 2022) or the adoption of health apps in general (Huseynov, 2020; Su et al., 2020).

Regarding nutrition, the findings on the relationship between Agreeableness and healthy eating behaviors are mixed. While some results indicated no association with higher fruit and vegetable intake (Keller & Siegrist, 2015), others have found that agreeable individuals are more receptive to dietary advice (Kikuchi & Watanabe, 2000) and to better consider nutritional balance in meals (Kim et al., 2020). Additionally, Agreeableness was associated with a negative preference for non-recommended beverages, such as soft drinks and sweetened fruit juices (Golestanbagh et al., 2021; Keller & Siegrist, 2015). Findings have shown that Agreeableness is negatively associated with meat consumption, especially amongst women (Keller & Siegrist, 2015; Kim et al., 2020). However, due to the pronounced empathy and altruism in agreeable individuals, they might be more likely to adopt a diet based on ethical concerns (Keller & Siegrist, 2015) than on health concerns.

Although, in general, Agreeableness seems to be uncorrelated to physical health outcomes (Pletzer et al., 2023), Agreeableness might have a positive impact on health outcomes which are often not included as health markers in many studies (Pletzer et al., 2023). For instance, agreeable individuals tend to avoid risky health behaviors, show higher levels of adherence to medication, higher levels of better mental health (Pletzer et al., 2023), lower levels of stress (Ervasti et al., 2019) and are associated with the use of mHealth apps for stress management (Borghouts et al., 2021). With their empathetic and collaborative nature, compatible individuals may place more emphasis on psychological well-being (Pletzer et al., 2023) and could be therefore drawn to apps that support mental health over physical health.

Their greater adherence to health recommendations (Kikuchi & Watanabe, 2000; Pletzer et al., 2023) could be partly attributed to a stronger alignment with social norms and a tendency to conform to peer expectations (Aisyah et al., 2021), as well as a generally trusting and conflict-averse nature (Joshi et al., 2023; Xu et al., 2016). These characteristics suggest that agreeable individuals might be more likely to follow others' recommendations (Joshi et al., 2023), making them more receptive to adopting mHealth apps when these apps are popular or recommended by their social network.

Openness

Openness is typically characterized by being creative, daring, broad-mindedness, and a preference for a wide range of interests (McCrae & Costa, 1987). Thus, individuals high in Openness are more inclined to try new things and be receptive to novel ideas (McCrae & Costa, 1987). Research has shown that individuals high in Openness tend to be early adopters of new technologies (Joshi et al., 2023) and show a higher awareness of digital advancements (Ross et al., 2009). They also demonstrate greater acceptance of digital information and communication formats, such as online education and various forms of online activities (Joshi et al., 2023). Since open individuals feel drawn to novelty and innovation, they might tend to be more receptive to adopting new technologies and digital applications (Joshi et al., 2023).

The relationship between Openness and physical health outcomes seems more complex. While some studies indicate that Openness might foster health related behaviors (Keller & Siegrist, 2015; Mõttus et al., 2012; Mõttus et al., 2013; Nunes et al., 2018; Pristyna et al., 2022), a meta-analysis by Strickhouser et al., (2017) found no significant association with Openness. However, this result could be since people high in Openness seek new experiences and exploration (Prystina et al., 2022 and are more likely to engage in risky behaviors which could be less beneficial for their health (Pletzer et al., 2024).

When it comes to physical activity, previous research has found only a weak or no association between Openness and physical activity (Strickhouser et al., 2017; Müller, 2023). This aligns with findings that Openness was not associated with the perceived usefulness of fitness apps (Alshawmar et al., 2022). Since most studies focus on exercising when investigating physical activity and personality traits, this might partly explain the weak relationship with Openness (Müller, 2023). Individuals high in Openness were found to prefer engaging in outdoor activities over traditional forms of exercise, such as running or going to the gym, as they might better fulfill their need for new and diverse experiences (Courneya & Hellsten, 1998; Wilson & Rhodes, 2021). In addition, individuals high in Openness enjoy engaging in creative and imaginative activities, which is why they might prioritize mental over physical stimulation (Müller, 2023).

In terms of nutrition, Research indicates that Openness is generally associated with healthy eating habits (Keller & Siegrist, 2015; Mõttus et al., 2012; Pristyna et al., 2022) such as the consumption of fruits and vegetables (Keller & Siegrist, 2015; Pristyna et al., 2022) and the adoption of a health-beneficial diets, such as a Mediterranean (Mõttus et al., 2013), vegetarian or pescetarian diet (Forestell et al., 2011). This might be explained by the fact that individuals high in Openness are more likely to try new dietary patterns and overcome food aversions (Mõttus et al., 2013). Since open individuals might find it easier to adhere to dietary guidelines (Keller & Siegrist, 2015; Pristyna et al., 2022) they might perceive a lower need for using nutrition apps. Additionally, nutrition apps often involve repetitive features, such as food tracking, that may not satisfy their need for novelty.

However, when faced with specific health issues, open individuals may turn to mHealth apps for support. Research has shown that Openness was associated with sustained use of mHealth apps that promoted self-management strategies for conditions such as hypertension (Breil et al., 2019) and diabetes (Su et al., 2020), as well as those offering mindfulness techniques for cancer patients (Mikolasek et al., 2018). Other findings indicated that while Openness was not significantly related with the intention to use mHealth apps in younger adults, Openness was found to be predictive for older individuals, especially for those above 55 years (Nunes et al., 2018). In a preprint by Chang et al. (2023), Openness has also been found to positively influence the intention to use mHealth in older adults.

Based on those findings it appears that no clear conclusion can be drawn whether open individuals feel more inclined to use mHealth apps or not. mHealth apps might not offer enough novelty, especially in terms of nutrition apps, and often focus on traditional forms of exercise, which seem to be less appealing to open individuals (Courneya & Hellsten, 1998; Müller, 2023; Wilson & Rhodes, 2021). Yet, research indicates that Openness could be a supportive factor when adopting mHealth apps, especially when health-concerns arise (Breil et al., 2019; Mikolasek et al., 2018; Su et al., 2020) or in older individuals (Chang et al., 2023; Nunes et al., 2018).

Conscientiousness

Conscientiousness is widely recognized as one of the strongest predictors of health-related behaviors (Pletzer et al., 2024; Strickhouser et al., 2017). Individuals who score high in Conscientiousness are characterized by being ambitious, hard-working, persevering and self-controlled by nature (McCrae & Costa, 1987). It was shown that conscientious individuals tend to make more responsible decisions and develop behaviors that reduce health-related risks (Bogg & Roberts, 2004).

According to a meta-analysis by Pletzer et al. (2024), Conscientiousness was found to be the most important personality trait when it comes to predicting health-related behaviors. For instance, Conscientiousness was consistently shown to be positively associated with meeting physical activity guidelines (Müller et al., 2023; Pletzer et al., 2024; Strickhouser et al., 2017), the adherence to a healthy diet (Keller & Siegrist, 2015; Mõttus et al., 2013; Pristyna et al., 2022) and a healthy body weight (Pristyna et al., 2022). Characteristics of conscientious individuals, such as heightened self-control (McCrae & Costa, 1987) might facilitate the adoption of regulatory restrained eating, and therefore make it easier to maintain dietary goals (Keller & Siegrist, 2015).

As individuals high in Conscientiousness display a goal-oriented mindset and tend to recognize health-related benefits of an active lifestyle (Rhodes & Pfaeffli, 2012), they might be more likely to prioritize engaging in sustained healthy behaviors (Müller et al., 2023). Additionally, conscientious individuals were also shown to be more likely to adopt health-related behaviors, when health concerns arise (Weston & Jackson, 2014).

In terms of technologies and mHealth adoption, conscientious individuals were found to be less inclined to adopt leisure-oriented apps, because they may perceive them as unproductive or distracting (Xu et al., 2016). Similarly, a meta-analysis by Joshi et al. (2023) found that conscientious individuals tend to use technologies which enable them to be more organized, achieve their goals and foster skill development. This is complemented by findings which showed that moderate to high levels of Conscientiousness positively influenced the frequent launch of physical health apps (Aziz et al.,2023). In line with these findings, other studies reported that Conscientiousness was positively related to the use of physical health apps (Burtăverde et al., 2019) as well as their perceived usefulness (Alshawmar et al., 2022). These findings are consistent with another study, where conscientious individuals were found to be the most engaged users in a weight loss app (Hales et al., 2017). Surprisingly, Conscientiousness was not found to be related to the adoption and active use of a self-management mHealth app for patients with diabetes (Su et al., 2020). Su et al. (2020) suggest that age could negatively impact the use of mHealth apps in older individuals. This is supported other by findings where Openness, but not Conscientiousness, was related to the intention to use mHealth apps, especially among older participants (Chang et al., 2023; Nunes et al., 2018). As the use of technology, and particularly mHealth services, is less prevalent in this age group (Krebs & Duncan, 2015), it could be more important for individuals to be open-minded than conscientious to adopt such apps.

Additionally, as conscientious individuals have been shown to prefer structured approaches to achieve their health goals (Aziz et al., 2023) and are self-disciplined and organized by nature (McCrae & Costa, 1987), the use of an app to support them might not always be needed and could depend on additional characteristics or the design of an app. For instance, a study on mental health apps demonstrated that individuals with higher levels of

Conscientiousness were more likely to engage with journaling and audio-based interventions than with game and video formats (Khwaja et al., 2021). Thus, the wide range of features available in mHealth apps might not always align with the preferences of individuals who favor structured approaches (Aziz et al., 2023; Khwaja et al., 2021). In general, however, results from the literature tend to indicate that conscientious people are more likely to use fitness and nutrition apps.

Conscientiousness as a Moderator

Existing literature suggests that Conscientiousness positively influences the relationship between various factors and health-related behaviors (Aziz et al., 2023; Shanahan et al., 2014; Stieger et al., 2020). However, to what extent is not yet fully understood. As mentioned before, individuals with high levels of Neuroticism used physical health apps more frequently (Aziz et al., 2023) and were more likely to increase their daily steps during a physical activity intervention (Stieger et al., 2020) when paired with higher levels of Conscientiousness. Since neurotic individuals often show health-related anxiety (Weston & Jackson, 2014), literature suggests that Conscientiousness could help to transform those worries into positive health behaviors (Aziz et al., 2023; Pristyna et al., 2022; Stieger et al., 2020). Another study found that low levels of Extraversion and Agreeableness were only associated with a higher mortality risk when combined with low levels of Conscientiousness, suggesting that low levels of Conscientiousness negatively impact health-related behaviors (Jokela et al., 2013). Data from a longitudinal study demonstrated that individuals with higher levels of Conscientiousness were associated with a lower physical health risk, which was partly attributed to their greater perception of being active (Milad & Bogg, 2020). The researchers suggest that a greater engagement in daily activities could lead to more social, cognitive and physical stimulation which could have a multidimensional influence on health and buffer negative effects of less healthy behaviors.

Since Conscientiousness is often associated with orderliness, responsibility and self-control, which foster the planning and realization of health-related behaviors (Shanahan et al., 2014), high levels of Conscientiousness could buffer negative behavioral tendencies and reinforce positive ones. In turn, low levels of Conscientiousness could negatively impact the effect of other personality traits on health-related behaviors (Milad & Bogg, 2020; Shanahan et al., 2014). Based on these assumptions, it was suggested that high levels of Conscientiousness have a positive effect on the relationship between the other Big Five traits and the active use of fitness and nutrition apps.

The Present Study

Research indicates that mHealth apps hold great potential to make health promotion more effective and accessible (Amagai, 2022; Burke et al., 2011; Cho, 2015; ESPON, 2019; Gama & Laher, 2023; Lieneck, 2024; Sarcona et al., 2017; Standen & Rothman, 2023;Wang et al., 2024; Yerraklava et al., 2019). However, only a small amount of the population actively uses such offers, especially in the long-term (Amagai et al., 2022; Conway et al., 2015; Hershman, 2019; Krebs & Duncan, 2015; Lee et al., 2018). Simultaneously, more and more people are not able to meet recommended physical activity and nutritional guidelines, which increases the risk for obesity and non-communicable diseases (Global Nutrition Report, 2022; World Health Organization, 2020; World Health Organization 2024) and the burden on the health care system (Albrecht, 2016; Duijvestijn et al., 2023; ESPON, 2019; Gama & Laher, 2023; Lantzsch, 2022). Given the potential benefits of mHealth apps, this highlights the need for a better understanding of the reasons for use and non-use to ultimately increase long-term user rates.

In the literature, personalization of digital services has been shown to enhance user engagement and to lead to more successful health outcomes (Madeira et al., 2018; Zanker et al., 2019). To achieve successful personalization, it is therefore important to identify and characterize specific target groups (Alshawamar et al., 2022; Khwaja et al., 2021; König et al., 2018). Based on that information, mHealth apps can be tailored more effectively to different types of users and non-users and enhance the chance for sustained engagement (De Heredia et al., 2018; König et al., 2018). Prior research has demonstrated that the Big Five could provide valuable information about differences in health-related behavior (Keller & Siegrist, 2015; Pletzer et al., 2024; Prystina et al., 2022; Rhodes & Smith, 2006; Strickhouser et al., 2017; Sutin & Terracciano, 2015; Wilson & Rhodes, 2021) and the use of digital technologies (Devaraj et al., 2008; Joshi & Das, 2023; Kaptein et al., 2015; Peltonen et al., 2020; Xu et al., 2016).

These findings highlight the potential of personality traits to characterize target groups and tailor mHealth accordingly (Alshawmar et al., 2022; Avanesova et al., 2022; Aziz et al., 2023; Khwaja et al., 2021). However, given that user characteristics and preferences have been found to vary in different health contexts (Egli et al., 2011; Elavsky et al., 2017; König et al., 2018; Krebs & Duncan, 2015; Molanorouzi et al., 2015), it is needed to distinguish between different mHealth domains. Since fitness and nutrition apps seem to be the most popular health-related lifestyle apps (Pires et al., 2020), the present study has focused on investigating personality traits in relation to these two app categories. However, to date, only little is known about these relationships and the findings are inconsistent (Alshawmar et al., 2022; Aziz et al., 2023; Belmon et al., 2015; Bregenzer et al., 2017; Elavsky et al., 2017; Halko & Kientz, 2010; Lurz et al., 2024; Meixner et al., 2020).

Nevertheless, existing literature on the Big Five and overall mHealth apps, as well as on health-related and digital behavior, suggest that the Big Five could play a role in the adoption of fitness and nutrition apps (Alshawmar et al., 2022; Alqahtani et al. 2020; Avanesova et al., 2022; Aziz et al., 2023; Bregenzer et al., 2017; Chang et al., 2023; Joshi & Das, 2023; Khwaja et al., 2021; Wilson & Rhodes, 2021). Decisions regarding mHealth app use can be based on different reasons and motivational processes (Lippke & Ziegelmann, 2005; König et al., 2018; Lee et al., 2018; Schwarzer, 2008; Sniehotta & Aunger, 2010; Weinstein & Sandman, 1992). Consequently, it is important to distinguish between different types of non-users, for instance, between those who have never considered using an app before and those, who have already used an app but stopped doing so. Therefore, in the present study, a stage model approach for the behavioral adoption process of fitness and nutrition apps by König et al. (2018) was used to categorize individuals into five different motivational stages ("unengaged", "decided to act", "decided not to act", "acting", and "disengaged") and to characterize them according to their Big Five personality traits.

Research Questions and Hypotheses

The aim of this study was to gain a better understanding of personality traits in the context of fitness and nutrition app adoption. As Conscientiousness has been found to be a strong predictor for health-related behavior, it was also investigated whether Conscientiousness positively influences the effect of other traits on the active use of fitness and nutrition apps. The present study therefore aimed to address the following research questions and hypotheses:

RQ_1: Do individuals in different behavioral stages of mHealth app adoption show different levels of the Big Five personality traits?

H_{1a}: *Individuals in different behavioral stages of fitness app adoption differ in terms of the Big Five personality traits.*

H_{1b}: *Individuals in different behavioral stages of nutrition app adoption differ in terms of the Big Five personality traits.*

RQ$_2$: Does Conscientiousness play a moderating role in the relationship between the other Big Five personality traits and active mHealth app use?

H$_{2a}$: *Conscientiousness positively moderates the relationship between the other Big Five personality traits and the "acting" stage of fitness app adoption.*

H$_{2b}$: *Conscientiousness positively moderates the relationship between the other Big Five personality traits and the "acting" stage of nutrition app adoption.*

Method

The present thesis was preregistered before the analysis of the data was carried out. Deviations from the preregistration will be mentioned in the respective sections. The preregistration, materials, data and analysis scripts of this thesis are stored in the internal study database of the Department of Health Psychology.

Ethical Considerations

The study was authorized by the ethics committee of the University of Vienna on the 3 May of 2024.

Study Design

The study was part of a cross-sectional digital health online survey (König et al., 2024), which also served as a basis for several master's theses. The study had a between-subject design in a representative sample from Germany and Austria (N = 1,510). The survey was designed and performed on the digital platform *Unipark* (Tivian XI GmbH, 2021) and the data collection was conducted in May 2024.

Procedure

Before participants were able to participate in the survey, they were informed about the purpose and procedure of the study. Only if they had provided informed consent by ticking a box, they were presented with the questionnaires of the digital health study. After the assessment of sociodemographic data and personality traits, they were asked to indicate which digital devices they currently own. Only individuals who indicated that their current country of residence was Germany or Austria were able to participate in this study. Additionally, only those who indicated a current ownership of a smartphone were presented with the measures for behavioral stages of fitness and nutrition app adoption and thus included in this study. The survey included three attention check items ("Select „*disagree strongly* ", "If you are reading this sentence, please select *I disagree strongly*", "Please select *very true of me* as your answer to this question"). Participants who failed two of the attention check items, dropouts or those who did not want to provide an answer, were screened out and replaced.

Sample

The digital health survey included an initial sample of N = 1,510 individuals. Participants were recruited by the panel provider of the market research institute Bilendi and financially compensated after they have successfully completed the survey. To ensure population representativeness across Germany and Austria, participants were stratified by gender, age and education levels prior to data collection (see Appendix A) and recruited accordingly. The sample size was determined to detect Pearson correlations of r =.07 (two-sided) with 80% statistical power, calculated using G*Power 3.1 (Faul et al., 2009) and was partly based on available funding.

As the collection of the data was conducted online, a digital device was required to participate in the study. Further, participants needed to be at least 18 years old, live in Germany or Austria, and be sufficiently fluent in German to complete the survey. For the present study, individuals also needed to indicate the ownership of a smartphone. Those without a smartphone (n = 75) did not fulfill the eligible criteria and were not presented with the measures for fitness and nutrition app adoption. Additionally, an analysis of outliers was conducted, followed by a detailed examination of these cases. Seven cases with indication of response biases were identified and removed (participant ID code *lfdn*: 1708, 111, 835, 376, 1167, 452, 689).

The final sample of the present study consisted of N = 1,428 participants. The mean age was 48.18 years (SD = 16.62) in an age range between 18 and 83, with 66.53% (n = 950) residing in Germany and 33.47% (n = 478) in Austria. Regarding the gender distribution of the sample, 50.07% (n = 715) identified themselves as female, 49.65% (n = 709) as male, and 0.28% (n = 4) as gender diverse. The average years of education among participants were 14.18 (SD = 2.69). Baseline characteristics of the sample are presented in Table 1.

Table 1

Baseline Characteristics of the Sample

Baseline Characteristics	*M* (*Mdn*)	*SD*	*n*	%
Age	48.18	16.62	-	-
Years of Education	14.18	2.69	-	-
Big Five				
Extraversion	3.10 (3)	0.92	-	-
Agreeableness	3.12 (3)	0.74	-	-
Conscientiousness	3.70 (3.5)	0.78	-	-
Neuroticism	2.83 (3)	0.93	-	-
Openness	3.31 (3.5)	0.95	-	-
Gender				
Female	-	-	715	50.07
Male	-	-	709	49.65
Gender Diverse	-	-	4	0.28
Country of Residence				
Germany	-	-	950	66.53
Austria	-	-	478	33.47
Behavioral Stages of Fitness App Adoption				
Stage 1 “unengaged”	-	-	586	41.04
Stage 2 “decided to act”	-	-	167	11.69
Stage 3 “decided not to act”	-	-	98	6.86
Stage 4 “acting”	-	-	383	26.82
Stage 5 “disengaged”	-	-	194	13.59
Behavioral Stages of Nutrition App Adoption				
Stage 1 “unengaged”	-	-	903	63.24
Stage 2 “decided to act”	-	-	141	9.87
Stage 3 “decided not to act”	-	-	123	8.61
Stage 4 “acting”	-	-	96	6.72
Stage 5 “disengaged”	-	-	165	11.55

Note. The total sample size was $N = 1{,}428$.

