The Use of Health-Related Lifestyle Apps in 2024: Predictors of Use, Experiences and the Connection with Mental Well-Being – A Quantitative Study

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Abstract

Background: Health-related lifestyle apps are becoming more relevant in improving physical health and promoting health behaviours. Overall, physical health app use remains low while positive experiences are reported. Research into the use and experience of different types of health-related lifestyle apps is limited. Younger age, higher income, higher education and higher e-literacy skills seem to predict health app use. Moreover, conscientiousness and neuroticism seem to predict use.

Aim: In the current study, the aim was to investigate [1] participants' use of and experience with different types of health-related lifestyle apps, [2] the correlation between personality, background variables and mobile health app use, and [3] the correlation between mental well-being and physical health app use.

Methods: A cross-sectional online survey was conducted (N = 111) to measure participants' use of different types of health-related lifestyle apps using a self-developed questionnaire, the association of this use with user-related background variables, the association of this use with personality using the Big Five Inventory-10 (BFI-10), and the association of this use with mental well-being using the Mental Health Continuum Short-Form (MHC-SF) was assessed with Kendall Tau correlations and Pearsons correlation analyses.

Results: Most participants have tried a physical health app (83.9%). Mobile health app use positively correlated with the subscale of conscientiousness (r = .24, p =.012) and positively with the subscale of neuroticism (r = .34, p = .037). Age was negatively correlated to mHealth app use (r = -.24, p =.002) and average screen time was positively correlated to app use (r = .21, p =.006). A positive correlation was also found between the total use of physical health apps and mental well-being (r = .12, p =.005) and psychological well-being (r = .14, p =.012).

Conclusion: With the cross-sectional design of the study, the rather small sample size and the unrepresentative sample in regard to the general population, future research that uses a longitudinal design to test the effects of health-related lifestyle apps on a representative and sizable sample is needed.

Keywords: mHealth apps, physical health, lifestyle apps, personality, mental well-being

Introduction

In today's digital age smartphones are an integral part of human life. Almost everyone uses a smartphone on a daily basis. The 2022 Global Attitudes Survey, which questioned people from 18 developed countries, revealed that around 85% of the population owns a smartphone (Pew Research Center, 2022). Of the remaining 15%, 11% said they own a mobile phone and only 3% indicated that they do not own a phone at all. But it's not just smartphones, smartwatches have also gained popularity over the years, with an estimated 224 million users worldwide, according to Shewale (2024). Another data report (Kemp, 2023) indicates that in January 2023 almost 30% of internet users aged 16 to 64 owned a smartwatch or smart wristband. With smartphones and smartwatches, there comes a variety of apps. One category of apps that has become more and more popular in the last years is mobile health apps (Bol et al., 2018). Of around 2 million available apps in the Apple App Store and 2.4 million apps in the Google Play Store, 72.174 and 71.728 respectively, were health and fitness apps (AppBrain, 2024; Curry, 2024; Statista, 2024). According to the Health Information National Trends Survey (HINTS) from 2018 and 2019, almost 60% of the U.S. population used mHealth apps. In 2023, there were over 300 million health app users (Wylie, 2024). This major increase in mHealth app users shows a growing reliance on technology for personal health but also raises important questions about about how effective these tools really are and what they mean for the future of healthcare.

Lifestyle Apps – Definition and Classification

Mobile health applications (mHealth apps) are defined as "software applications, related to health knowledge and research, used by health care professionals and patients to improve health treatments and public health." (Pires et al., 2020, p. 2). Within the category of mHealth apps, there are different sub-categories. The most commonly used health apps are lifestyle apps (Keller & Ercsey, 2023). Examples of these apps are fitness and diet applications. Other subcategories include medical record apps or diagnosis assistant apps. Since health-related lifestyle apps are the most common subcategory of apps within the sphere of mHealth apps, the focus will be on these apps in this bachelor thesis. There is no clear definition of lifestyle apps in the literature. However, it can be said that lifestyle apps are not targeted at patient groups with specific diseases, as is often the case with other mHealth apps (Pires et al., 2020). Therefore, they can be used by the wider public and can have a larger influence on public health. However, the literature on lifestyle apps is scarce (Shabir et al., 2022). That is why it is crucial to analyse the usage of these apps and the effects of lifestyle apps on personal health and mental well-being.