Measures

All materials used in this study are provided in Appendix D.

Big Five Personality Traits

The Big Five personality traits were the outcome variables of interest. Each personality trait (Extraversion, Agreeableness, Conscientiousness, Neuroticism and Openness) was analyzed separately as a single outcome variable. The Big Five were assessed with two items for each dimension via the German form of the Big Five Inventory-10 (BFI-10) and scored accordingly (Rammstedt & John, 2007). Acceptable reliability and validity for the BFI-10 was demonstrated by Rammstedt and John (2007).

Other than preregistered, internal consistency and reliability of the BFI-10 were analyzed using Spearman-Brown coefficients instead of Pearson correlations, as this is the recommended choice for two-items scales, particularly if the data is not normally distributed (Eisinga et al., 2013).

The items were measured with a 5-point Likert scale, ranging from “I agree completely” to “I do not agree at all”. Each of the dimensions is measured by one positively and one negatively polarized item. The negatively polarized items were first recoded (items 1, 3, 4, 5 and 7) and then the mean value for each dimension was calculated from the recoded and non-recoded item. The final scores could range from 1 to 5, whereas higher values indicated higher levels in the respective personality trait.

Extraversion ($\rho = .69$) was measured using the items "I see myself as someone who is outgoing, sociable" and "I see myself as someone who is reserved" (reversed), Agreeableness ($\rho = .18$) with "I see myself as someone who is generally trusting" and "I see myself as someone who tends to find fault with others" (reversed), Conscientiousness ($\rho = .46$) with the items "I see myself as someone who does a thorough job" and "I see myself as someone who tends to be lazy" (reversed), Neuroticism ($\rho = .65$) with "I see myself as someone who gets nervous easily" and "I see myself as someone who is relaxed, handles stress well" (reversed) and Openness ($\rho = .54$) with "I see myself as someone who has an active imagination" and "I see myself as someone who has few artistic interests" (reversed).

Reliability estimates were compared to the results from Rammstedt et al. (2012) who evaluated the retest reliability of the BFI-10 over a time interval of six to eight weeks in a representative German sample. Overall, the reliability estimates in the present sample, except for Agreeableness, were similar to those from Rammstedt et al. (2012) and considered acceptable.

Participants scored lowest on Neuroticism (M = 2.82, SD = 0.92) and highest on Conscientiousness (M = 3.70, SD = 0.78), indicating that the sample was, on average, relatively conscientious and emotionally stable. Means, medians and standard deviations for all Big Five traits are presented in Table 1.

Ownership of Digital Devices

Participants were asked to indicate whether they owned one or more of the following devices: smartphone, cellphone, tablet, digital console ("yes" or "no").

Behavioral Stages of Fitness App Adoption

Behavioral stages of fitness app adoption were the predictor variables of interest for H_{1a}, measured via a stage model approach for the behavioral adoption of fitness apps based on König et al. (2018). To determine the individuals' current stage of fitness app adoption, they were presented with five different statements and asked to select the statement they agree with the most. Each response represents a different stage in the adoption process of a fitness app: stage 1) "I've never thought about using a fitness tracker or fitness app" ("unengaged" non-user), stage 2) "I have already planned to use a fitness tracker or fitness app, but haven't done so yet" (non-user that has "decided to act"), stage 3) "I have already thought about using a fitness tracker or fitness app, but it is not necessary for me to do so" (non-user that has "decided not to act"), stage 4) "I currently use a fitness tracker or fitness app and plan to use it in the future" ("acting" user), stage 5) "I have used a fitness tracker or fitness app before, but I no longer do so" ("disengaged" non-user). If participants currently use or previously used a fitness app or tracker, they were asked to indicate the name.

At the time of data collection, approximately one quarter of the sample (26.82%, n = 383) indicated to currently use a fitness app or tracker and were therefore categorized as "acting" users (stage 4). Most of the individuals, however, were categorized as "unengaged" non-users (stage 1) (41.04%, n = 586). Detailed frequency distributions for behavioral stages of fitness app adoption are presented in Table 1.

Behavioral Stages of Nutrition App Adoption

Behavioral stages of nutrition app adoption were the predictor variables of interest of H_{1b}, measured via a stage model approach for the behavioral adoption of nutrition apps based on König et al. (2018). To determine the individuals' current stage of nutrition app adoption, they were presented with five different statements. Participants were asked to select the statement they agree with the most. Each response represents a different stage in the adoption process of a nutrition app: stage 1) “I've never thought about using a nutrition app” (“unengaged” non-user), stage 2) “I have already planned to use a nutrition app, but haven't done so yet” (non-user that has “decided to act”), stage 3) “I have already thought about using a nutrition app, but it is not necessary for me to do so” (non-user that has “decided not to act”), stage 4) “I currently use a nutrition app and plan to use it in the future” (“acting” user), stage 5) “I have used a nutrition app before, but I no longer do so” (“disengaged” non-user). If participants currently use or previously used a nutrition app, they were asked to indicate the name.

Across all stages of nutrition app adoption, “acting” users (stage 4) were the least represented group. Only 6.72% (n = 96) indicated that they were currently using a nutrition app, while the majority of the sample (63.24%, n = 903) were categorized as “unengaged” non-users (stage 1). Detailed frequency distributions for all behavioral stages of nutrition app adoption are presented in Table 1.

Sociodemographic Variables

Participants indicated age, gender and country of residence. Additionally, participants indicated their highest level of school leaving qualification and educational qualification, which were then converted into years of attended education. The sum of years of school and vocational education was then calculated as the new variable “years of education”. Other than preregistered, sociodemographic descriptives of the behavioral stages of fitness and nutrition apps are also reported in this thesis and presented below. As the differences observed in the sample only refer to a descriptive analysis, it should be noted that they are not statistically confirmed. For a detailed sociodemographic description for all stages of fitness and nutrition app adoption see Table 2 and Table 3.

Age

Due to the broad age variability within the sample, the standard deviations are relatively high. Consequently, means should be interpreted with caution. Nonetheless, an overall age trend between the groups was observed. For fitness apps, the youngest participants across the stages of fitness app adoption were “disengaged” non-users (M = 42.32, SD = 16.07), while “unengaged” non-users showed the highest mean age (M = 53.54, SD = 15.67). For nutrition apps, the youngest participants were “acting” users (M = 40.14, SD = 14.99) and “disengaged” non-users (M = 39.14, SD = 15.66), while the oldest participants were “unengaged” non-users (M = 52.36, SD = 15.62).

Gender

Overall, no substantial gender differences for men and women were observed between the stages of fitness and nutrition app adoption. However, slightly more men compared to women were categorized as "unengaged" non-users for fitness and nutrition apps, while more women than men were represented among "disengaged" non-users.

Years of Education

For fitness apps, "acting" users showed higher educational attainment than non-users (M = 14.79, SD = 2.57), whereas "disengaged" non-users demonstrated the lowest mean for years of education in that app category (M = 13.81, SD = 2.70). For nutrition apps, "acting" users (M = 14.75, SD = 2.61) showed a slightly higher mean for years of education than individuals from the other stages, while "unengaged" non-users (M = 14.09, SD = 2.67) showed the lowest mean.

Table 2

Sociodemographic Descriptives for Behavioral Stages of Fitness App Adoption

Behavioral Stages of Fitness App Adoption	Age	YoE	Gender[a]			Country of Residence[b]	
			f	m	d	Germany	Austria
	M (SD)	*M (SD)*	% (*n*)	% (*n*)	% (*n*)	% (*n*)	% (*n*)
Stage 1 “unengaged”	53.54 (15.67)	13.81 (2.70)	38.74 (277)	43.30 (307)	50.0 (2)	40.84 (388)	41.42 (198)
Stage 2 “decided to act”	43.92 (15.71)	14.03 (2.73)	10.49 (75)	12.98 (92)	0.0 (0)	13.37 (127)	8.37 (40)
Stage 3 “decided not to act”	44.99 (15.35)	14.38 (2.73)	6.71 (48)	6.91 (49)	25.0 (1)	7.05 (67)	6.49 (31)
Stage 4 “acting”	45.62 (16.72)	14.79 (2.57)	27.69 (198)	26.09 (185)	0.0 (0)	27.05 (257)	26.36 (126)
Stage 5 “disengaged”	42.32 (16.07)	14.15 (2.70)	16.36 (117)	10.72 (76)	25.0 (1)	11.68 (111)	17.36 (83)

Note. YoE = Years of Education.

[a] Percentages and frequencies refer to the number of people of the respective gender and not to the whole sample. 715 people identified as female (f), 709 as male (m) and 4 respondents identified as gender diverse (d).

[b] Percentages and frequencies refer to the number of people of the respective country and not to the whole sample. In total, the sample consisted of 950 German individuals and 478 Austrian individuals.

Table 3

Sociodemographic Descriptives for Behavioral Stages Nutrition App Adoption

Behavioral Stages of Nutrition App Adoption	Age	YoE	Gender			Country of Residence	
			f	m	d	Germany	Austria
	M (SD)	*M (SD)*	*% (n)*	*% (n)*	*% (n)*	*% (n)*	*% (n)*
Stage 1 “unengaged”	52.36 (15.62)	14.09 (2.67)	60.70 (434)	66.01 (468)	25.0 (1)	61.37 (583)	66.95 (320)
Stage 2 “decided to act”	44.03 (17.55)	14.47 (2.60)	9.09 (65)	10.72 (76)	0.0 (0)	11.37 (108)	6.90 (33)
Stage 3 “decided not to act”	40.62 (14.16)	14.28 (2.85)	7.83 (56)	9.31 (66)	25.0 (1)	8.95 (85)	7.95 (38)
Stage 4 “acting”	40.14 (14.99)	14.75 (2.61)	6.99 (50)	6.35 (45)	25.0 (1)	7.16 (68)	5.86 (28)
Stage 5 “disengaged”	39.14 (15.66)	14.10 (2.81)	15.38 (110)	7.62 (76)	25.0 (1)	11.16 (106)	12.34 (59)

Note. YoE = Years of Education.

[a] Percentages and frequencies refer to the number of people of the respective gender and not to the whole sample. 715 people identified as female (f), 709 as male (m) and 4 respondents identified as gender diverse (d).

[b] Percentages and frequencies refer to the number of people of the respective country and not to the whole sample. In total, the sample consisted of 950 German individuals and 478 Austrian individuals.

Analytical strategy

The analysis was focused on examining differences in the Big Five personality traits across the behavioral stages of fitness and nutrition app adoption. Additionally, it was tested whether Conscientiousness positively moderates the relationship between the other Big Five traits and active app use ("acting" users, stage 4). Analyses were performed using *IBM SPSS Statistics* (Version 30.0.0) (IBM Corp., 2024).

Hypotheses H_{1a} and H_{1b}

Initially, one-way analysis of variance (ANOVA) with Tukey post-hoc tests was the preferred method to test whether the stages of fitness and nutrition app adoption differ in terms of their personality traits (H_{1a}, H_{1b}). To analyze whether all test assumptions are met by the data, Levene's tests were performed to test the condition of homogeneity of variances and Shapiro-Wilk tests to test normal distribution of the data. However, the assumptions for conducting an ANOVA were not met. For all traits, Shapiro-Wilk tests were significant ($p < .001$), indicating that trait means were not normally distributed across the sample. Further, Levene's tests demonstrated homogeneity of variances for Extraversion Agreeableness, Conscientiousness and Openness but not for Neuroticism. For nutrition apps, no homogeneity was given for Extraversion and Neuroticism, while variances for Conscientiousness, Agreeableness and Openness were normally distributed. Exact results of the assumption tests are presented below in the analysis section (see Table 4 for fitness apps and Table 5 for nutrition apps).

Normal distribution of the data was assumed due to sufficiently large sample size. However, since no normal distribution of the Big Five was given, other than preregistered, non-parametric Kruskal-Wallis ANOVA with Dunn-Bonferroni post-hoc tests were conducted for Hypotheses H_{1a} and H_{1b}. Since it was hypothesized that Big Five means will differ across the stages of nutrition and fitness app adoption, the hypotheses were tested one-tailed with a significance level of $\alpha = .05$ for each Kruskal-Wallis ANOVA. Bonferroni corrections were used in all post-hoc tests to account for multiple comparisons and to control the familywise error rate. Due to the changes in the statistical analyses, *F*, partial eta-squared and confidence intervals were not reported for the results of H_{1a} and H_{1b}. Instead, *H*, degrees of freedom, and eta-squared were reported for the results of the Kruskal-Wallis tests. Additionally, means, medians, *z*-values and *r* were reported for the Dunn-Bonferroni post-hoc tests. Given that *IBM SPSS Statistics* (Version 30.0.0) (IBM Corp., 2024) does not directly provide eta-squared and *r*, these were calculated manually based on Tomczak and Tomczak

(2014) and Walther (2024). The exact calculation of the effect sizes can be found in Appendix B.

Hypotheses H_{2a} and H_{2b}

To analyze whether Conscientiousness positively moderates the relationship between the other Big Five personality traits (Extraversion, Neuroticism, Openness, Agreeableness) and the active use of fitness and nutrition apps (H_{2a}, H_{2b}), moderation analyses using hierarchical regression analysis with an interaction term were conducted. Other than preregistered, binary logistic regressions instead of linear regressions were used to analyze the data. This was due to a more thorough understanding of the statistical model than at the time of preregistration. Since the stages of fitness and nutrition app adoption are categorial variables, they had to be dummy-coded at first (stage 1,2,3,5 = 0, stage 4 = 1) to obtain the desired outcome variable "acting" user (stage 4) for the moderation analyses. To account for the binary outcome variable, a binary logistic regression had to be used to conduct hierarchical regressions. To analyze the effect of Conscientiousness as a moderator, the variables are sequentially entered by blocks into the regression models. In the first Block, only the trait and the moderator are included in the model. Results provide the model fit and the main effect of each variable on the outcome while the other variable is held constant. The second block represents the regression model with the moderation. Therefore, not only the main effects are presented for the variables, but also the effect of the interaction of the moderator and the respective trait.

The effect of the interaction term indicates whether Conscientiousness influences the relationship between the other Big Five and the active use of a fitness or nutrition app. If the regression of the interaction term on being an "acting" user (stage 4) demonstrates statistical significance, this suggests a moderating effect of Conscientiousness on this trait. Additionally, the models from Block 1 and Block 2 can be compared to analyze whether the moderation model shows improved model fit and is able to explain more of the variance in the outcome.

Due to modifications in the moderation analysis, the preregistered parameters ΔR^2, Pearson correlations and significance regions were no longer considered to be appropriate for Hypotheses H_{2a} and H_{2b}. Instead, for the overall models, x^2, degrees of freedom, *p*-value, -2 Log Likelihood and Cox & Snell and Nagelkerke pseudo-R^2 were reported as well as x^2, degrees of freedom and *p*-value for the respective Hosmer-Lemeshow Tests. Additionally, regression coefficient *B* including standard error, *p*-value, odds ratio and 95% confidence intervals (95 CI) for the odds ratio were reported for main and interaction effects of H_{2a} and H_{2b}.

Results

Results of Hypotheses H_{1a} and H_{1b}

A Kruskal-Wallis ANOVA was conducted for each trait to analyze whether the medians of the Big Five significantly differ across the five stages of fitness and nutrition app adoption ("unengaged", "decided to act", "decided not to act", "acting", "disengaged"). The exact parameters for the results of the Kruskal-Wallis ANOVA for hypothesis H_{1a} are listed in Table 4 and for hypothesis H_{1b} in Table 5. For significant traits, Dunn-Bonferroni post-hoc tests were conducted (see Figure 2 and Figure 3 for hypothesis H_{1a} and Figure 4 for hypothesis H_{1b}).

Median Differences in the Big Five across Stages of Fitness App Adoption (H_{1a})

For behavioral stages of fitness app adoption, it was assumed that individuals would differ in terms of their levels in the Big Five. This was not confirmed for Extraversion and Agreeableness, since no significant differences in medians across the stages were found. Also, contrary to previous assumptions, participants did not significantly differ in their Conscientiousness levels at the different stages of fitness app adoption. However, the Hypothesis was partially supported, with a significant omnibus test for Neuroticism (p = .003, $\eta^2 < .01$) and Openness (p = .003, $\eta^2 < .01$). For all traits, detailed parameters for the Kruskal-Wallis ANOVA are presented in Table 4.

Table 4

Results of the Kruskal-Wallis ANOVA for the Big Five and Fitness App Adoption

Big Five Traits	Shapiro-Wilk Test	Levene's Test	Kruskal-Wallis ANOVA			
	p	p	H^a	df	p	η^2
Extraversion	<.001***	.139	4.08	4	.395	< .01
Agreeableness	<.001***	.504	4.37	4	.359	< .01
Conscientiousness	<.001***	.212	4.61	4	.329	< .01
Neuroticism	<.001***	.028*	15.77	4	.003**	< .01
Openness	<.001***	.418	15.79	4	.003**	< .01

[a] Test statistics were adjusted for ties.

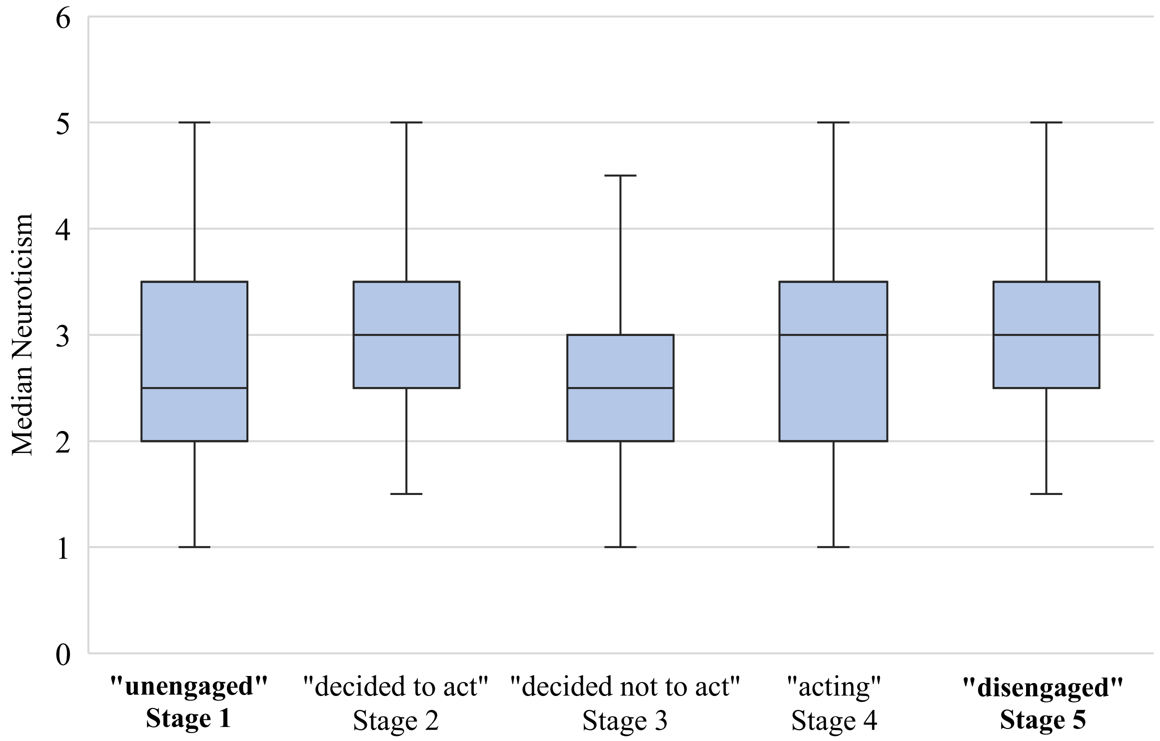
* $p < .05$; ** $p < .01$; *** $p < .001$.

Dunn-Bonferroni Post-Hoc Tests

For Neuroticism, Dunn-Bonferroni post-hoc analyses indicated significant differences between "unengaged" and the "disengaged" individuals (p = .006, r = .12). Compared to "disengaged" individuals, "unengaged" individuals showed lower Neuroticism medians (see Figure 2). For Openness, "unengaged" individuals also exhibited significantly lower Openness medians than "acting" individuals (p = .043, r = .09) and lower medians than those who have “decided to act" (p = .010, r = .12) (see Figure 3).

Figure 2

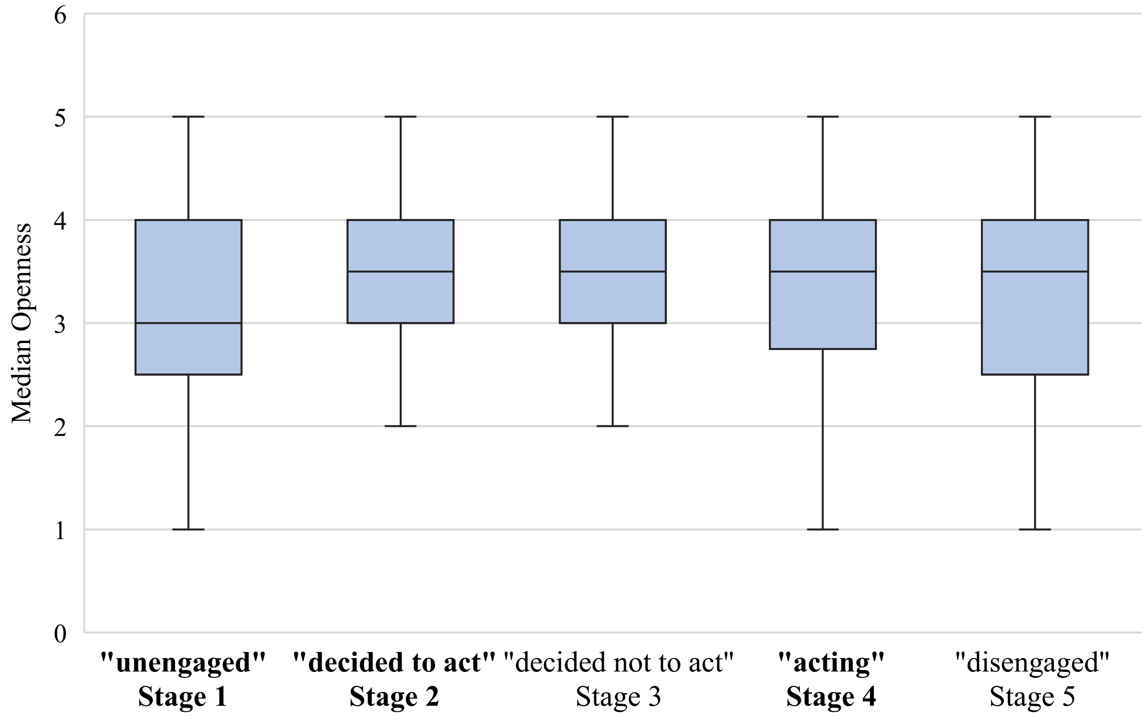
Results of Pairwise Comparisons of the Stages of Fitness App Adoption for Neuroticism



Note. Boxplots for Neuroticism medians of the Dunn-Bonferroni post-hoc tests for the behavioral stages of fitness app adoption. Stage 1 (*Mdn* = 2.5) differed significantly from Stage 5 (*Mdn* = 3.5, z = -3.44).

Figure 3

Results of Pairwise Comparisons of the Stages of Fitness App Adoption for Openness



Note. Boxplots for Openness medians of the Dunn-Bonferroni post-hoc tests for the behavioral stages of fitness app adoption. Stage 1 (*Mdn* = 3.0) differed significantly from Stage 2 (*Mdn* = 3.5, z = -3.30) and Stage 4 (*Mdn* = 3.5, z = -2.86).

Median Differences in the Big Five across Stages of Nutrition App Adoption (H_{1b})

For behavioral stages of nutrition app adoption, it was assumed that individuals would differ in terms of their levels in the Big Five. However, the results demonstrated no significant differences in medians for Extraversion and Agreeableness across the stages. Although significant effects were found for Conscientiousness (p = .002) and Openness (p = .017), Dunn-Bonferroni post-hoc tests could not detect any significant differences in Conscientiousness and Openness medians between the stages. For Neuroticism, however, significant differences were found for the omnibus test ($p < .001$, $\eta^2 = .02$) as well as in the post-hoc tests. For all traits, detailed parameters for the Kruskal-Wallis ANOVA are presented in Table 5.

Table 5

Results of the Kruskal-Wallis ANOVA for the Big Five and Nutrition App Adoption

Big Five Traits	Shapiro-Wilk Test	Levene's Test	Kruskal-Wallis ANOVA			
	p	*p*	H^a	df	*p*	η^2
Extraversion	<.001***	.006**	0.35	4	.987	<.01
Agreeableness	<.001***	.057	1.87	4	.759	<.01
Conscientiousness	<.001***	.154	17.50	4	.002**	<.01
Neuroticism	<.001***	<.001***	29.26	4	<.001***	.02
Openness	<.001***	.552	12.06	4	.017*	<.01

[a] Test statistics were adjusted for ties.

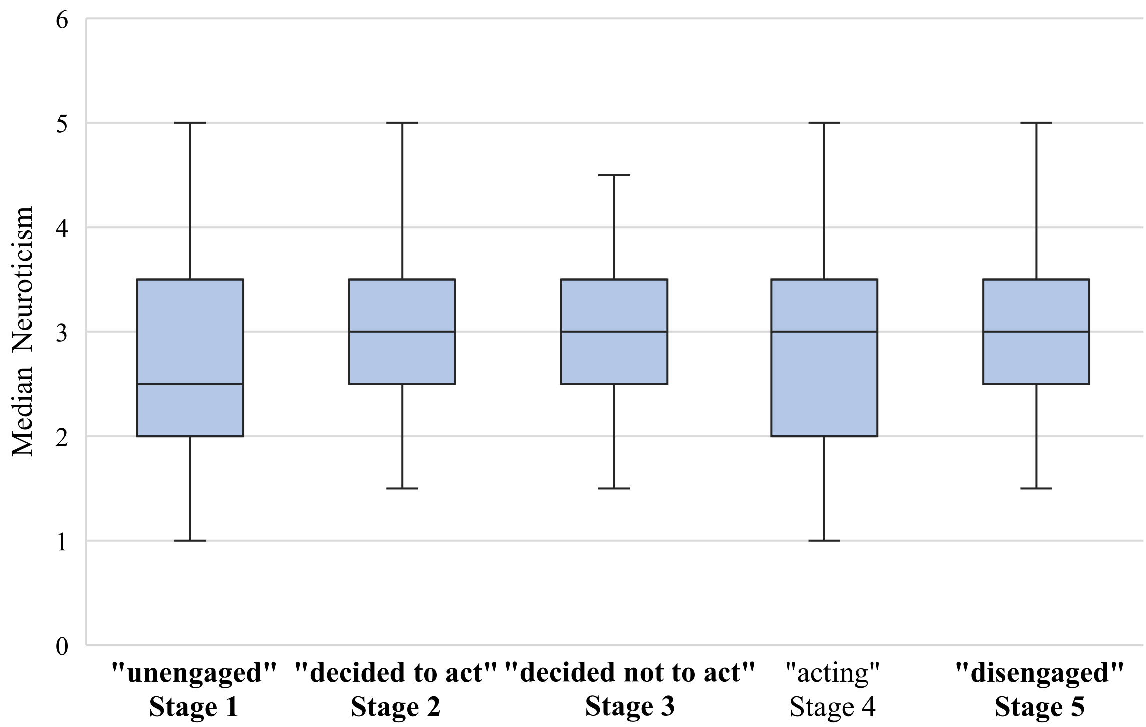
* $p < .05$; ** $p < .01$; *** $p < .001$.

Dunn-Bonferroni Post-Hoc Tests

Among all five stages, "unengaged" individuals demonstrated the lowest Neuroticism scores. Dunn-Bonferroni post-hoc tests demonstrated that “unengaged” participants significantly differed from "disengaged" participants (p = .001, r =.12), participants that have “decided to act" (p = .002, r = .11) and participants that have "decided not to act" (p = .039, r = .09) (see Figure 4).

Figure 4

Results of Pairwise Comparisons of the Stages of Nutrition App Adoption for Neuroticism



Note. Boxplots for Neuroticism medians of the Dunn-Bonferroni post-hoc tests for the behavioral stages of nutrition app adoption. Stage 1 (*Mdn* = 2.5) differed significantly from Stage 2 (*Mdn* = 3.0, z = -3.68), Stage 3 (*Mdn* = 3.0, z = -2.88) and Stage 5 (*Mdn* = 3.0, z = -3.87).

Results of Hypotheses H_{2a} and H_{2b}

To test whether Conscientiousness positively moderates the relationship between the Big Five traits and the active use of fitness and nutrition apps, moderation analyses using hierarchical binary logistic regressions with an interaction term were conducted. The assumptions for conducting a binary logistic regression were tested before (see Table 6). The exact parameters for the results of hypothesis H_{2a} are listed in Table 7 and Table 8. Table 9 and Table 10 report the parameters for hypothesis H_{2b}.

Testing of Assumptions

For all traits, linearity between predictor and the respective logit function on the outcome variables were given, except for Agreeableness on stage 4 of fitness app adoption (p = .032) and Extraversion on stage 4 for nutrition app adoption (p = .046). To address the violations of linearity, Agreeableness and Extraversion were log-transformed before calculating the respective moderation analysis. Further, Variance Inflation Factors (VIF) were < 10, indicating no severe multicollinearity between the predictors. However, to ensure an improved interpretation of the results, all traits were centered before the analysis. Cook's Distance values for all observations were below the threshold of 1 (min = 0.00, max = .006 for fitness apps; min = 0.00, max = 0.03 for nutrition apps) suggesting no influential outliers and therefore met the assumptions. The exact parameters for the analysis of test assumptions for each trait are presented below.

Table 6

Results of the Analysis of Test Assumptions for Binary Logistic Regression

Big Five	VIF[a]	Linearity (Fitness App, *p*)[b]	Linearity (Nutrition App, *p*)[b]
Extraversion	1.16	.931	.046*
Agreeableness	1.04	.032*	.90
Conscientiousness	1.13	.917	.433
Neuroticism	1.16	.878	.072
Openness	1.05	.551	.998

[a] VIF values are reported for the centered variables of all traits.

[b] Effect of the interaction term of the log-transformed trait and respective trait on stage 4 of fitness/ nutrition app adoption.

* $p < .05$.

Moderation Analysis for the Effect of Conscientiousness on the Big Five and the Active Use of Fitness Apps (H_{2a})

Model Fit

For fitness app adoption, all models of the omnibus tests indicated similar model fit, with -2 Log-Likelihood values ranging from 1,655.01 to 1,660.45. However, -2 Log-Likelihood values were comparable to those from Block 1, suggesting no improvement of model fit for the moderation models. Further, for all models, Cox & Snell pseudo-R^2 and Nagelkerke pseudo-R^2 were <.01, suggesting a negligible effect of these traits. Hosmer-Lemeshow test were not significant across all models *(p* > .05) indicating an adequate model fit. For exact parameters of the overall models for Block 1 and Block 2, see Table 7.

Table 7

Model Coefficients for Block 1 and Block 2 of the Hierarchical Binary Logistic Regression with Conscientiousness as a Moderator (Fitness Apps)

Big Five	x^2(df), p	-2*LL*	Pseudo-R^2		Hosmer-Lemeshow Test
			Cox & Snell	Nagelkerke	x^2 (df), p
Block 1					
Extraversion	5.83(2), .747	1,660.09	<.001	.001	5.84(8), .665
Agreeableness	3.73(2), .155	1,655.94	.003	.004	8.38(8), .397
Neuroticism	2.16(2), .898	1,660.45	<.001	<.001	4.07(8), .851
Openness	1.61(2), .446	1,656.06	.001	.002	9.98(8), .266
Block 2					
Extraversion	3.61(3), .306	1,657.05	.003	.004	4.56(8), .803
Agreeableness	5.67(3), .129	1,655.01	.004	.006	2.31(8), .913
Neuroticism	0.28(3), .973	1,660.45	<.001	<.001	4.16(8), .843
Openness	4.30(3), .230	1,656.37	.003	.004	6.98(8), .539

Main Effects

The main effects of the Big Five traits and the moderator Conscientiousness on the likelihood of being an “acting” user of fitness apps were not significant for all regressions in Block 2, although the main effect of Agreeableness approached significance (p = .055) with an odds ratio of 1.59 and B = 1.07 (SE = 0.56).

Interaction Effects

For all traits, the interaction effects between Extraversion, Agreeableness, Neuroticism and Openness and the moderator on stage 4 were not significant. The odds ratios for all interaction effects ranged between 0.38 and 1.01, indicating that Conscientiousness does not add to a change in odds of being an “acting” user of fitness apps. This suggests that Conscientiousness has no moderating effect on the other Big Five traits and the active use of fitness apps. Detailed parameters for the main and interaction effects for each trait are presented in Table 8.

Table 8

Results for Binary Logistic Regressions with Conscientiousness as a Moderator (Fitness App Adoption)

Big Five	*B* (SE)	*p*	Exp(*B*)	95 CI Exp(*B*) [LL, UL]
Extraversion (E)				
Main Effect E	0.06 (0.07)	.407	1.06	[0.93, 1.20]
Main Effect C	-.001 (0.08)	.990	0.99	[0.86, 1.17]
Interaction ExC	-0.98 (0.06)	.084	0.88	[0.75, 1.02]
Agreeableness (A)				
Main Effect A	1.07 (0.56)	.055	1.59	[0.98, 8.73]
Main Effect C	0.47 (0.35)	.188	1.60	[0.80, 3.20]
Interaction AxC	-0.97 (0.70)	.167	0.38	[0.71, 1.50]
Neuroticism (N)				
Main Effect N	0.03 (0.08)	.653	1.03	[0.90, 1.17]
Main Effect C	0.02 (0.07)	.827	1.01	[0.87, 1.19]
Interaction NxC	.008 (0.08)	.917	1.01	[0.86, 1.18]
Openness (O)				
Main Effect O	0.09 (0.06)	.166	1.09	[0.96, 1.24]
Main Effect C	0.001 (0.08)	.994	1.00	[0.86, 1.17]
Interaction OxC	-0.13 (0.08)	.103	0.88	[0.76, 1.03]

Note. All parameters refer to model coefficients for Block 2 (model with interaction term).
[a] Conscientiousness (C).

Moderation Analysis for the Effect of Conscientiousness on the Big Five and the Active Use of Nutrition Apps (H_{2b})

Model Fit

Similar to fitness app adoption, the models for the omnibus tests exhibited comparable -2 Log-Likelihood values to those from Block 1, indicating no substantial improvement in model fit. Among all traits, only the model for Openness demonstrated significance [x^2 = 8.49(3), p = .037]. Further, Cox & Snell as well as Nagelkerke pseudo-R^2values across all traits were small (<.05), indicating that the traits only explained a small proportion of the variance. Non-significant Hosmer-Lemeshow tests across all traits demonstrated an adequate model fit. Exact parameters for the models of Block 1 and Block 2 are presented in Table 9.

Table 9

Model Coefficients for Block 1 and Block 2 of the Hierarchical Binary Logistic Regression with Conscientiousness as a Moderator (Nutrition Apps)

Big Five	x^2(df), *p*	-2*LL*	Pseudo-R^2		Hosmer-Lemeshow Test
			Cox & Snell	Nagelkerke	x^2 (df), *p*
Block 1					
Extraversion	1.93(2), .379	701.80	.001	.003	5.56(8), .697
Agreeableness	2.65(2), .266	701.10	.002	.005	0.96(8), .998
Neuroticism	1.57(2), .453	702.15	.001	.003	7.67(8), .467
Openness	8.28(2), .016*	695.46	.006	.015	6.52(8), .590
Block 2					
Extraversion	2.53(3), .443	701.21	.002	.005	4.94(8), .765
Agreeableness	6.72(3), .081	697.01	.005	.012	5.03(8), .754
Neuroticism	1.76(3), .623	701.97	.001	.003	6.20(8), .625
Openness	8.49(3), .037*	695.24	.006	.015	9.03(8), .339

* $p < .05$.

Main Effects

The main effects of the Big Five traits Extraversion, Agreeableness, Neuroticism and the main effects of Conscientiousness were not significant. However, Openness showed a significant main effect with an odds ratio of 1.35 ($B = 0.30$, $SE = 0.12$). This indicates that higher levels of Openness are associated with an increased likelihood of being an “acting” user of nutrition apps while the effect of Conscientiousness and the interaction is held constant.

Interaction Effects

The interaction effects for Extraversion and Neuroticism on stage 4 for of nutrition app adoption were not significant. For these traits, Conscientiousness does not significantly change the odds of being an “acting” user of nutrition apps. Additionally, while the main effect of Openness was significant, no significant effect of the interaction term was found.

This indicates that Openness enhances the likelihood of being an "acting" user of nutrition apps, regardless of the levels of Conscientiousness. Further, the interaction effect of Agreeableness and Conscientiousness demonstrated statistical significance, indicating that for agreeable people, higher Conscientiousness increases the likelihood of being an „acting" user of nutrition apps [Exp(*B*) = 1.40, *B* = 0.34, *SE* = 0.12]. However, it should be kept in mind that the model for Agreeableness in Block 2 was not significant and pseudo-R^2 were low.

The exact parameters for the main and interaction effects for each trait are presented in Table 10.

Table 10

Results for Binary Logistic Regressions with Conscientiousness as a Moderator (Nutrition App Adoption)

Big Five	*B* (SE)	*p*	Exp(*B*)	95 CI Exp(*B*) [LL, UL]
Extraversion (E)				
Main Effect E	0.34 (0.75)	.651	1.13	[0.32, 6.18]
Main Effect C[a]	0.13 (0.44)	.768	0.83	[0.48, 2.68]
Interaction ExC	-0.67(0.87)	.446	0.86	[0.09, 2.83]
Agreeableness (A)				
Main Effect A	0.17 (0.15)	.248	1.18	[0.89, 1.58|
Main Effect C	-0.23 (0.14)	.101	0.79	[0.60, 1.05]
Interaction AxC	0.34 (0.12)	.039*	1.40	[1.02, 1.94]
Neuroticism (N)				
Main Effect N	-0.01 (0.02)	.918	0.98	[0.78, 1.25]
Main Effect C	-0.17 (0.14)	.212	0.84	[0.64, 1.10]
Interaction NxC	-0.06 (0.12)	.674	0.94	[0.72, 1.24]
Openness (O)				
Main Effect O	0.30 (0.12)	.010*	1.35	[1.08, 1.67]
Main Effect C	-0.24 (0.14)	.086	0.78	[0.60, 1.04]
Interaction OxC	0.64 (0.13)	.635	1.06	[0.82, 1.39]

Note. All parameters refer to model coefficients for Block 2 (model with interaction term).

[a] Conscientiousness (C).

* *p* < .05.

Discussion

The overall purpose of the present study was to gain a better understanding of psychological characteristics of mHealth app users and non-users. Using a stage model approach based on König et al. (2018), this study investigated the relationship between the Big Five and different behavioral stages of fitness and nutrition app adoption.