Before analysing the current literature on the topic, it is important to categorise and classify health-related lifestyle apps. These apps can be used for different purposes and there are a variety of categories these apps can be classified in. In a Dutch study, mHealth apps have already been classified (Bol et al., 2018). However, no classification has been done in regard to lifestyle apps in previous studies. Nevertheless, specific lifestyle apps have been mentioned and investigated in the literature. For instance, Pires et al. (2020) name fitness and nutrition apps as the most relevant health-related lifestyle apps (LAs). In addition to that, Shabir et al. (2022) mentioned exercise & fitness apps, diet & weight management apps, as well as sleep hygiene apps. In another study, Chen et al. (2016) made a differentiation between apps covering physical activity, nutrition, weight and sleep. Keller & Ercsey (2023) also specified calorie-counting apps as one category. The Dutch study by Bol et al. (2018) about mobile health app use also suggested apps to monitor vital signs and support in case of an emergency as one category. Moreover, mindfulness apps, reproductive health apps, wearable apps, and health dashboard apps were discussed. Based on the usage of the LAs in the specific categories and the fitting to this study several categories were selected (see Table 1). Mindfulness apps were not further investigated as the focus of this research is on health-related LAs that target physical health. Reproductive health apps were not analysed because they have a specific target group of young women, as they are apps for pregnancy, ovulation and menstruation (Bol et al., 2018). The target group is too small to expect significant results with the existing sample. Wearable apps were also not included as a category since there are many apps that can be downloaded on a smartphone and a smartwatch and therefore it could cause misunderstandings in a questionnaire. Furthermore, health dashboard apps were excluded because they store health data from other apps and are used to get an overview of personal health data (Bol et al., 2018). Accordingly, they can only be used when other LAs are used.

Table 1

Classification of health-related lifestyle apps

	Description	Examples
Fitness Apps		
Fitness Apps	Apps to find workouts, receive training plans or do online training	Nike Training Club, FitOn, Adidas Training
Exercise Trackers	Apps to track workouts or exercises	Strava, FitNotes, Fitbod, Nike+ Run Clubs
Step Counters	Apps to track your daily steps	StepsApp Pedometer, Pedometer++, Pedometer a – Step Counter
Calorie Counters	Apps to keep track of the daily calories eaten	MyFitnessPal, YAZIO, Fddb
Sleep Trackers	Apps to evaluate sleep quality and sleep habits	SleepCycle, SleepWatch, Calm
Weight-Tracking Apps	Apps to keep track of your weight as well as other weight-related variables	Withings, Monitor My Weight, WeightWatchers: Weight Health

Bodily Function Trackers	Apps to measure body functions like the heart rate or the level of oxygen	Instant Heart Rate: HR Monitor, Cardiio: Heart Rate Monitor, Blood Oxygen App + Monitor

The first selected category is fitness apps. They are the most popular lifestyle apps, with 52% of the Dutch population using at least one fitness app (Bol et al., 2018). In this study, the broad category of fitness apps is split into three categories to get more specific results. One of them is called fitness apps in this study. They are used to find workouts, receive training plans or do online training. Examples include Nike Training Club, FitOn or Adidas Training. The second one is called exercise trackers. They are made to track workouts or exercises. For instance, they are used to track runs. Examples are Strava, FitNotes, Fitbod or Nike+ Run Clubs. The third one is step counters. They are used to track your daily steps. The fourth selected category for this study is calorie counters. Examples are MyFitnessPal, YAZIO or Fddb. These apps are used to keep track of the daily calories eaten. The fifth category is sleep trackers. They are used to evaluate sleep quality and sleep habits (Attie & Meyer-Waarden, 2023). Examples include SleepCycle, SleepWatch or Calm. The sixth category consists of weight-tracking apps. They are used to keep track of your weight as well as your BMI and other weight-related variables. The last category is bodily function trackers. These are apps that are mostly used on smartwatches and that can measure body functions like the heart rate or the level of oxygen.

Potential Benefits and Limitations of Health-Related Lifestyle Apps

The general population has seen a rise in the need for mHealth apps in recent years (Zhao et al., 2016). Mobile app programs have been used to to prevent and manage risk factors of diseases, by trying to reduce obesity, stress, smoking, and other risk factors, as well as to improve dietary habits, increase physical activity, and promote weight loss (Laing et al., 2014; Rabbi et al., 2015; Zhao et al., 2016). Especially adolescents are often physically inactive with around 80% of school children, 11-17 years old, not meeting the WHO physical activity guidelines in 2016 (World Health Organization, 2022). mHealth apps were shown to be modestly beneficial in promoting physical activity and good eating habits in a recent research study (Schoeppe et al., 2016). In the research project by Schoeppe et al. (2016), conducting a systematic literature search, twenty-seven studies that used mobile health interventions were selected. They were analysed regarding the efficacy of mobile health apps in improving physical health. It was found that health apps can be effective in improving diet, physical activity and sedentary behaviour but that multi-component interventions seem to be more effective (Schoeppe et al., 2016). Another study from the UK found that users of health-related LAs showed decreases in sedentary time, increases in steps per day, as well as increases in fitness, at least in trials of three months or shorter (Yerrakalva et al., 2019). In an American study, there was also a correlation found between mobile health app use and positive eating behaviours and improvements in lifestyle (Sarcona et al., 2017). Moreover, the use of weight-tracking apps often resulted in weight loss according to a previous study (Burke et al., 2012). Thus, health apps can be part of the solution to tackle the problem of high overweight and obesity rates in developed countries with a majority of adults and children not consuming the appropriate amounts of fruits and vegetables or participating in the recommended amount of daily physical exercise (Forouzanfar et al., 2016). A study investigating the effects of a specific mobile health intervention app, called #LIFEGOALS, on physical health also showed that mobile health apps can have a positive effect on sleep quality and mood (Peuters et al., 2024).