As mentioned before, literature on the link between personality traits and mHealth apps is limited. Particularly for fitness and nutrition apps, not many studies have yet investigated this relationship, with the studies differing in their design, sample and outcomes (Alshawmar et al., 2022; Aziz et al., 2023; Belmon et al., 2015; Bregenzer et al., 2017; Elavsky et al., 2017; Halko & Kientz, 2010; Lurz et al., 2024; Meixner et al., 2020). Additionally, previous studies have often used a binary categorization of users vs. non-users, while, to the best of my knowledge, no study has ever before used stage models to categorize non-users more specifically while examining their relationship with the Big Five. However, findings of a large body of research on the Big Five and the use of technologies, health-related behaviors and mHealth apps led to the assumption that certain personality traits would differ across the behavioral stages of fitness app adoption (H_{1a}) and nutrition app adoption (H_{1b}). Further, it was hypothesized that Conscientiousness positively influences the effect of the other Big Five traits on the active use of fitness apps (H_{2a}) and nutrition apps (H_{2b}). The results of the present study could partially support the hypotheses and will be discussed below.

General Engagement of the Sample with mHealth Apps

In the current sample, for both, fitness and nutrition apps, only a few people were categorized as “acting” users while the majority of the participants were identified as “unengaged” non-users (see Table 1). This aligns with the current body of research that indicates that only a small proportion of the population actively uses mHealth apps. Another large part of the sample was categorized as “disengaged” non-users (see Table 1), which highlights the challenge of long-term use after downloading an app in the mHealth domain (Amagai et al., 2022; Conway et al., 2015; Krebs & Duncan, 2015; Lee et al., 2018).

Further, descriptive analyses of the sample have shown that active users of both, fitness and nutrition apps, were on average younger and indicated higher years of education compared to individuals of the “unengaged” group (see Table 2 and Table 3). This is in line with previous literature which reports that users from mHealth apps tend to be younger and more educated (König et al., 2018; Krebs & Duncan, 2015; Su et al., 2020). In turn, previous literature has often only differentiated between users and non-users, which might have led to the assumption that all non-users were on average older and show lower levels of education.

However, in the sample of the present study not only “acting” users (stage 4), but also non-users from stage 2,3 and 5 were younger than the “unengaged” non-users (stage 1). This suggests that non-users should not be generalized and highlights the strength of stage model approaches for investigating non-users, since, at least in the present study, descriptive analysis revealed that only "unengaged" individuals tend to be older.

Previous findings indicated that elderly people show less interest in new technologies or show concerns about data security (Fox, 2004). Additionally, they often lack digital literacy, which refers to the ability to understand digital information and use digital devices (Vercruyssen et al., 2023) and are therefore less likely to engage with new technologies (Fox, 2004; Vercruyssen et al., 2023). This might explain why especially older people have never considered using mHealth apps before and are thus overrepresented among "unengaged" non-users. This could provide new insightful information to characterize different subgroups more precisely in the future.

Conscientiousness

Other than expected, neither Conscientiousness was significantly associated with the active use of fitness and nutrition apps, nor did Conscientious levels differ across the stages for both app categories. While Conscientiousness demonstrated statistical significance in the Kruskal-Wallis ANOVA for nutrition apps (see Table 5), subsequent post-hoc tests were not able to find any significant pairwise comparisons under the Bonferroni correction for multiple tests. Further, although Conscientiousness moderated the effect of Agreeableness on the active use of nutrition apps (see Table 10), no moderation effect was found for the other traits, with a non-significant overall model for Agreeableness and low pseudo-R^2, indicating a very small effect (see Table 9).

This finding was opposed to prior research which has demonstrated that Conscientiousness is clearly linked to positive health-behaviors (Keller & Siegrist, 2015; Mõttus et al., 2013; Müller, 2023; Pletzer et al., 2024; Pristyna et al., 2022; Strickhouser et al., 2017). Moreover, conscientious individuals tend to be more aware of the benefits of an active lifestyle (Rhodes & Pfaeffli, 2012) and therefore prioritize engaging in sustained healthy behaviors (Müller et al., 2023). However, while it might be possible that Conscientiousness is not associated with a greater willingness to use fitness or nutrition apps, there are several explanations for the results of the present study.

One possible explanation for the non-significant results could be that age moderates the effect of Conscientiousness. As mentioned before, literature indicates that older people are less likely to engage in mHealth app and technology use in general (Fox, 2004; König et al., 2018; Krebs & Duncan, 2015; Su et al., 2020; Vercruyssen et al., 2023). Although the sample of the present study (*M* = 48.18, *SD* = 16.62) does not show an overall high mean age, it had a broad age range, including individuals from middle to late adulthood. In contrast, previous studies which found a positive association between Conscientiousness and physical health apps often involved younger participants. For instance, findings which have shown a positive relationship between Conscientiousness and the perceived use of fitness apps, was conducted within a sample predominantly consisting of young adults between 18 to 34 years (Alshawmar et al., 2022). Another study by Aziz et al. (2023) found that Conscientiousness was a determinant factor for the frequent launching of physical health apps, with half of the sample consisting of individuals between 15 and 24 years. In turn, a study that included a sample with a higher mean age (*M* = 59.23, *SD* = 9.05) did not find a relationship between Conscientiousness and the active use of a self-management mHealth app (Su et al., 2020). Since younger individuals show higher levels of digital literacy (Vercruyssen et al., 2023), Conscientiousness could be more relevant in that age group for mHealth use. This would be supported by Svendsen et al. (2011), who argue that personality traits might not be directly linked to the intention to use technologies, but through the effect of a trait on perceived use, ease of use and social norms. Thus, despite high Conscientiousness levels, older individuals might not consider mHealth as a possible way to manage their health due to a lack of digital skills or interest in technologies.

Another reason could be a mismatch between app design and preferences of conscientious individuals. Conscientiousness was positively associated with a preference for structured approaches in the context of a mental health apps, favoring journaling and audio-based interventions while less conscientious individuals showed greater interest in interventions using game and video formats (Khwaja et al., 2021). However, since many fitness apps incorporate gamification elements (Meixner et al., 2020), this might not always appeal to them. Additionally, conscientious individuals are characterized by being self-disciplined and organized by nature (McCrae & Costa, 1987) which could make it easier for them to stick to healthy routines, such as a healthy diet (Keller & Siegrist, 2015) and to adhere to medical recommendations (Hill & Roberts, 2011). Thus, contentious individuals might not feel the need to use an app to manage their health, and especially older people when their digital skills are limited.

While Conscientiousness was shown to be an important factor for healthy behaviors in general, it should be considered whether other factors might have a greater impact on mHealth app use. Some findings indicate that the positive effect of Conscientiousness on health outcomes could be mediated by socioeconomic attainment (Shanahan et al., 2014). For instance, individuals with high levels of Conscientiousness are more likely to show higher educational attainment, a higher income and greater wealth (Poropat, 2009; Boyce & Wood, 2011), which strongly influences the prevention and treatment of health problems (Phelan et al., 2010). Further, education was also shown to be associated with knowledge about health-related technological progress (Glied & Lleras-Muney, 2008), which therefore makes it more likely for more educated people to be aware of mHealth offers and its benefits. This aligns with findings that users of mHealth apps are, on average, more educated (Krebs & Duncan, 2015), indicating a possible mediating effect on Conscientiousness.

Further, other findings have also indicated that obesity was positively associated mHealth app use (Bhuyan et al., 2016; Ernsting et al., 2017; Krebs & Duncan, 2015). This could suggest that mHealth users might be more likely to use an app to achieve a certain health goal instead of maintaining their health. As conscientious individuals tend to be more likely to engage in health-related behaviors when concerns arise (Stieger et al., 2020; Aziz et al., 2023), the presence of a certain health condition or specific health-goals could influence the effect of Conscientiousness on active mHealth app use.

Additionally, methodological and analytical limitations of the study could have impacted the present results. Notably, the sample demonstrated above-average levels of Conscientiousness (see Table 1) which might have caused a ceiling effect in the data. This could have happened due to an upper limit in the BFI-10 for assessing higher levels of Conscientiousness. A ceiling effect leads to less variability in the data and a reduced test sensitivity. Since this impacts statistical test estimates, it makes it harder to detect differences in Conscientiousness across the stages of mHealth adoption. Two factors might have contributed to this effect: First, the study design may have favored more conscientious individuals, as it was required to complete the whole survey to be included in the study. Thus, participants which completed the extensive survey could exhibit higher levels of Conscientiousness compared to those who did not finish and dropped out earlier.

Second, the BFI-10 (Rammstedt & John, 2007) might not have been sufficiently sensitive to differentiate among varying levels of conscientiousness. Although Rammstedt et al. (2012) considered the retest reliability of the BFI-10 acceptable, they noted that they did not meet the recommended thresholds by Aiken and Groth-Marnat (2006). In the current sample, Spearman-Brown coefficients for the BFI-10 were similar to the reliability coefficients reported by Rammstedt et al. (2012) and therefore considered as adequate for assessing the Big Five. However, when compared to the Spearman-Brown thresholds suggested by De Vet et al. (2017), classifying ρ-values between .5 and .7 as acceptable and values above .7 as good, especially Agreeableness ($\rho = .18$) and Conscientiousness ($\rho = .46$), fell below these thresholds. A lower sensitivity of the BFI-10 might also explain why none of the traits were normally distributed, which was unexpected given that a large sample size typically approaches normal distribution. Since Conscientiousness was assessed using the items "I see myself as someone who does a thorough job" and the reversed-coded item "I see myself as someone who tends to be lazy", the discriminatory power of these items could have also not been high enough. Given that laziness is viewed as a negative characteristic, many people might feel reluctant to describe themselves as such, potentially due to social desirability. Response biases might have led to higher Conscientiousness scores in the sample while low Conscientiousness scores could have been underrepresented.

Agreeableness

The results indicated that individuals of different stages of fitness app adoption do not differ in their levels of Agreeableness. This supports previous findings which could not find any significant results for the perceived usefulness of a fitness app (Alshawmar et al., 2022), the adoption of health apps in general (Huseynov, 2020; Su et al., 2020) or a relationship between Agreeableness and engagement in physical activity (Müller, 2023; Rhodes & Smith, 2006; Strickhouser et al. 2017; Wilson & Dishman, 2014). Overall, Agreeableness was not found to be correlated with health outcomes (Pletzer et al., 2023).
It is possible that Agreeableness could be less important when it comes to health-related behaviors and might be more important in the prediction of social behaviors instead (Martin-Raugh et al., 2015).

The moderation results regarding the active use of nutrition apps indicated that only Agreeableness was shown to be positively influenced by Conscientiousness (see Table 10). Given the weak association of Agreeableness with health outcomes, it could be that the positive effect of Conscientiousness on health-related behaviors has a greater impact on Agreeableness compared to other traits which are more strongly associated with health-related behavioral tendencies. Agreeable people were shown to be more likely to follow other's recommendations (Joshi & Das, 2023), including stronger adherence to health recommendations (Pletzer et al., 2023), be more conflict-averse (Xu et al., 2016), and to be more likely to conform to peer expectations (Aisyah et al., 2021). Therefore, it was suggested that Agreeable people may be more likely to engage with mHealth apps due to trends or recommendations from their social networks. Since higher levels of Agreeableness were not directly associated with active app use, Conscientiousness may also play a role in sustained app engagement, when the app is no longer popular or recommended by others, or by recognizing the benefits of health-related behaviors.

However, while the interaction term of Agreeableness and Conscientiousness was significant, the overall model for the regression model was not and pseudo-R^2 values were low, indicating small practical relevance (see Table 9). Since the model's ability to explain variance in the outcome did not significantly improve, not too much emphasis should be put on this result.

Extraversion

Similar to existing literature, the present results did not lead to a clear conclusion about Extraversion and mHealth app adoption: Fitness apps may appeal equally to individuals with high or low Extraversion levels, as no significant differences were observed across the stages of fitness adoption. While some studies suggested that extraverts might find fitness apps more appealing due to their perceived usefulness (Alshawmar et al., 2022) or higher physical activity levels (Müller et al., 2023), this might not necessarily predict the intention or the actual use of a fitness app. In line with this, other findings have shown that extraverts perceived a physical activity app as less enjoyable and useful and were also less likely to use it (Halko & Kientz, 2010). Extraverted people also seem to enjoy offline socialization and activities (Cieślik et al., 2023; Hayat et al., 2023; Ross et al., 2009) while introverts have been shown to prefer participating in individual activities (Xu et al., 2016; Wilson & Rhodes, 2021) and are more likely to experience negative affect in highly stimulating situations (Wilson & Rhodes, 2021). This could make introverts more open to the idea of mHealth as these offers can be used while being at home or an environment which is positively perceived by them.

The results also did not find any significant differences in Extraversion across the stages of nutrition apps. While Extraversion has been linked to unhealthy eating habits and obesity (Keller & Siegrist, 2015; Pristyna et al., 2022; Tsatsapakis & Zafeiroudi, 2024), which could potentially motivate nutrition app use, extraverts often prefer face-to-face interactions and social support (Connor-Smith & Flachsbart, 2007; Su et al., 2020) which could make them less inclined to use such apps.

Their preferences could also not match the design and features of nutrition apps, e.g., repetitive features like food tracking, as this might lack external stimulation which extraverts often seek. Diabetes patients with high levels of Extraversion were also found to be less likely to use a mHealth app for self-management strategies, even though it included social features which were thought be more appealing to extraverts (Su et al., 2020).

Based on the present findings and in accordance with inconsistent literature, introverts and extroverts might be equally likely to use or not use nutrition and fitness apps. Thus, for further research into the personalization of mHealth apps, other factors could be more relevant than Extraversion.

Neuroticism

The results indicated that Neuroticism could play a role in the adoption of fitness and nutrition apps, with significant differences for Neuroticism levels across the stages of fitness (see Table 4) and nutrition app adoption (see Table 5). It was shown that especially "unengaged" non-users showed lower levels of Neuroticism, indicating that they express higher levels of emotional stability, for both fitness and nutrition apps.

Neurotic people often experience negative feelings, such as anxiety and depression (McCrae & Costa, 1987), which aligns with research showing that Neuroticism is associated with lower subjective well-being (Friedman et al., 2010; Rhodes & Smith, 2006), increased worry (McCrae & Costa, 1987) and health-related anxiety (Weston & Jackson, 2014). Neuroticism is also negatively correlated with overall physical health (Friedman et al., 2010), such as lower levels of physical activity (Müller, 2023; Rhodes & Smith, 2006; Stieger et al. 2020) and less healthy dietary patterns (Keller & Siegrist, 2015; Pristyna et al., 2022; Tiainen et al., 2013), which makes them a desired target group for mHealth apps. Therefore, their heightened levels of health-related worries could have the potential to lead to positive health outcomes if those worries were transformed into healthy behaviors (Stieger et al., 2020).

This is supported by findings by Aziz et al. (2023) which identified personality archetypes and found that the most frequent users of a fitness app were neurotics with high levels of Conscientiousness. Further, neurotic individuals were shown to have greater interest in using a support app for stress-overeating (Lurz, 2024) and existing literature has found that Neuroticism was positively associated with the use of stress-reducing mHealth apps (Aziz et al., 2023; Borghouts et al., 2021). This suggests that neurotic people could show a greater willingness and intention to use mHealth apps due to their proneness to negative health outcomes while being worried about their health.

Supporting this assumption, the results showed that those who have "decided to act" expressed higher Neuroticism levels than "unengaged" non-users for nutrition apps (see Figure 4). Since neurotic individuals are at higher risk for emotional eating and consuming unhealthy foods (Keller & Siegrist, 2015; Pristyna et al., 2022), especially when stress or negative emotions arise (Groesz et al., 2012), they might show their greater interest in nutrition apps.

However, contrary to these results, the present analysis has shown that those who have "decided not to act" also showed higher medians in Neuroticism for nutrition apps (see Figure 4), suggesting that additional factors could influence this relationship. As mentioned before, neurotic individuals were shown to engage in healthy behaviors when paired with higher levels of Conscientiousness (Aziz et al., 2023; Stieger et al., 2020), which could suggest that Conscientiousness might be the driving force that transforms their health-related worries into action (Stieger et al., 2020). Although our results could not support a moderating effect of Conscientiousness on Neuroticism and mHealth app use, the limitations of the study should be considered when discussing the present outcome. Additionally, previously discussed factors such as age and digital literacy or socioeconomic factors could also influence the relationship of Neuroticism and mHealth app adoption.

Findings from the analysis further demonstrated that "disengaged" individuals showed significantly higher levels of Neuroticism for fitness apps (see Figure 2) and nutrition apps (see Figure 4) compared to "unengaged" individuals. This could suggest that neurotic individuals are more inclined to use mHealth apps yet struggle with long-term engagement. However, it remains unclear why those people have stopped using them and whether this is related to characteristics of neurotic individuals. Findings have shown that neurotic young adults rated app features such as self-monitoring and feedback as negative (Belmon et al., 2015), and other results indicated that active self-monitoring led to a greater chance of depressive episodes in people with a mental disorder (Faurholt-Jepsen et al. 2020). Since mental disorders are associated with higher levels of Neuroticism (Stein & Stein, 2008), and self-monitoring and feedback are common features in fitness and nutrition apps (Pires et al., 2020), this could heighten their feelings of stress or anxiety and hinder long-term engagement. Additionally, their higher engagement with mental health and stress-reducing apps (Aziz et al., 2023; Borghouts et al., 2021) suggests a need for a consideration of their negative feelings and emotional support while using mHealth apps. Since neurotic people tend to be more self-conscious and embarrassed (McCrae & Costa, 1987) and more easily demotivated by critique or setbacks (Robinson et al., 2010; Swift & Peterson, 2018), fitness and nutrition apps could focus more on supportive feedback strategies and features which encourage neurotic people.

While the results suggest that neurotic individuals express a heightened interest in fitness and nutrition apps ("decided to act"), the transition to the "acting" stage, as well as sustained mHealth app use still remains a challenge. However, this highlights the importance of a stage model and investigating non-users more closely. As previous research has not come to a clear conclusion about whether neurotic individuals are more likely to use mHealth apps, these findings allow further insights by a better differentiation of neurotic non-users. In the future, stage-based approaches tailored to specific emotional needs of neurotic individuals could be considered to enhance the likelihood of active and long-term app use.

Openness

The results for fitness app adoption indicated that "unengaged" individuals were less open compared to "acting" individuals and those who have "decided to act" (see Figure 3). While the omnibus test of the Kruskal-Wallis ANOVA was also significant for the stages of nutrition app adoption, subsequent Dunn-Bonferroni post-hoc tests did not yield any significant findings. In the moderation analysis using binary logistic regression, it was shown that main effect of Openness on the active use of nutrition apps was significant (see Table 10), indicating that Openness enhances the likelihood of being an "acting" user of nutrition apps by 1.35 times. However, it is important to note that the effect sizes for the post-hoc tests and the main effect of the regression analysis were both low, which suggests limited practical relevance (see Table 9).

At first, it might appear contradictory that significant differences were observed in Openness medians for the stages of fitness app adoption but not for nutrition apps while Openness increased the likelihood for being an active user of nutrition apps. However, this could be explained by the different analytical focus of the tests. The Kruskal-Wallis ANOVA compares the stages for significant differences in their Openness levels with no information about whether Openness could predict that individuals would belong to a certain stage. In contrast, the binary logistic regression analyzes whether Openness can significantly increase the likelihood for belonging to the active users. In this case, it means that higher Openness levels were not predictive for being an "acting" fitness app user, but that individuals in that stage demonstrated higher Openness levels than individuals from other stages. Additionally, due to small effect sizes, the effect of Openness might have been too subtle to detect a notable difference in a group comparison, and especially in Dunn-Bonferroni post-hoc test with stricter significance levels. For nutrition apps, it implies that while individuals do not significantly differ across the stages, higher Openness levels could nevertheless increase the likelihood of using a nutrition app. This indicates that characteristics of open people could be relevant for predicting active app use.

Taken together, the findings could suggest that higher levels of Openness are associated with a greater interest in fitness and nutrition apps and could play an important role in the app adoption process. This seems plausible given that open people are thought to be more receptive to new ideas and the adoption of new technologies and apps (Joshi et al., 2023) as well as tend to be broad-minded and to have a wide range of interests (McCrae & Costa, 1987). Further, some findings also indicated that Openness is associated with health-related behaviors (Keller & Siegrist, 2015; Mõttus et al., 2012; Mõttus et al., 2013; Pristyna et al., 2022) and previous research has shown that open individuals were more likely to use mHealth apps when faced with specific health conditions (Mikolasek et al., 2018; Breil et al., 2019; Su et al., 2020). It was considered before that open individuals could find fitness apps less appealing due to a preference for non-traditional ways of exercising (Courneya & Hellsten, 1998; Wilson & Rhodes, 2021) and results indicated no association between Openness and the perceived usefulness of fitness apps (Alshawmar et al., 2022). However, it might be that especially when concerned about their health or having a certain health goal in mind, open individuals could be more likely to try out new approaches compared to traditional strategies.

Especially regarding age, Openness could play an important factor for the adoption of mHealth apps. Compared to findings with younger samples, Openness seemed to be particularly relevant in older samples: for instance, in a study that was conducted within middle-aged patients, long-term user of a diabetes self-management app displayed higher levels of Openness than non- and short-term users (Su et al., 2020). Similarly, Nunes et al. (2018) found that higher levels of Openness were predictive for the intention to use mHealth apps in older adults, but not in younger ones. This is also in line with other findings which showed that Openness seemed to be the most important factor for elderly individuals showing greater intention to use mHealth offers (Chang et al., 2023).

These findings align with existing literature indicating that older people show less knowledge about how to navigate new technologies and are less likely to engage with them (Fox, 2004; Vercruyssen et al., 2023). Therefore, since older individuals with higher levels of Openness might be more interested and skilled in using technologies, they could be more likely to adopt mHealth apps. Openness could thus play a crucial role for mHealth adoption, especially among elderly populations (Chang et al., 2023; McCrae & Costa, 1987; Joshi & Das, 2023; Nunes et al., 2018; Su et al., 2020).

Limitations

There are some limitations of the study that should be considered when interpreting the findings. First, although the reliability measures of the BFI-10 for Extraversion, Openness and Neuroticism were comparable to prior results (Rammstedt et al., 2012), higher reliability would have been desirable to meet the standards for good reliability. Further, reliability for

Conscientiousness and Agreeableness were relatively low and fell below recommended thresholds (De Vet, 2017). This raises concerns about the reliability of the BFI-10 and the conclusions that can be drawn from it. Although the BFI-10 has demonstrated sufficient validity (Rammstedt et al., 2012), a reduction of the original 44-item Big Five Inventory (BFI-44; John et al., 1991) still raises the question of to which extent only 10 items can accurately measure the complexity of each personality dimension. Unfortunately, the present results could not be compared to previous studies which have investigated the Big Five and mHealth apps using the BFI-10, since they have not reported any reliability measures in their work (Alqahtani et al., 2020; Aziz et al., 2023; Lurz et al., 2024). Further, the unusual distribution of the Big Five in the present study, which was unexpected due to a large and representative sample, might support concerns regarding the BFI-10. The limitations of the assessment instrument might have therefore influenced the present results. Additionally, the BFI-10 may have resulted in a potential ceiling effect for Conscientiousness, limiting observed variability within the trait, and could have led to potentially underestimating its effects. However, as discussed before, another explanation would be that the study design attracted individuals which were particularly high in Conscientiousness.

It must be noted, however, that the present study was part of a larger survey (König et al., 2024), which served as a basis for several research questions and was therefore not the focus of the study design. Future research which focusses solely on personality traits and mHealth app adoption should consider assessing additional facets of the Big Five with a more complex measure (e.g., BFI-44) to obtain more robust and meaningful results.

Another limitation is the unequal group size across the stages of fitness and nutrition app adoption. While, for example, 903 individuals were in the "unengaged" group for nutrition apps, only 96 individuals were identified as "acting" users. These differences in sample size might have reduced test power and could make it harder to detect differences between the groups, especially if effect sizes are small. Since a smaller amount of people in one group contribute less information to the analysis, this can lead to biased results and less reliable estimates. In the future, oversampling certain stages of fitness and nutrition app adoption or considering a stratification of the sample by stages of fitness and nutrition app adoption could be beneficial to achieve more balanced group sizes for each stage.

Another constraint of the study is its cross-sectional design. Therefore, no causal inferences regarding the relationships between the Big Five and mHealth app adoption can be made. Particularly, since the literature indicates that many people dropout of mHealth use within the short-term (Amagai et al., 2022; Conway et al., 2015; Hershman, 2019; Krebs &

Duncan, 2015; Lee et al., 2018), longitudinal data could better identify long-term, active users and those who have become "disengaged". This could help characterizing these groups more precisely and make the findings more reliable.

Further, the literature suggests people disengage in using mHealth apps not because they have achieved their health goals, but rather because of other factors, e.g., time constraint (Murnane, 2015). Since the reasons for disengagement were not assessed in the current study, it remains possible that individuals have reached their goals and were able to maintain healthy behaviors without using an app. This indicates that "disengaged" non-users might also differ in their characteristics, depending on why they no longer use the app. Since different reasons for disengagement could be associated with different traits, an additional categorization of these individuals could help to reveal significant differences between the different stages. Finally, it must be kept in mind that results from self-reported data might be less reliable due to their strong susceptibility to response biases.

Strengths

While discussing methodological and analytical limitations, the present study also demonstrates notable strengths that should not go unmentioned. Since non-users were often not specified in more detail, the existing research on who uses mHealth and who does not has resulted in inconsistent findings, especially for fitness and nutrition apps (Alshawmar et al., 2022; Aziz et al., 2023; Belmon et al., 2015; Bregenzer et al., 2017; Elavsky et al., 2017; Halko & Kientz, 2010; Lurz et al., 2024; Meixner et al., 2020). Using a stage model approach for the behavioral adoption of fitness and nutrition apps (König et al., 2018) contributes to a better understanding of mHealth app users and non-users. This study therefore provides a promising approach for a more nuanced characterization of different mHealth non-user groups regarding their personality traits. The present findings showed that a large proportion of the sample still appears to be unaware or has never considered using fitness or nutrition apps before ("unengaged"). However, it was also shown that many non-users seem to be interested in fitness and nutrition app use ("disengaged", "decided to act"), although they not actively use these apps. The stage model approach does not only allow a more thorough understanding of these groups but also allows to develop interventions which can be adapted to the characteristics of each stage (Lippke & Ziegelmann, 2005; Schwarzer, 2008; Sniehotta & Aunger, 2010; Weinstein & Sandman, 1992; Weinstein et al., 2008). Research from health psychology demonstrated that tailoring interventions to specific stages was effective in increasing recruitment and sustained engagement in positive behavior change (Prochaska, 2018; Schwarzer et al., 2010).

For instance, "unengaged" individuals often benefit from additional information since they have not familiarized themselves with mHealth apps (Sniehotta & Aunger, 2010). However, since other non-users might be aware of its potential benefits, their non-use could stem from other reasons. This is important when designing advertisements and interventions to the desired target group, as "disengaged" individuals and those who have "decided to act" would not profit from further information (Sniehotta & Aunger, 2010). Instead, interventions should be tailored to their needs and preferences to address barriers which keep them from engaging in mHealth app use and long-term commitment.

Additionally, the large and representative sample of the present study, which included a broad age range and educational levels, provides a general snapshot of current attitudes towards fitness and nutrition apps in Germany and Austria.

Since this is the first study, to the best of my knowledge, that investigated the Big Five personality traits within a stage model approach of mHealth adoption, it could serve as a basis for further studies to gain a better understanding of the specific needs, challenges and preferences of different non-users.

Implications and Future Research

According to the World Health Organization (2020; 2024a), insufficient physical activity and poor nutrition are becoming more common worldwide, increasing the risk of non-communicable diseases and obesity. Since most people nowadays own a smartphone and can access it almost anytime and anywhere (Gama & Laher, 2023; Pires et al., 2020), mHealth apps offer a low-threshold and affordable way to promote health among the population (Albrecht, 2016; Amagai, 2022; ESPON, 2019; Gama & Laher, 2023; Lantzsch, 2022).

Findings indicate a rapid growth of the mHealth app market (Dittrich et al., 2023; Statista, 2024) while daily smartphone use is increasing (Gama & Laher, 2023). Therefore, mHealth holds great potential to reach a large proportion of the population (Elavsky et al., 2017) and measures should be taken to convince individuals of the benefits of mHealth apps and ensure sustained app use.

In the long term, this could not only improve the individuals' well-being (Aldenaini et al., 2020; Burke et al., 2012; Cho et al., 2015; Lieneck et al., 2024; Orji et al., 2012; Sarcona et al., 2017; Standen & Rothman, 2023; Yettakalva et al., 2019) but also minimize financial and personnel burdens on the healthcare system (Albrecht, 2016; ESPON, 2019; Gama & Laher, 2023; Lantzsch, 2022). Given that only a small percentage of the population actively uses such offers (Amagai et al., 2022; Conway et al., 2015; Krebs & Duncan, 2015; Lee et al.,

2018) this highlights the importance of research in that area to identify variables which prevent people from adopting them.

Therefore, the present study aimed to shed more light into potential factors causing use or non-use by examining personality traits. A better understanding of which characteristics are linked to a greater willingness to use fitness and nutrition apps allows more targeted research on specific subgroups and designing advertisements and apps accordingly (Alqahtani et al., 2021; Avanesova et al., 2022; Bregenzer et al., 2017; Elavsky et al., 2017; Khwaja et al., 2021; Madeira et al., 2018). Based on the findings of the present study, some suggestions for future research have been identified:

First, longitudinal studies would be helpful to accurately categorize individuals into the different stages of mHealth adoption, increasing the reliability of the results. Further, qualitative research might offer a more profound understanding of why people stop using these apps in the first place, such as identifying personal motivations, barriers, and concerns while assessing their personality traits. Additionally, factors like age, digital literacy, and current health goals might influence this relationship and should be considered in future research (Bhuyan et al., 2016; Chang et al., 2023; Cho et al., 2014;Ernsting et al., 2017; Krebs & Duncan, 2015; Lurz et al., 2024; Nunes et al., 2018; Su et al., 2020). To achieve more reliable results, a balanced number of people from different stages of mHealth adoption should be recruited, for instance by using methods like oversampling or a stratification of the sample by stages of behavioral adoption and sociodemographic characteristics.

Based on more detailed research on different non-users, interventions should be tailored to different personality types and address barriers such as lacking digital skills or health literacy. For instance, people who are more neurotic could benefit from additional emotional or psychological support, considering their tendency towards having a negative self-image and worry (Belmon et al., 2015; McCrae & Costa, 1987; Robinson et al., 2010; Swift & Peterson, 2018). For elderly individuals, app features and advertisement should match age-related needs and topics. While issues like digital literacy and education might be harder to address by the app designers, more awareness could be raised by the public healthcare to enhance digital literacy and introduce individuals to mHealth offers (World Health Organization, 2024b).

Conclusion

This study was the first of its kind to examine the relationship between personality traits and behavioral stages of mHealth app adoption, offering further insights into the characteristics influencing the engagement with fitness and nutrition apps. In accordance with previous findings, the results indicated that particularly Neuroticism and Openness were associated with specific stages of mHealth app adoption. While Neuroticism was linked to stages indicating a willingness to use fitness and nutrition apps ("decided to act", "disengaged"), potentially due to their higher risk for poorer health and a tendency to health-related anxiety, it was not associated with its actual use. Further, both, individuals who have "decided to act" and "decided not to act", showed higher levels of Neuroticism for nutrition app adoption, suggesting that there might be additional variables which could influence whether neurotic individuals consider using a nutrition app. Since higher levels of Neuroticism are often associated with negative health outcomes, this makes them a desired target group for mHealth apps and worthy of further investigation

Similarly, individuals with high levels of Openness demonstrated greater interest and engagement with fitness apps ("acting", "decided to act"), which might be explained by their open-mindedness and receptiveness to new technologies. Especially in its interaction with age, Openness might be an important factor for the acceptance of mHealth apps.

Further, Agreeableness was found to be moderated by higher levels of Conscientiousness when predicting active nutrition app use. As Agreeableness is often uncorrelated with health behaviors, conscientious characteristics like being disciplined and hard-working, could cause them to engage more in health-related behaviors. While discussing the present results, one key takeaway is that personality traits alone might not sufficiently explain differences in the stages of mHealth app adoption.

Nevertheless, since research on personality traits and fitness and nutrition apps is still limited, the present study was a first step towards a more thorough understanding of different types of mHealth users and non-users. By using a stage model approach within the context of mHealth research, the results offered some insights into the diversity of non-users and highlight the potential of a more detailed examination of these groups. Future research could address the study's limitations by assessing the Big Five with a more reliable and detailed measure, using longitudinal designs and aiming for balanced group sizes across the stages of mHealth app adoption. In addition, considering how traits interact with factors like digital literacy, age, or health status could help to better understand the impact of personality traits on the adoption of fitness and nutrition apps. This information could improve the development of more targeted mHealth interventions and ultimately increase sustained engagement.

References

Aguiar, M., Trujillo, M., Chaves, D., Álvarez, R., & Epelde, G. (2022). MHealth Apps using behavior change techniques to self-report data: Systematic review. *JMIR Mhealth and Uhealth*, *10*(9), e33247. https://doi.org/10.2196/33247

Aiken, L. R., & Groth-Marnat, G. (2006). *Psychological Testing and Assessment* (12th ed.). Pearson.

Aisyah S., Sutrisno S., Madjid A., & Suud F.M. (2021). The influence of peer conformity on the student's agreeableness personality. *Psychology and Education Journal*, 58 (3), 3934 – 3942.

Albrecht, U.-V. (2016). Kapitel Rationale. In *U.-V. Albrecht, (Ed.), Chancen und Risiken von Gesundheits-Apps (CHARISMHA).* Medizinische Hochschule Hannover. https://doi.org/10.24355/dbbs.084-201210110913-54

Aldenaini, N., Alqahtani, F., Orji, R., & Sampalli, S. (2020). Trends in persuasive technologies for physical activity and sedentary behavior: A systematic review. *Frontiers in Artificial Intelligence*, 3. https://doi.org/10.3389/frai.2020.00007

Allen, M. S., Walter, E. E., & McDermott, M. S. (2016). Personality and sedentary behavior: A systematic review and meta-analysis. *Health Psychology*, 36(3), 255–263. https://doi.org/10.1037/hea0000429

Alqahtani, F., Meier, S., & Orji, R. (2021). Personality-based approach for tailoring persuasive mental health applications. *User Modeling and User-adapted Interaction*, 32(3), 253–295. https://doi.org/10.1007/s11257-021-09289-5

Alshawmar, M., Tulu, B., & Hall-Phillips, A. (2022). Influence of personality traits on the continued use of fitness apps. *Proceedings of the Annual Hawaii International Conference on System Sciences*. https://doi.org/10.24251/hicss.2022.478

Amagai, S., Pila, S., Kaat, A. J., Nowinski, C. J., & Gershon, R. C. (2022). Challenges in participant engagement and retention using mobile health apps: Literature review. *Journal of Medical Internet Research*, *24*(4), e35120. https://doi.og/10.2196/35120

Amichai-Hamburger, Y., Wainapel, G., & Fox, S. (2002). On the internet no one knows I'm an introvert: Extroversion, neuroticism, and internet interaction. *Cyber Psychology & Behavior*, *5*(2), 125–128. https://doi.org/10.1089/109493102753770507

An, H., Chen, W., Wang, C., Yang, H., Huang, W., & Fan, S. (2020). The relationships between physical activity and life satisfaction and happiness among young, middle-aged, and older adults. *International Journal of Environmental Research and Public Health*, *17*(13), 4817. https://doi.org/10.3390/ijerph17134817

Arteaga, S. M., González, V. M., Kurniawan, S., & Benavides, R. A. (2012). Mobile games and design requirements to increase teenagers' physical activity. *Pervasive and Mobile Computing*, *8*(6), 900–908. https://doi.org/10.1016/j.pmcj.2012.08.002

Avanesova, J., & Lieldidža-Kolbina, J. (2022). MHealth and user interaction improvement by personality traits-based personalization. *Applied Computer Systems*, *27*(1), 55–61. https://doi.org/10.2478/acss-2022-0006

Aziz, M., Erbad, A., Belhaouari, S. B., Almourad, M. B., Altuwairiqi, M., & Ali, R. (2023). Who uses mHealth? user archetypes for physical and mental health apps. *Digital Health*, *9*. https://doi.org/10.1177/20552076231152175

Belmon, L. S., Middelweerd, A., Velde, S. J. T., & Brug, J. (2015). Dutch young adults ratings of behavior change techniques applied in mobile phone apps to promote physical activity: A cross-sectional survey. *JMIR mHealth and uHealth*, *3*(4), https://doi.org/10.2196/mhealth.4383

Ben-Zeev, D., Kaiser, S. M., Brenner, C. J., Begale, M., Duffecy, J., & Mohr, D. C. (2013). Development and usability testing of FOCUS: A smartphone system for self-management of schizophrenia. *Psychiatric Rehabilitation Journal*, *36*(4), 289–296. https://doi.org/10.1037/prj0000019

Bhuyan, S.S., Lu, N., Chandak, A. *et al.* Use of Mobile Health Applications for Health-Seeking Behavior Among US Adults. *J Med Syst* **40**, 153 (2016). https://doi.org/10.1007/s10916-016-0492-7

Blom, J.O. (2004). Challenges for user-centric personalization research. In C.M. Karat, J.O. Blom, J. Karat (Eds.), *Designing Personalized User Experiences in eCommerce. Human-Computer Interaction Series*, (HCIS, vol 5, pp.333-348). Springer. https://doi.org/10.1007/1-4020-2148-8_18

Bogg, T., & Roberts, B. W. (2004). Conscientiousness and health-related behaviors: A meta-analysis of the leading behavioral contributors to mortality. *Psychological Bulletin*, *130*(6), 887–919. https://doi.org/10.1037/ 0033-2909.130.6.887

Borghouts, J., Eikey, E., Mark, G., De Leon, C., Schueller, S. M., Schneider, M., Stadnick, N., Zheng, K., Mukamel, D., & Sorkin, D. H. (2021). Barriers to and facilitators of user engagement with digital mental health interventions: systematic review. *Journal of Medical Internet Research*, *23*(3), e24387. https://doi.org/10.2196/24387

Both, L. E. (2021). Willingness to share personal information. *Psychological Applications and Trends*, *4*, 438–440. https://doi.org/10.36315/2021inpact096

Bregenzer, A., Wagner-Hartl, V., & Jiménez, P. R. (2017). Who uses apps in health promotion? A target group analysis of leaders. *Health Informatics Journal*, *25*(3), 1038–1052. https://doi.org/10.1177/1460458217738121

Breil, B., Kremer, L., Hennemann, S., & Apolinário-Hagen, J. (2019). Acceptance of mHealth apps for self-management among people with hypertension. *PubMed*, *267*, 282–288. https://doi.org/10.3233/shti190839

Bundeskanzleramt. (2021). *Frauen und Männer in Österreich.*

Burke, L. E., Conroy, M. B., Sereika, S. M., Elci, O. U., Styn, M. A., Acharya, S. D., Sevick, M. A., Ewing, L. J., & Glanz, K. (2011). The effect of electronic self-monitoring on weight loss and dietary intake: a randomized behavioral weight loss trial. *Obesity (Silver Spring, Md.)*, *19*(2), 338–344. https://doi.org/10.1038/oby.2010.208

Burtăverde, V., Vlăsceanu, S., & Avram, E. (2019). Exploring the relationship between personality structure and smartphone usage. *Current Psychology*, *40*(11), 5613–5625. https://doi.org/10.1007/s12144-019-00521-5

Chang, J., Li, A., Yang, X., Li, C., Mai, Y., Zhang, D., Yan, W., Chen, J. & Wu, Y. (2023). The effect of the Big Five Personality on the intention to use mHealth applications among the Chinese elderly: A National-based Study (Preprint). DOI: 10.2196/preprints.51182

Chittaranjan, G., Blom, J., & Gatica-Perez, D. (2011). Who's who with big-five: analyzing and classifying personality traits with smartphones. *Proceedings of the 15th International Symposium on Wearable Computers (ISWC)*, *323* (15504816), 29-36. https://doi.org/10.1109/ISWC.2011.2

Cho, J. (2015). The impact of post-adoption beliefs on the continued use of health apps. *International Journal of Medical Informatics*, *87*, 75-83. https://doi.org/10.1016/j.ijmedinf.2015.12.016

Cho, J., Park, D., & Lee, H. E. (2014). Cognitive factors of using health apps: Systematic analysis of relationships among health consciousness, health information orientation, eHealth literacy, and health app use efficacy. *Journal of Medical Internet Research*, 16(5), e125. https://doi.org/10.2196/jmir.3283

Cieślik, B., Kuligowski, T., Cacciante, L., & Kiper, P. (2023). The impact of personality traits on patient satisfaction after telerehabilitation: A comparative study of remote and face-to-face musculoskeletal rehabilitation during COVID-19 lockdown. *International*

Journal of Environmental Research and Public Health, *20*(6), https://doi.org/10.3390/ijerph20065019

Connor-Smith, J. K., & Flachsbart, C. (2007). Relations between personality and poping: A meta-analysis. *Journal of Personality and Social Psychology, 93(6),* 1080–1107. https://doi.org/10.1037/0022-3514.93.6.1080

Conway, N., Campbell, I., Forbes, P., Cunningham, S., & Wake, D. (2015). mHealth applications for diabetes: User preference and implications for app development. *Health Informatics Journal, 22(4),* 1111–1120. https://doi.org/10.1177/1460458215616265

Costa, P. T., Jr., & McCrae, R. R. (2008). The revised NEO personality inventory (NEO-PI-R). In G.J. Boyle, G. Matthews & D.H. Saklofske (Eds.), *The SAGE Handbook of Personality Theory and Assessment* (Vol. 2. Personality Measurement and Testing, pp. 179–198). Sage Publications, Inc. https://doi.org/10.4135/9781849200479.n9

Courneya, K. S., & Hellsten, L. A. M. (1998). Personality correlates of exercise behavior, motives, barriers and preferences: An application of the five-factor model. *Personality and Individual Differences*, *24*(5), 625–633. https://doi.org/10.1016/s0191-8869(97)00231-6

De Heredia, A. G., Goodman-Deane, J., Waller, S., Clarkson, P. J., Justel, D., Iriarte, I., & Hernández, J. (2018). Personas for policy-making and healthcare design. In N. Bojecetic, M. Storga, D. Marjanovic, S. Skec, N. Pavkovic (Eds.). *Proceedings of the International Design Conference (*pp. 2645-2656). Faculty of Mechanical Engineering and Naval Architecture. https://doi.org/10.21278/idc.2018.0438

Dennison, L., Morrison, L., Conway, G., & Yardley, L. (2013). Opportunities and challenges for smartphone applications in supporting health behavior change: Qualitative study. *Journal of Medical Internet Research*, *15*(4), e86. https://doi.org/10.2196/jmir.2583

Devaraj, S., Easley, R. F., & Crant, J. M. (2008). Research note—How does personality matter? Relating the Five-Factor Model to technology acceptance and use. *Information Systems Research*, *19*(1), 93-105. https://doi.org/10.1287/isre.1070.0153

Directorate-General for Health and Food Safety (2012). *eHealth Action Plan 2012-2020 - Innovative Healthcare for the 21st Century.* European Commission. https://health.ec.europa.eu/publications/ehealth-action-plan-2012-2020_en

Dittrich, F., Mielitz, A., Pustozerov, E., Lawin, D., Von Jan, U., & Albrecht, U. (2023). Digital health applications from a government-regulated directory of reimbursable health apps in Germany—A systematic review for evidence and bias. *mHealth*, *9*, 35. https://doi.org/10.21037/mhealth-23-17

Duijvestijn, M., De Wit, G. A., Van Gils, P. F., & Wendel-Vos, G. C. W. (2023). Impact of physical activity on healthcare costs: A systematic review. *BMC Health Services Research*, *23*(1). https://doi.org/10.1186/s12913-023-09556-8

Egli, T., Bland, H. W., Melton, B. F., & Czech, D. R. (2011). Influence of age, sex, and race on college students' exercise motivation of physical activity. *Journal of American College Health*, *59*(5), 399–406. doi:10.1080/07448481.2010.513074

Eisinga, R., te Grotenhuis, M., & Pelzer, B. (2013). The reliability of a two-item scale: Pearson, Cronbach, or Spearman-Brown? *International Journal of Public Health, 58*(4), 637–642. https://doi.org/10.1007/s00038-012-0416-3

Elavsky, S., Smahel, D., & Machackova, H. (2017). Who are mobile app users from healthy lifestyle websites? Analysis of patterns of app use and user characteristics. *Translational Behavioral Medicine*, *7*(4), 891–901. https://doi.org/10.1007/s13142-017-0525-x

Ervasti, M., Kallio, J., Määttänen, I., Mäntyjärvi, J., & Jokela, M. (2019). Influence of personality and differences in stress processing among finnish students on interest to use a mobile stress management app: Survey study. *JMIR Mental Health*, *6*(5), e10039. https://doi.org/10.2196/10039

Essén, A., Stern, A. D., Haase, C. B., Car, J., Greaves, F., Paparova, D., Vandeput, S., Wehrens, R., & Bates, D. W. (2022). Health app policy: international comparison of nine countries' approaches. *Npj DigitalMedicine*, *5*(1). https://doi.org/10.1038/s41746-022-00573-1

ESPON (2019). *eHealth – Future digital health in the EU* (final report). https://archive.espon.eu/sites/default/files/attachments/Final%20report.%202019%2003%2025_final%20version_0.pdf

Eysenck, H. J., Nias, D. K., & Cox, D. N. (1982). Sport and personality. *Advances in Behaviour Research and Therapy, 4*(1), 1–56. https://doi.org/10.1016/0146-6402(82)90004-2

Fan, H., & Poole, M. S. (2006). What Is personalization? Perspectives on the design and implementation of personalization in information systems. *Journal of Organizational Computing and Electronic Commerce*, *16*(3), 179–202. https://doi.org/10.1080/10919392.2006.9681199

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using

G* Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149-1160.

Faurholt-Jepsen, M., Frost, M., Christensen, E. M., Bardram, J. E., Vinberg, M., & Kessing, L. V. (2020). The effect of smartphone-based monitoring on illness activity in bipolar disorder: the MONARCA II randomized controlled single-blinded trial. *Psychological Medicine*, *50*(5), 838–848. doi:10.1017/S0033291719000710

Forestell, C. A., Spaeth, A. M., & Kane, S. A. (2011). To eat or not to eat red meat. A closer look at the relationship between restrained eating and vegetarianism in college females. *Appetite*, *58*(1), 319–325. https://doi.org/10.1016/j.appet.2011.10.015

Friedman, H. S., Kern, M. L., & Reynolds, C. A. (2010). Personality and health, subjective well-being, and longevity. *Journal of Personality*, *78*(1), 179–215.

Gama, B., & Laher, S. (2023). Self-help: A systematic review of the efficacy of mental health apps for low- and middle-income communities. *Journal of Technology in Behavioral Science, 9, 428-439*. https://doi.org/10.1007/s41347-023-00360-z

Ghose, A., Guo, X., Li, B., & Dang, Y. (2021). Empowering Patients Using Smart Mobile Health Platforms: Evidence from a Randomized Field Experiment. *SSRN Electronic Journal*. https://autopapers.ssrn.com/sol3/papers.cfm?abstract_id=3773184

Global Nutrition Report (2022). *Executive summary – Global Nutrition Report 2022.* https://globalnutritionreport.org/reports/2022-global-nutrition-report/executive-summary/

Goldberg, L. R. (1992). The development of markers for the Big-Five Factor structure. *Psychological Assessment, 4*(1), 26–42. https://doi.org/10.1037/1040-3590.4.1.26

Golestanbagh, N., Miraghajani, M., Amani, R., Symonds, M., Neamatpour, S., & Haghighizadeh, M. (2021). Association of personality traits with dietary habits and food/taste preferences. *International Journal of Preventive Medicine*, *12*, 92 - 92. https://doi.org/10.4103/ijpvm.IJPVM_19_19

Gómez-Cuesta, N., Mateo-Orcajada, A., Meroño, L., Abenza-Cano, L., & Vaquero-Cristóbal, R. (2024). A mobile app-based intervention improves anthropometry, body composition and fitness, regardless of previous active-inactive status: a randomized controlled trial. *Frontiers in Public Health*, *12*, 1380621. https://doi.org/10.3389/fpubh.2024.1380621

Groesz, L. M., McCoy, S., Carl, J., Saslow, L., Stewart, J., Adler, N., Laraia, B., & Epel, E. (2011). What is eating you? Stress and the drive to eat. *Appetite*, *58*(2), 717–721. https://doi.org/10.1016/j.appet.2011.11.028

Guthold, R., Stevens, G. A., Riley, L. M., & Bull, F. C. (2018). Worldwide trends in insufficient physical activity from 2001 to 2016: A pooled analysis of 358 population-based surveys with 1.9 million participants. *The Lancet Global Health*, *6*(10), e1077–e1086. https://doi.org/10.1016/s2214-109x(18)30357-7

Hales, S., Turner-McGrievy, G. M., Wilcox, S., Davis, R. E., Fahim, A., Huhns, M., & Valafar, H. (2017). Trading pounds for points: Engagement and weight loss in a mobile health intervention. *Digital Health*, *3*, https://doi.org/10.1177/2055207617702252

Halko, S., & Kientz, J.A. (2010). Personality and persuasive technology: An exploratory study on health-promoting mobile applications. In T. Ploug, P. Hasle & H. Oinas-Kukkonen (Eds.) *Persuasive Technology. PERSUASIVE 2010.* (vol 6137., pp. 150–161). Springer. https://doi.org/10.1007/978-3-642-13226-1_16

Hayat, T., Samuel-Azran, T., Goldberg, S., & Amichai-Hamburger, Y. (2023). Introversion-extraversion and online course satisfaction. *Online Information Review*, *48*(2), 409–424. https://doi.org/10.1108/oir-01-2023-0028

Heaven, P. C. L., Mulligan, K., Merrilees, R., Woods, T., & Fairooz, Y. (2001). Neuroticism and conscientiousness as predictors of emotional, external, and restrained eating behaviors. *International Journal of Eating Disorders*, *30*(2), 161–166.

Hershman, S.G., Bot, B.M., Shcherbina, A., et al. (2019). Physical activity, sleep and cardiovascular health data for 50,000 individuals from the MyHeart Counts Study. *Scientific Data 6*, (24). https://doi.org/10.1038/s41597-019-0016-7

Hill, P., & Roberts, B. (2011). The role of adherence in the relationship between conscientiousness and perceived health. *Health psychology : official journal of the Division of Health Psychology, American Psychological Association*, 30 6, 797-804. https://doi.org/10.1037/a0023860

Hruby, A., & Hu, F. B. (2014). The epidemiology of obesity: A big picture. *Pharmaco Economics*, *33*(7), 673–689. https://doi.org/10.1007/s40273-014-0243-x

Huseynov, F. (2020). Understanding usage behavior of different mobile application categories based on personality traits. *Interacting with Computers*, *32*(1), 66-80. https://doi.org/10.1093/iwc/iwaa005

IBM Corp. (2024). *IBM SPSS Statistics for macOS, Version 30.0*. Armonk, NY: IBM Corp.

John, O. P., Donahue, E. M., & Kentle, R. L. (1991). *Big Five Inventory (BFI)* [Database record]. APA PsycTests. https://doi.org/10.1037/t07550-000

Jokela, M., Batty, G. D., Nyberg, S. T., Virtanen, M., Nabi, H., Singh-Manoux, A., & Kivimäki, M. (2013). Personality and All-Cause Mortality: Individual-Participant Meta-Analysis of 3,947 deaths in 76,150 adults. *American Journal of Epidemiology*, *178*(5), 667–675. https://doi.org/10.1093/aje/kwt170

Joshi, A., Das, S., & Sekar, S. (2023). How Big Five personality traits affect information and communication technology use: A meta-analysis. *Australasian Journal of Information Systems*, *27*. https://doi.org/10.3127/ajis.v27i0.3985

Kaptein, M., Markopoulos, P., De Ruyter, B., & Aarts, E. (2015). Personalizing persuasive technologies: Explicit and implicit personalization using persuasion profiles. *International Journal of Human-Computer Studies*, *77*, 38–51. https://doi.org/10.1016/j.ijhcs.2015.01.004

Keller, C., & Siegrist, M. (2015). Does personality influence eating styles and food choices? Direct and indirect effects. *Appetite*, *84*, 128–138. https://doi.org/10.1016/j.appet.2014.10.003

Keller, V., & Ercsey, I. (2023). Thematic analysis of google play reviews of lifestyle apps. *Human Technology*, *19*(1), 82–102. https://doi.org/10.14254/1795-6889.2023.19-1.6

Khwaja, M.K., Pieritz, S., Faisal, A.A., & Matic, A. (2021). Personality and engagement with digital mental health interventions. In J. Masthoff, E. Herder, N. Tintarev & M. Tklačič (Eds.). *Proceedings of the 29th ACM Conference on User Modeling, Adaptation and Personalization (UMAP '21)* (pp. 235–239). Association for Computing Machinery. https://doi.org/10.1145/3450613.3456823

Kikuchi, Y., & Watanabe, S. (2000). Personality and dietary habits. *Journal of Epidemiology*, *10* (3), 191-198. https://doi.org/10.2188/JEA.10.191

Kim, N., Kim, J., & Kye, S. (2020). Food habits, health behaviors related to the personality in Korean college students. *The Korean Journal of Nutrition*, *53*, 13-26. https://doi.org/10.4163/jnh.2020.53.1.13.

Kim, Y., Briley, D. A., & Ocepek, M. G. (2014). Differential innovation of smartphone and application use by sociodemographics and personality. *Computers in Human Behavior*, *44*, 141–147. https://doi.org/10.1016/j.chb.2014.11.059

Kolasa, K. M., Peery, A., Harris, N. G., & Shovelin, K. (2001). Food literacy partners program. *Topics in Clinical Nutrition*, *16*(4), 1–10. https://doi.org/10.1097/00008486-200116040-00002

König, L. M., Sproesser, G., Schupp, H. T., & Renner, B. (2018). Describing the process of adopting nutrition and fitness apps: Behavior Stage Model approach. *JMIR Mhealth and Uhealth*, *6*(3), e55. https://doi.org/10.2196/mhealth.8261

König, L. M., Ruf, A., Koch, T. J. S., Volpi, L., Salvatore, G., Lapitan, E., … Arigo, D. (2024, May 6). (Digital) health survey in a representative German and Austrian sample. https://doi.org/10.17605/OSF.IO/S2WYA

Krebs, P., & Duncan, D. T. (2015). Health app use among US mobile phone owners: a national survey. *JMIR Mhealth and Uhealth*, *3*(4), e101. https://doi.org/10.2196/mhealth.4924

Lahey, B. B. (2009). Public health significance of neuroticism. *American Psychologist, 64*(4), 241–256. https://doi.org/10.1037/a0015309

Lantzsch, H., Eckhardt, H., Campione, A., Busse, R., & Henschke, C. (2022). Digital health applications and the fast-track pathway to public health coverage in Germany: Challenges and opportunities based on first results. *BMC Health Services Research*, *22*(1). https://doi.org/10.1186/s12913-022-08500-6

Lee, K., Kwon, H., Lee, B., Lee, G., Lee, J., Park, Y., & Shin, S. (2018). Effect of self-monitoring on long-term patient engagement with mobile health applications. *PLoS ONE*, 13. https://doi.org/10.1371/journal.pone.0201166.

Lieneck, C., Carr, E., Voss, M., Smith, D., Townsend, D., Washington, C., & Wallace, A. (2024) Assessing use of mHealth applications since 2022: A systematic review. *Reports on Global Health Research, 7*(2). https://doi.org/10.29011/2690-9480.100203

Lin, J. Y. C., Chen, L. S. L., Wang, E. S. T., & Cheng, J. M. S. (2007). The relationship between extroversion and leisure motivation: Evidence from fitness center participation. *Social Behavior and Personality: An International Journal*, *35*(10), 1317–1322. https://doi.org/10.2224/sbp.2007.35.10.1317

Lippke, S., & Ziegelmann, J. P. (2005). Understanding and modeling health behavior. *Journal of Health Psychology*, *11*(1), 37–50. https://doi.org/10.1177/1359105306058845

Lurz, M., Gemesi, K., Holzmann, S. L., Kretzschmar, B., Wintergerst, M., Groh, G., Böhm, M., Gedrich, K., Hauner, H., Krcmar, H., & Holzapfel, C. (2024). Characterization of adults concerning the use of a hypothetical mHealth application addressing stress-overeating: an online survey. *BMC Public Health, 24*(1), 958. https://doi.org/10.1186/s12889-024-18383-3

Madeira, R. N., Germano, H., Macedo, P., & Correia, N. (2018). Personalising the user experience of a mobile health application towards patient engagement. *Procedia Computer Science*, *141*, 428–433. https://doi.org/10.1016/j.procs.2018.10.173

Marcolino, M. S., Oliveira, J. A. Q., D'Agostino, M., Ribeiro, A. L., Alkmim, M. B. M. & Novillo-Ortiz, D. (2018). The impact of mHealth interventions: Systematic review of systematic reviews. *JMIR Mhealth And Uhealth*, *6*(1), e23. https://doi.org/10.2196/mhealth.8873

Martin-Raugh, M. P., Kell, H. J., & Motowidlo, S. J. (2015). Prosocial knowledge mediates effects of agreeableness and emotional intelligence on prosocial behavior. *Personality and Individual Differences*, *90*, 41–49. https://doi.org/10.1016/j.paid.2015.10.024

McCrae, R. R., & Costa, P. T. (1987). Validation of the five-factor model of personality across instruments and observers. *Journal of Personality and Social Psychology*, *52*(1), 81–90. https://doi.org/10.1037/0022-3514.52.1.81

Meixner, C., Baumann, H., & Wollesen, B. (2020). Personality traits, gamification and features to develop an app to reduce physical inactivity. *Information*, *11*(7), 367. https://doi.org/10.3390/info11070367

Mikolasek, M., Witt, C. M. & Barth, J. (2018). Adherence to a mindfulness and relaxation self-sare app for cancer patients: Mixed-methods feasibility study. *JMIR Mhealth And Uhealth*, *6*(12), e11271. https://doi.org/10.2196/11271

Molanorouzi, K., Khoo, S., & Morris, T. (2015). Motives for adult participation in physical activity: Type of activity, age, and gender. *BMC Public Health*, *15*(1), 66. https://doi.org/10.1186/s12889-015-1429-7

Mõttus, R., Realo, A., Allik, J., Deary, I. J., Esko, T., & Metspalu, A. (2012). Personality traits and eating habits in a large sample of Estonians. *Health Psychology, 31*(6), 806–814. https://doi.org/10.1037/a0027041

Mõttus, R., McNeill, G., Jia, X., Craig, L. C., Starr, J. M., & Deary, I. J. (2013). The associations between personality, diet and body mass index in older people. *Health psychology*, *32*(4), 353–360. https://doi.org/10.1037/a0025537

Murnane, E. L., Huffaker, D., & Kossinets, G. (2015). Mobile health apps: Adoption, adherence, and abandonment. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers.* Association for Computing Machinery. https://doi.org/10.1145/2800835.2800943

Müller, C. (2023). Personality traits and physical activity: Insights from German university students. *European Journal of Investigation in Health Psychology and Education*, *13*(8), 1423–1440. https://doi.org/10.3390/ejihpe13080104

Nopiana, N., Egie, J., & Mers, O. (2022). The impact of internet addiction on introvert personality. *World Psychology*, *1*(2), 1–17. https://doi.org/10.55849/wp.v1i2.97

Nunes, A., Limpo, T. & Castro, S. L. (2018). Effects of Age, Gender, and Personality on Individuals' Behavioral Intention to Use Health Applications. In P.D. Bamidis, M. Ziefle & L. Maciaszek (Eds.). *Proceedings of the 4th International Conference on Information and Communication Technologies for Ageing Well and E- Health-ICT4AWE* (Volume 1, pp.103-110*).* https://doi.org/10.5220/0006674101030110

OECD. (2021). *Adult education level.* https://www.oecd.org/en/data/indicators/adult-education-level.html?oecdcontrol-00b22b2429-var3=2021

Orji, R., Mandryk, R. L., Vassileva, J., & Gerling, K. M. (2013). Tailoring persuasive health games to gamer type. In *31st International Conference on Human Factor in Computing Systems (CHI 2013)* (pp. 2467-2476). Association for Computing Machinery. https://doi.org/10.1145/2470654.2481341

Orji, R., Nacke, L. E., & Di Marco, C. (2017). Towards personality-driven persuasive health games and gamified systems. In *ACM SIGCHI Conference on Human Factors in Computing Systems -CHI* (pp.1015-1027*)*. Association for Computing Machinery. https://doi.org/10.1145/3025453.3025577

Orji, R., Vassileva, J. & Mandryk, R. L. (2012). Lunch time: A slow-casual game for long-term dietary behavior change. *Personal and Ubiquitous Computing*, *17*(6), 1211–1221. https://doi.org/10.1007/s00779-012-0590-6

Paunonen, S. V. (2003). Big Five Factors of personality and replicated predictions of behavior. *Journal of Personality and Social Psychology, 84*(2), 411–424. https://doi.org/10.1037/0022-3514.84.2.411

Peltonen, E., Sharmila, P., Asare, K. O., Visuri, A., Lagerspetz, E., & Ferreira, D. (2020). When phones get personal: Predicting Big Five personality traits from application usage. *Pervasive and Mobile Computing*, 69, 101269. https://doi.org/10.1016/j.pmcj.2020.101269

Phelan, J. C., Link, B. G., & Tehranifar, P. (2010). Social conditions as fundamental causes of health inequalities: theory, evidence, and policy implications. *Journal of Health and Social Behavior*, *51 Suppl*, 28–40. https://doi.org/10.1177/0022146510383498

Piercy, K. L., & Troiano, R. P. (2018). Physical activity guidelines for Americans from the US Department of Health and Human Services. *Circulation Cardiovascular Quality and Outcomes*, *11*(11). https://doi.org/10.1161/circoutcomes.118.005263

Pires, I. M., Marques, G., Garcia, N. M., Flórez-revuelta, F., Ponciano, V., & Oniani, S. (2020). A research on the classification and applicability of the mobile health applications. *Journal of Personalized Medicine,* 10 (1). https://doi.org/10.3390/jpm10010011

Pletzer, J., Thielmann, I., & Zettler, I. (2023). Who is healthier? A meta-analysis of the relations between the HEXACO personality domains and health outcomes. *European Journal of Personality, 38*(2). https://doi.org/10.1177/08902070231174574

Pristyna, G., Mahmudiono, T., Rifqi, M. A., & Indriani, D. (2022). The relationship between Big Five Personality Traits, eating habits, physical activity, and obesity in Indonesia based on analysis of the 5th wave Indonesia Family Life Survey (2014). *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.881436

Prochaska, J. O., & Velicer, W. F. (1997). The transtheoretical model of health behavior change. *American Journal of Health Promotion*, *12*(1), 38–48. https://doi.org/10.4278/0890-1171-12.1.38

Prochaska, J. O. (2018). Transtheoretical model of behavior change. In Gellman, N. (Ed.). *Encyclopedia of Behavioral Medicine* (pp. 1–5). Springer. https://doi.org/10.1007/978-1-4614-6439-6_70-2

Purcell, K. (2011, November 2). *Half of adult cell phone owners have apps on their phones*. Pew Research Center. https://www.pewresearch.org/internet/2011/11/02/half-of-adult-cell-phone-owners-have-apps-on-their-phones-2/

Rammstedt, B., & John, O. P. (2007). Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German. *Journal of Research in Personality*, *41*(1), 203–212. https://doi.org/10.1016/j.jrp.2006.02.001

Rammstedt, B., Kemper, C. J., Klein, M. C., Beierlein, C., & Kovaleva, A. (2012). Eine kurze Skala zur Messung der fünf Dimensionen der Persönlichkeit: Big-Five-Inventory-10 (BFI-10). *Methoden, Daten, Analysen (Mda)*, *7*(2), 32. https://madoc.bib.uni-mannheim.de/54728/

Rhodes, R. E., & Pfaeffli, L. A. (2012). Personality and physical activity. In Acevedo, E.O. (Ed.), *The Oxford Handbook of Exercise Psychology* (pp. 195–223. Oxford Academic. https://doi.org/10.1093/oxfordhb/9780195394313.013.0011

Rhodes, R., & Smith, N. (2006). Personality correlates of physical activity: A review and meta-analysis. *British Journal of Sports Medicine*, *40*, 958 - 965. https://doi.org/10.1136/bjsm.2006.028860

Robinson, M. D., Moeller, S. K., & Fetterman, A. K. (2010). Neuroticism and responsiveness to error feedback: Adaptive self-regulation versus affective reactivity. *Journal of Personality*, *78*(5), 1469–1496. https://doi.org/10.1111/j.1467-6494.2010.00658.x

Ross, C., Orr, E. S., Sisic, M., Arseneault, J. M., Simmering, M. G., & Orr, R. R. (2009). Personality and motivations associated with facebook use. *Computers in Human Behavior, 25*(2), 578–586. https://doi.org/10.1016/j.chb.2008.12.024

Ryan, T., & Xenos, S. (2011). Who uses Facebook? An investigation into the relationship between the Big Five, shyness, narcissism, loneliness, and Facebook usage. *Computers in Human Behavior*, *27*(5), 1658–1664. https://doi.org/10.1016/j.chb.2011.02.004

Sarcona, A., Kovacs, L., Wright, J., & Williams, C. (2017). Differences in eating behavior, physical activity, and health-related lifestyle choices between users and nonusers of mobile health apps. *American Journal of Health Education*, *48*(5), 298–305. https://doi.org/10.1080/19325037.2017.1335630

Schwarzer, R. (2008). Modeling health behavior change: How to predict and modify the adoption and maintenance of health behaviors. *Applied Psychology*, *57*(1), 1–29. https://doi.org/10.1111/j.1464-0597.2007.00325.x

Schwarzer, R., Cao, D. S., & Lippke, S. (2010). Stage-matched minimal interventions to enhance physical activity in Chinese adolescents. *Journal of Adolescent Health*, *47*(6), 533–539. https://doi.org/10.1016/j.jadohealth.2010.03.015

Shanahan, M. J., Hill, P. L., Roberts, B. W., Eccles, J., & Friedman, H. S. (2014). Conscientiousness, health, and aging: The Life Course of Personality Model. *Developmental Psychology, 50*(5), 1407-1425. https://doi.org/10.1037/a0031130

Sherman, R. A., Rauthmann, J. F., Brown, N. A., Serfass, D. G., & Jones, A. B. (2015). The independent effects of personality and situations on real-time expressions of behavior and emotion. *Journal of Personality and Social Psychology*, *109*(5), 872–888. https://doi.org/10.1037/pspp0000036

Sniehotta, F. F., & Aunger, R. (2010) Stage models of behaviour change. In D.P. French, A. Kaptein, K. Vedhara & J. Weinman (Eds). *Health Psychology* (2nd edition). Blackwell.

Sørensen, K., Pelikan, J. M., Röthlin, F., Ganahl, K., Slonska, Z., Doyle, G., Fullam, J., Kondilis, B., Agrafiotis, D., Uiters, E., Falcon, M., Mensing, M., Tchamov, K., Van Den Broucke, S., & Brand, H. (2015). Health literacy in Europe: comparative results of the European health literacy survey (HLS-EU). *European Journal of Public Health*, *25*(6), 1053–1058. https://doi.org/10.1093/eurpub/ckv043

Standen, E. C., & Rothman, A. J. (2023). Capitalizing on the potential of mobile health applications as behavioral interventions: A research agenda for calorie-tracking and activity-tracking applications. *Social and Personality Psychology Compass*, *17*(3). https://doi.org/10.1111/spc3.12731

Statista. (2024, September 6). *Mobile app revenue worldwide 2019-2027, by segment*. https://www.statista.com/forecasts/1262892/mobile-app-revenue-worldwide-by-segment

Statistik Austria. (2024). *Bevölkerung nach Alter/Geschlecht*. Retrieved 26 February 2024 from https://www.statistik.at/statistiken/bevoelkerung-und-soziales/bevoelkerung/bevoelkerungsstand/bevoelkerung-nach-alter/geschlecht

Statistisches Bundesamt. (2022). *Bevölkerung: Deutschland, Stichtag, Altersjahre*. https://data.europa.eu/data/datasets/30303031-3234-4031-312d-303030350000?locale=de

Statistisches Bundesamt. (2023). *Bevölkerung nach Nationalität und Geschlecht (Quartalszahlen)*. Retrieved 26 February 2024 from https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bevoelkerung/Bevoelkerungsstand/Tabellen/liste-zensus-geschlecht-staatsangehoerigkeit.html#651186

Stein, M. B., & Stein, D. J. (2008). Social anxiety disorder. *The Lancet*, *371*(9618), 1115–1125. https://doi.org/10.1016/s0140-6736(08)60488-2

Stieger, M., Robinson, S. A., Bisson, A. N., & Lachman, M. E. (2020). The relationship of personality and behavior change in a physical activity intervention: The role of conscientiousness and healthy neuroticism. *Personality and Individual Differences*, *166*, 110224. https://doi.org/10.1016/j.paid.2020.110224

Strickhouser, J. E., Zell, E. & Krizan, Z. (2017). Does personality predict health and well-being? A metasynthesis. *Health Psychology*, *36*(8), 797–810. https://doi.org/10.1037/hea0000475

Su, J., Dugas, M., Guo, X., & Gao, G. (2020). Influence of personality on mHealth use in patients with diabetes: Prospective pilot study. *JMIR Mhealth And Uhealth*, *8*(8), e17709. https://doi.org/10.2196/17709

Sutin, A. R., & Terracciano, A. (2015). Personality traits and body mass index: modifiers and mechanisms. *Psychology & Health, 31*, 259–275. doi: 10.1080/ 08870446.2015.1082561

Svendsen, G. B., Johnsen, J. K., Almås-Sørensen, L., & Vittersø, J. (2011). Personality and technology acceptance: the influence of personality factors on the core constructs of the Technology Acceptance Model. *Behaviour and Information Technology*, *32*(4), 323–334. https://doi.org/10.1080/0144929x.2011.553740

Swift, V., & Peterson, J. B. (2018). Improving the effectiveness of performance feedback by considering personality traits and task demands. *PLoS ONE*, *13*(5), e0197810. https://doi.org/10.1371/journal.pone.0197810

Tiainen, A. K., Männistö, S., Lahti, M., Blomstedt, P. A., Lahti, J., Perälä, M., Räikkönen, K., Kajantie, E., & Eriksson, J. G. (2013). Personality and dietary intake – Findings in the Helsinki birth cohort study. *PLoS ONE*, *8*(7), e68284. https://doi.org/10.1371/journal.pone.0068284

Tivian XI GmbH (2021). *Unipark*. Köln. https://www.unipark.com/

Tomczak, M., & Tomczak, E. (2014). The need to report effect size estimates revisited. An overview of some recommended measures of effect size. *Trends in Sport Sciences*, *1*(21).

Tsartsapakis, I., & Zafeiroudi, A. (2024). Personality traits and healthy eating habits and behaviors: A narrative review. *Journal of Educational and Social Research*, *14*(2), 11. https://doi.org/10.36941/jesr-2024-0022

Vaitkeviciute, R., Ball, L.E., & Harris, N. (2015). The relationship between food literacy and dietary intake in adolescents: A systematic review. *Public Health Nutrition*, *18*(4), 649-658. https://doi.org/10.1017/S1368980014000962

Vercruyssen, A., Schirmer, W., Geerts, N., & Mortelmans, D. (2023). How "basic" is basic digital literacy for older adults? Insights from digital skills instructors. *Frontiers in Education*, *8*. https://doi.org/10.3389/feduc.2023.1231701

Vinciarelli, A., & Mohammadi, G. (2014). A survey of personality computing. *IEEE Transactions on Affective Computing*, *5*(3), 273-291. https://doi.org/10.1109/taffc.2014.2330816

Walther, B. (2024, September 18). *Kruskal-Wallis-Test in SPSS rechnen*. Björn Walther. https://bjoernwalther.com/kruskal-wallis-test-in-spss-rechnen/

Wang, J. W., Zhu, Z., Shuling, Z., Fan, J., Jin, Y., Gao, Z. L., Chen, W. D., & Li, X. (2024). Effectiveness of mHealth app-based interventions for increasing physical activity and improving physical fitness in children and adolescents: Systematic review and meta-analysis. *JMIR mHealth and uHealth*, *12*, e51478. https://doi.org/10.2196/51478

Ward, R. M., & Hay, M. C. (2014). Depression, coping, hassles, and body dissatisfaction: Factors associated with disordered eating. *Eating Behaviors*, *17*, 14–18. https://doi.org/10.1016/j.eatbeh.2014.12.002

Weinstein, N. D. & Sandman, P. M. (1992). A model of the precaution adoption process: Evidence from home radon resting. *Health Psychology*, *11*(3), 170–180. https://doi.org/10.1037/0278-6133.11.3.170

Weinstein, N. D., Sandman, P. M., & Blalock, S. J. (2008). The Precaution Adoption Process Model. In K. Glanz, B. K. Rimer, & K. Viswanath (Eds.), *Health behavior and Health Education: Theory, Research, and Practice* (4th ed., pp. 123–147). Jossey-Bass.

Weston, S. J., & Jackson, J. J. (2014). Identification of the healthy neurotic: Personality traits predict smoking after disease onset. *Journal of Research in Personality*, *54*, 61–69. https://doi.org/10.1016/j.jrp.2014.04.008

Whitehead, L., & Seaton, P. (2016). The Effectiveness of Self-Management Mobile Phone and Tablet Apps in Long-term Condition Management: A Systematic Review. *Journal of Medical Internet Research*, 18. https://doi.org/10.2196/jmir.4883.

Wijayaratne, S. P., Reid, M., Westberg, K., Worsley, A., & Mavondo, F. (2018). Food literacy, healthy eating barriers and household diet. *European Journal of Marketing*, *52*(12), 2449–2477. https://doi.org/10.1108/ejm-10-2017-0760

Wilmot, M. P., & Ones, D. S. (2019). A century of research on conscientiousness at work. *Proceedings of the National Academy of Sciences*, 116(46), 23004–23010. https://doi.org/10.1073/pnas.1908430116

Wilson, K. E., & Dishman, R. K. (2014). Personality and physical activity: A systematic review and meta-analysis. *Personality and Individual Differences*, *72*, 230–242. https://doi.org/10.1016/j.paid.2014.08.023

Wilson, K. E., & Rhodes, R. E. (2021). Personality and physical activity. In Z. Zenko & L. Jones (Eds.). Essentials of exercise and sport psychology: An open access textbook (pp. 114–149). Society for Transparency, Openness, and Replication in Kinesiology. https://doi.org/10.51224/B1006

WHO Global Observatory for eHealth (2011). mHealth: new horizons for health through mobile technologies: second global survey on eHealth. World Health Organization. https://iris.who.int/handle/10665/44607

World Health Organization (2020, April 29). *Healthy diet*. https://www.who.int/news-room/fact-sheets/detail/healthy-diet

World Health Organization (2024a, June 26). *Physical activity*. https://www.who.int/news-room/fact-sheets/detail/physical-activity

World Health Organization (2024b, August 5). *Health literacy*. https://www.who.int/news-room/fact-sheets/detail/health-literacy

Xu, R., Frey, R. M., Fleisch, E., & Ilic, A. (2016). Understanding the impact of personality traits on mobile app adoption – Insights from a large-scale field study. *Computers in Human Behavior*, *62*, 244–256. https://doi.org/10.1016/j.chb.2016.04.011

Yerrakalva, D., Yerrakalva, D., Hajna, S., & Griffin, S. (2019). Effects of mobile health app interventions on sedentary time, physical activity, and fitness in older adults: Systematic review and meta-analysis. *Journal of Medical Internet Research*, *21*(11). https://doi.org/10.2196/14343

Zanker, M., Rook, L. & Jannach, D. (2019). Measuring the impact of online personalisation: Past, present and future. *International Journal of Human-Computer Studies*, *131*, 160–168. https://doi.org/10.1016/j.ijhcs.2019.06.006

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Appendix A

Quota for Sociodemographic Characteristics for the Stratification of the Sample

Table 11

Quota for the Stratification of the Sample by Gender

Gender	Austria	Germany
	% (*n*)	% (*n*)
Male	50.80 (254)	49.29 (493)
Female	49.20 (246)	50.71 (507)

Note. For Austria, the data was obtained from *Frauen und Männer in Österreich* by Bundeskanzleramt, 2021 and for Germany from *Bevölkerung nach Nationalität und Geschlecht* by Statistisches Bundesamt, 2023.

Table 12

Quota for the Stratification of the Sample by Age Groups

Age	Austria	Germany
	% (*n*)	% (*n*)
18-24	9.12 (46)	10.33(103)
25-34	16.30 (82)	15.06 (151)
35-44	16.13 (81)	14.32 (143)
45-54	17.30 (86)	17.70 (177)
55-64	17.63 (88)	17.18 (172)
65+	23.52 (118)	25.41 (254)

Note. For Austria, the data was obtained from *Bevölkerung nach Alter/Geschlecht* by Statistik Austria (2024) and for Germany from *Bevölkerung: Deutschland, Stichtag, Altersjahre* by Statistisches Bundesamt, 2022.

Table 13

Quota for the Stratification of the Sample by Education Levels

Education Levels	Austria	Germany
	% (*n*)	% (*n*)
Below upper secondary	14.05 (70)	16.46 (165)
Upper secondary	50.39 (252)	51.03 (510)
Tertiary	35.55 (178)	32.52 (325)

Note. The data was obtained from *adult education level indicator* by OECD, 2021 for both Austria and Germany.

Appendix B

Calculation of Effect Sizes – Kruskal-Wallis ANOVA

The effect size η^2 was calculated manually and based on following formula (Tomczak and Tomczak, 2014; Walther, 2024):

$$\eta^2 = \frac{H - k + 1}{n - k}$$

k (number of groups) = 5

n (total number of observations) = 1,428

Fitness Apps (η^2)

Extraversion ($H = 4.08$): $\eta^2 = -.001349$ (<.01)

Agreeableness ($H = 4.37$): $\eta^2 = -.001145$ (<.01)

Conscientiousness ($H = 4.61$): $\eta^2 = -.00097$ (<.01)

Neuroticism ($H = 15.77$): $\eta^2 = .00686$ (<.01)

Openness ($H = 15.79$): $\eta^2 = .00687$ (<.01)

Nutrition Apps (η^2)

Extraversion ($H = 0.35$): $\eta^2 = -.00397$ (<.01)

Agreeableness ($H = 1.87$): $\eta^2 = -.00290$ (<.01)

Conscientiousness ($H = 17.50$): $\eta^2 = .00808$ (<.01)

Neuroticism ($H = 29.26$): $\eta^2 = .01634$ (.02)

Openness ($H = 12.06$): $\eta^2 = .00425$ (<.01)

Calculation of Effect Sizes – Dunn-Bonferroni Post-Hoc Tests

The effect size r was calculated manually and based on following formula (Tomczak and Tomczak, 2014; Walther, 2024):

$$r = \frac{|z|}{\sqrt{n}}$$

$|z|$ = standardized z – value for group 1 and group 2

n = total number of observations, sum of n (group 1) and n (group 2)

Fitness Apps (r)

Neuroticism: "unengaged" group (n = 586), "disengaged" group (n = 194):
n (sum) = 780, z = -3.44
r = .12317 (.12)
Openness: "unengaged" group (n = 586), "acting" group (n = 383):
n (sum) = 969, z = -2.85
r = .09155 (.09)
Openness: "unengaged" group (n = 586), "decided to act" group (n = 167):
n (*sum*) = 753, z = -3.29
r = 0.11989 (.12)

Nutrition Apps (*r*)

Neuroticism: unengaged" group (n = 903), "disengaged" group (n = 165):
n (sum) = 1068, z = -3.86
r = .11811 (.12)
Neuroticism: unengaged" group (n = 903), "decided to act" group (n = 141):
n (sum) = 1044, z = -3.67
r = .11358 (.11)
Neuroticism: unengaged" group (n = 903), "decided not to act" group (n = 123):
n (sum) = 1026, z = -2.88
r = .08991 (.09)

Appendix C

Abstract (English)

Mobile health (mHealth) apps hold great potential for accessible and effective health promotion. However, only a small proportion of the population uses them, especially in the long-term. A better understanding of the characteristics of users and non-users could help develop personalized interventions to promote long-term engagement. In a digital health survey (N = 1,428) from Germany and Austria, individuals were categorized into different motivational stages during the process of fitness and nutrition app adoption ("unengaged", "decided to act", "decided not to act", "acting", "disengaged"). Additionally, their Big Five personality traits were assessed. It was assumed that Big Five levels differ across the stages of fitness and nutrition app adoption and that Conscientiousness is a moderator for active app use. For fitness apps, "unengaged" non-users (*Mdn* = 3.0) showed lower Openness levels than "acting" users (*Mdn* = 3.5, z = -2.86, p = .043) and those who had "decided to act" (*Mdn* = 3.5, z = -3.30, p = .010). "Disengaged" non-users (*Mdn* = 3.5) demonstrated higher Neuroticism levels compared to "unengaged" individuals (*Mdn* = 2.5, z = -3.44, p = .006). For nutrition apps, Neuroticism levels were higher for those who had "decided to act" (*Mdn* = 3.0, z = -3.68, p = .002), "decided not to act" (*Mdn* = 3.0, z = -2.88, p = .039), and "disengaged" non-users (*Mdn* = 3.0, z = -3.87, p = .001) when compared to "unengaged" individuals (*Mdn* = 2.5). Only Agreeableness was positively moderated by Conscientiousness for active nutrition app use [Exp(B) =1.40, p = .039]. However, the overall model was not significant [$x^2(3) = 6.72$, p = .081]. The findings suggest limited relevance of Conscientiousness for active app use, while Neuroticism might be associated with a greater willingness to adopt mHealth apps. However, sustained app use remains a challenge. Additionally, Openness could be an important factor for mHealth acceptance, especially in older individuals. Previous research on personality traits and the use of fitness and nutrition apps has shown inconsistent results. Stage models in the present study could provide clearer results due to a more nuanced differentiation of users and non-users. Ultimately, insights about the relationship between personality traits and motivational processes could help reduce barriers to sustained mHealth app engagement.

Abstract (German)

Mobile Health (mHealth) Apps bieten ein großes Potenzial für eine zugängliche und effektive Gesundheitsförderung. Allerdings werden sie nur von wenigen Personen aktiv und langfristig genutzt. Ein besseres Verständnis der Eigenschaften von Nutzer*innen und Nicht-Nutzer*innen könnte dazu beitragen, durch personalisierte Interventionen eine langfristige Nutzung zu fördern. In einer Umfrage zu Digital Health (N = 1.428) wurden Teilnehmende aus Deutschland und Österreich hinsichtlich unterschiedlicher motivationaler Stufen während des Adoptionsprozesses von Fitness- und Ernährungs-Apps untersucht („absichtslos", „entschlossen zu handeln", „entschlossen nicht zu handeln", „handelnd", „aufgehört zu handeln"). Zudem wurden Big-Five-Persönlichkeitsmerkmale erfasst. Bei der Adoption von Fitness Apps wiesen „absichtslose" Personen (*Mdn* = 3,0) signifikant geringere Werte in Offenheit auf als „handelnde" Personen (*Mdn* = 3,5, z = -2,86, p = .043) und als Personen, die „entschlossen sind zu handeln" (*Mdn* = 3,5, z = -3,30, p = .010). Für Neurotizismus zeigten jene, die "aufgehört haben zu handeln" (*Mdn* = 3,5) höhere Werte als „absichtslose" Personen (*Mdn* = 2,5, z = -3,44, p = .006). Für die Adoption von Ernährungs-Apps waren Neurotizismus Werte von "absichtslosen" Personen (*Mdn* = 2,5) niedriger als von Personen, die „entschlossen sind zu handeln" (*Mdn* = 3,0, z = -3,68, p = .002), „entschlossen sind, nicht zu handeln" (*Mdn* = 3,0, z = -2,88, p = .039) und, die „aufgehört haben zu handeln" (*Mdn* = 3,0, z = -3,87, p = .001). Nur für Verträglichkeit hatte Gewissenhaftigkeit einen positiven Einfluss auf die aktive Nutzung von Ernährungs-Apps [Exp(B) =1,40, p = .039], jedoch wies das Gesamtmodell keine Signifikanz auf [$x^2(3)$ = 6,72, p = .081]. Die vorliegenden Ergebnisse deuten auf eine geringe Relevanz von Gewissenhaftigkeit für eine aktive App Nutzung hin, wohingegen Neurotizismus mit einer höheren Bereitschaft zur App Nutzung verbunden sein könnte. Die langfristige Nutzung von mHealth Apps bleibt jedoch eine Herausforderung. Offenheit könnte die Akzeptanz von mHealth Apps fördern, insbesondere bei älteren Personen. Frühere Forschung zu Persönlichkeitsmerkmalen und der Nutzung von Fitness- und Ernährungs-Apps zeigte bisher uneinheitliche Ergebnisse. Durch eine detailliertere Differenzierung von Nutzer*innen und Nicht-Nutzer*innen durch Stufenmodelle könnte die aktuelle Studie zu eindeutigeren Ergebnissen beitragen. Einblicke in die Beziehung zwischen Persönlichkeitsmerkmalen und unterschiedlichen motivationalen Stufen könnten dabei helfen, Hürden für eine langfristige mHealth App Nutzung abzubauen.

Appendix D

Study Materials (Original German Version)

Teilnehmer*inneninformation und Einwilligungserklärung zur Teilnahme an der Studie: Gesundheitsförderderung in Deutschland und Österreich

Sehr geehrte*r Teilnehmer*in,

wir laden Sie ein, an der oben genannten Studie teilzunehmen.

Ihre Teilnahme an dieser Studie erfolgt freiwillig. Sie können jederzeit, ohne Angabe von Gründen, Ihre Bereitschaft zur Teilnahme zurückziehen. Die Ablehnung der Teilnahme oder ein vorzeitiges Ausscheiden aus dieser Studie hat keine nachteiligen Folgen für Sie.

Diese Art von Studien ist notwendig, um verlässliche neue *wissenschaftliche* Forschungsergebnisse zu gewinnen. Unverzichtbare Voraussetzung für die Durchführung von Studien ist jedoch, dass Sie Ihr Einverständnis zur Teilnahme an dieser Studie schriftlich erklären. Bitte lesen Sie den folgenden Text sorgfältig durch und zögern Sie nicht, Fragen zu stellen.

Bitte unterschreiben Sie die Einwilligungserklärung nur

- wenn Sie Art und Ablauf der Studie vollständig verstanden haben,
- wenn Sie bereit sind, der Teilnahme zuzustimmen und
- wenn Sie sich über Ihre Rechte als Teilnehmer*in an dieser Studie im Klaren sind.

1. Was ist der Zweck der Studie?

Wie gesund sind Menschen in Deutschland und Österreich, und wie kann ihre Gesundheit bestmöglich gefördert werden? Mit dieser Befragung möchten wir abbilden, wie es der Bevölkerung in Deutschland und Österreich aktuell geht und was sie über eine Reihe von Möglichkeiten zur Gesundheitsförderung denken. Dazu möchten wir insgesamt 1500 Personen einladen, uns Fragen rund um ihre Person, verschiedene Gesundheitsverhaltensweisen (insb. Ernährung, Bewegung) sowie gesundheitlicher Beschwerden (insb. Menstruation) sowie die Nutzung von verschiedenen digitalen Angeboten zur Gesundheitsförderung zu beantworten.

2. Wie läuft die Studie ab?

Sie füllen einen Fragebogen zu den folgenden Themen aus:

- Angaben zu Ihrer Person und zu Ihrem aktuellen Lebensstandard
- Persönlichkeitseigenschaften
- Besitz technischer Geräte, Nutzung verschiedener digitaler Angebote zur Gesundheitsförderung und Meinung über verschiedene Inhalte dieser Angebote
- Beschwerden in Bezug auf den Menstruationszyklus (nur für Personen, die menstruieren) und Meinung über Menstruationsurlaub

- Gewichtsverlust, Ernährungsumstellung, Wohlfühlessen und Sport

Das Ausfüllen des Fragebogens wird ca. 25 Minuten in Anspruch nehmen.

3. Worin liegt der Nutzen einer Teilnahme an der Studie?

Sie unterstützen Forschung zur Gesundheitsförderung in Deutschland und Österreich. Sie erhalten Sie mit der Bilendi GmbH vereinbarte finanzielle Entlohnung für Ihre Teilnahme.

4. Gibt es Risiken bei der Durchführung der Studie und ist mit Beschwerden oder anderen Begleiterscheinungen zu rechnen?

Die Teilnahme an dieser Studie ist mit keinen Risiken verbunden, die über die Risiken des Alltags hinausgehen.

5. Hat die Teilnahme an der Studie sonstige Auswirkungen auf die Lebensführung und welche Verpflichtungen ergeben sich daraus?

Die Teilnahme an der Studie hat keine Auswirkungen auf Ihren Alltag.

6. Was ist zu tun beim Auftreten von Beschwerdesymptomen, unerwünschten Begleiterscheinungen und/oder Verletzungen?

Beim Beantworten der Fragen können Sie jederzeit eine Pause einlegen. Bitte wenden Sie sich an uns, falls während oder nach der Teilnahme Beschwerden bei Ihnen auftreten, die mit der Teilnahme an der Studie in Verbindung stehen könnten. Diese werden von uns dokumentiert. Bitte nutzen Sie dafür die Kontaktmöglichkeiten, die unter Punkt 10 angeführt sind.

7. Wann wird die Studie vorzeitig beendet?

Sie können jederzeit, auch ohne Angabe von Gründen, Ihre Teilnahmebereitschaft widerrufen und aus der Studie ausscheiden. Hieraus entstehen keinerlei Nachteile für Sie. Es ist aber auch möglich, dass Ihre Teilnahme an der Studie vorzeitig beendet, ohne vorher Ihr Einverständnis einzuholen. Gründe hierfür können sein:

- Sie entsprechen nicht den Teilnahmekriterien, weil Sie beispielsweise jünger als 18 Jahre alt sind.
- Sie füllen den Fragebogen unaufmerksam aus.

8. In welcher Weise werden die im Rahmen dieser Studie gesammelten Daten verwendet?

Die in dieser Studie erhobenen persönlichen Daten werden unter strenger Einhaltung der gesetzlichen Bestimmungen zum Datenschutz aufbewahrt. Es werden nur Daten erhoben, die für das Erreichen des Studienziels erforderlich sind. Nur die Projektleitung und die Versuchsleitung haben Zugang zu den Daten. Die Projektleitung und die Versuchsleitung unterliegen der Schweigepflicht. Ihre Teilnahme an der Studie ist anonym, d.h. es werden keine Informationen erfragt oder gespeichert, die einen Rückschluss auf Ihre Person erlauben.
Die Daten sind in codierter Form Fachleuten zur wissenschaftlichen Auswertung zugänglich. Die

Weitergabe der Daten erfolgt ausschließlich zu statistischen Zwecken und Sie werden darin ausnahmslos nicht namentlich genannt. Auch in etwaigen Veröffentlichungen der Daten dieser Studie werden Sie nicht namentlich genannt. Ihr Name wird in keiner Weise in Berichten oder Publikationen veröffentlicht, die aus der Studie hervorgehen.
Wenn Sie die Studie vorzeitig beenden, werden Ihre Daten gelöscht. Nach Abschicken des Fragebogens ist aufgrund der Anonymität keine Löschung der Daten mehr möglich.

9. Entstehen für die Teilnehmer*innen Kosten? Gibt es einen Kostenersatz oder eine Vergütung?

Durch Ihre Teilnahme an dieser Studie entstehen für Sie keine Kosten. Wenn Sie den Fragebogen vollständig ausgefüllt haben, erhalten Sie die mit dem Marktforschungsinstitut Bilendi vereinbarte finanzielle Vergütung.

10. Möglichkeit zur Diskussion weiterer Fragen

Für weitere Fragen im Zusammenhang mit dieser Studie steht Ihnen die Projektleitung gerne zur Verfügung. Auch Fragen, die Ihre Rechte als Teilnehmer*in dieser Studie betreffen, werden Ihnen gerne beantwortet. Bei unerwarteten oder unerwünschten Ereignissen, die während der Studie auftreten, können Sie sich jederzeit an die Projektleitung wenden.

Kontaktpersonen:

Projektleitung	Univ.-Prof. Dr. Laura M. König laura.koenig@univie.ac.at

11. Einwilligungserklärung

❑1	Ich möchte an der Studie teilnehmen. Ich bestätige, dass ich mindestens 18 Jahre alt bin, in Deutschland oder Österreich lebe und ausreichend Deutsch spreche, um die Fragen beantworten zu können.

Zu Ihrer Person

Ihr Alter: _____ Jahre

Sie sind: o weiblich o männlich o divers

Sie wohnen in o Deutschland o Österreich o einem anderen Land

Ihr höchster Schulabschluss	
(Noch) kein Schulabschluss	o
Volksschul- / Hauptschulabschluss	o
Mittlere Reife / Realschlussabschluss	o
Abschluss der Polytechnischen Oberschule	o
Abschluss einer (Berufs-)Fachschule	o
Hochschulreife (Abitur/ Matura)	o
Anderer Abschluss: ____	o

Ihr höchster Ausbildungsabschluss	
(Noch) keine abgeschlossene Berufsausbildung	o
Lehre	o
Fachoberschule/Berufsoberschule	o
Fachhochschule	o
Hochschule	o
Promotion	o
Anderer Abschluss: ____	o

	Trifft überhaupt nicht zu 1	Trifft eher nicht zu 2	Teils, teils 3	Trifft eher zu 4	Trifft voll und ganz zu 5
Ich bin eher zurückhaltend, reserviert.	o	o	o	o	o
Ich schenke anderen leicht Vertrauen, glaube an das Gute im Menschen.	o	o	o	o	o
Ich bin bequem, neige zur Faulheit.	o	o	o	o	o
Ich bin entspannt, lasse mich durch Stress nicht aus der Ruhe bringen.	o	o	o	o	o
Ich habe nur wenig künstlerisches Interesse.	o	o	o	o	o
Ich gehe aus mir heraus, bin gesellig.	o	o	o	o	o
Dies ist eine Kontrollfrage. Bitte klicken Sie hier „Trifft überhaupt nicht zu“ an.	o	o	o	o	o
Ich neige dazu, andere zu kritisieren.	o	o	o	o	o
Ich erledige Aufgaben gründlich.	o	o	o	o	o
Ich werde leicht nervös und unsicher.	o	o	o	o	o
Ich habe eine aktive Vorstellungskraft, bin fantasievoll.	o	o	o	o	o

Ich besitze…	ja	nein
… ein Smartphone	o	o
… ein Handy (kein Smartphone)	o	o
… ein Tablet	o	o
… eine Spielekonsole	o	o

Hier geht es um Ihre Nutzung von Fitness-Apps

Eine **Fitness-App** dient der Aufzeichnung von verschiedenen Aspekten der körperlichen Aktivität, z.B. der zurückgelegten Schritte oder Strecke oder die Dauer und/ oder Intensität von Trainingseinheiten. Sie können teilweise mit Fitness-Trackern gekoppelt werden, um die erfassten Daten anzuzeigen. Basierend auf den Daten geben viele Fitness-Apps Empfehlungen zu einem gesünderen Bewegungsverhalten oder stellen allgemein Informationen zur körperlichen Aktivität, Sport oder Fitness bereit. Beispiele für derartige Apps sind Google Fit, Runtastic und Apple Health.

Inwiefern nutzen Sie eine Fitness-App?	
Ich habe noch nie daran gedacht, einen Fitness-Tracker oder eine Fitness-App zu nutzen.	○
Ich habe bereits geplant, einen Fitness-Tracker oder eine Fitness-App zu nutzen, habe es bis jetzt aber noch nicht getan.	○
Ich habe schon einmal daran gedacht, einen Fitness-Tracker oder eine Fitness-App zu nutzen, aber es ist nicht notwendig, dass ich es tue.	○
Ich nutze momentan einen Fitness-Tracker oder eine Fitness-App und habe vor, ihn auch zukünftig zu nutzen.	○
Ich habe schon einmal einen Fitness-Tracker oder eine Fitness-App genutzt, tue das jetzt aber nicht mehr.	○

Welche Fitness-App nutzen Sie bzw. haben Sie genutzt?

Hier geht es um Ihre Nutzung von Ernährung-Apps

Eine **Ernährungs-App** dient der Aufzeichnung von verschiedenen Aspekten der Ernährung, z.B. der verzehrten Nahrungsmittel, Kalorien oder Nährstoffen. Dazu werden meist die verzehrten Speisen in ein Ernährungstagebuch auf dem Smartphone eingetragen. Basierend auf den Daten geben viele Ernährungs-Apps Empfehlungen für eine gesündere Ernährung oder stellen allgemein Informationen zur Ernährung bereit. Beispiele für derartige Apps sind Yazio, Lifesum und MyFitnessPal.

Inwiefern nutzen Sie eine Ernährungs-App?	
Ich habe noch nie daran gedacht, eine Ernährungs-App zu nutzen.	○
Ich habe bereits geplant, eine Ernährungs-App zu nutzen, habe es bis jetzt aber noch nicht getan.	○
Ich habe schon einmal daran gedacht, eine Ernährungs-App zu nutzen, aber es ist nicht notwendig, dass ich es tue.	○
Ich nutze momentan eine Ernährungs-App und habe vor, sie auch zukünftig zu nutzen.	○
Ich habe schon einmal eine Ernährungs-App genutzt, tue das jetzt aber nicht mehr.	○

Welche Ernährungs-App(s) nutzen Sie bzw. haben Sie genutzt?

Vielen Dank für Ihre Teilnahme

Durch Ihre Teilnahme ermöglichen Sie die Untersuchung verschiedener Fragestellungen wie zum Beispiel:

- Wer nutzt Ernährungs- und Fitness-Apps?
- Welche Speisen sind besonders beliebte Wohlfühlessen?
- Wie hoch ist der Anteil menstruierender Personen, der von Einschränkungen durch körperliche und/ oder psychische Einschränkungen vor und während der Menstruation betroffen ist?

Wenn Sie Rückfragen oder Anmerkungen zur Studie haben, können Sie sich an die Projektleitung wenden:

Univ.-Prof. Dr. Laura M. König
Universität Wien
Arbeitsbereich Gesundheitspsychologie
laura.koenig@univie.ac.at

Drücken Sie auf Weiter, um die Teilnahme zu beenden.

Appendix E

Declaration on the Use of Artificial intelligence (AI) (German)

Erklärung zur Verwendung von Künstlicher Intelligenz (KI)

Hiermit erkläre ich, dass ich die folgenden KI-Hilfsmittel zur Erstellung meiner Masterarbeit mit dem Titel "Who Uses Digital Lifestyle Interventions? The Relationship of Personality Traits and the Use of mHealth Apps" verwendet habe. Ich versichere, dass die Kennzeichnung der verwendeten KI-Hilfsmittel vollständig ist, inkl. Verwendungszweck, Produktname, als auch ggfs. Prompts und Outputs des KI-Hilfsmittels. Ich verantworte die Auswahl und die Übernahme sämtlicher Ergebnisse der von mir verwendeten KI-Hilfsmittel vollumfänglich selbst.

Verwendungszweck	**Produktname des KI-Hilfsmittels**
Hilfestellung bei Übersetzungen ins Englische/ Korrekturlesung der verfassten Texte auf sprachliche Richtigkeit	DeepL, ChatGPT
Verständnis von statistischen Modellen und statistischen Fragestellungen	StatsBot (MethodsHub)

Alternativ:

☐ Ich bestätige, dass ich zur Erstellung meiner Masterarbeit keine KI-Hilfsmittel verwendet habe.