On the other hand, gym memberships are very popular in Europe, with as many as 10.3 million memberships in Germany (Statista, 2022). That might be one explanation for the popularity of fitness and diet tracking apps. Exercise and diet are together with sleep the basic pillars of health (Shechter et al., 2014). Sleep is substantial for the human body as poor sleep can lead to negative consequences for physical health but also to negative psychological consequences (Clement-Carbonell et al., 2021). Since sleep, diet and exercise are so essential for our health, sleep trackers, calorie counters, fitness apps and weight tracking apps are important as they can help to improve these factors. Apart from that, bodily function trackers can help to see if the body functions properly and to recognise if something is wrong in case of emergency. This is relevant for high-risk groups, especially older people. Thus, learning more about the user experience with these apps, as well as identifying who uses them and who does not can be valuable.

Even though some studies report positive associations between mobile health app use and health-promoting behaviour, the research is not clear in this regard. There are studies that do not show a positive correlation. In a meta-analysis, focusing on 52 studies, no strong evidence for the effectiveness of health apps in improving health behaviours or outcomes was found (Milne-Ives et al., 2020). The reason for that was that only a few studies found significant differences between app and control groups. Furthermore, Lee et al. (2024) found that within the U.S., health apps are not effective in improving physical well-being. Also, the Chinese sample of this study did not report better health after using LAs. Another disadvantage of using health apps is often the amount of data that has to be shared and the accompanying privacy concerns (Adhikari et al., 2014; Krebs & Duncan, 2015). In a U.S. study, conducted by Krebs and Duncan (2015), 29% of the part of the sample that reported they downloaded health apps they no longer use complained about data being shared with friends. Additionally, high costs seem to be a disadvantage of some health-related lifestyle apps. In Krebs and Duncan's study (2015), 23% of non-health app users complained about high costs. Also, 36% of people who stopped using mobile health apps, named hidden costs as one of the reasons they discontinued using the apps (Krebs & Duncan, 2015).

There were also more problems with health-related lifestyle apps found in previous research. In a Hungarian study, where a thematic analysis of Google Play reviews of LAs was done, the negative comments of health apps were analysed and it was found that unreliable tracking, unreliable function, problems with updates and technical problems were the biggest issues (Keller & Ercsey, 2023). Moreover, many users of LAs complained about advertisements in the free version of apps and missing functions. These study results give a good overview of current problems with health apps.

The Connection between Health-Related Lifestyle Apps and Mental Wellbeing

Apart from the effects of lifestyle apps on physical health, it is necessary to understand the relationship between using health-related lifestyle apps and mental well-being. Does using LAs actually lead to a more fulfilling life? When looking at the relationship between mHealth app use and mental well-being, Sarcona et al. (2017) found that users of health apps felt better about themselves compared to non-users. Another study from 2024, where Chinese, Singaporean and American mHealth users were analysed, showed that in the US there is a positive correlation between health app use and psychological well-being (Lee et al., 2024). In the Chinese sample, there even was a positive relationship found between mHealth app use and psychological, emotional and social well-being.

Even though some studies have looked at the relationship between mHealth app use and mental well-being, there has not been a European study looking at the relationship. Moreover, there needs to be more research conducted evaluating the connection between using specific health-related lifestyle apps and mental well-being. In that respect, this study tries to contribute to the research on how the use of health apps influences the mental well-being of users.

Current Use of Health-Related Lifestyle Apps

It is important to understand how health-related LAs are being used and what the user experience is to know which features of mHealth apps have to be improved to reach higher and more engaged usage numbers. In general, it can be said that health apps are mostly used for nutrition and fitness (Krebs & Duncan, 2015). In the study by Krebs & Duncan (2015), 58% of their U.S. sample had downloaded a health app and 41% had downloaded more than five health-related LAs. The majority of respondents (65%) in the survey opened their health apps at least once per day and 44% used their mHealth apps for 1-10 minutes every day (Krebs & Duncan, 2015). The most common reasons given for installing health applications were to monitor their physical activity levels (53%), food intake (48%), weight loss (47%), and exercise instruction (34%). Compared to the American study, a Dutch study by Bol et al. (2018) found that in their sample 37% had installed mobile health apps on their smartphone. 29% of the total sample actually used health apps. On average, those who reported having a health app had three mobile health apps on their phone (Bol et al., 2018). The most common apps used in the study sample were fitness and nutrition apps. 15% of the total sample used fitness applications and 8% used nutrition apps.

Apart from the descriptive statistics, it is also important to understand how users evaluate the current use of mobile health apps. Therefore, U.S. researchers invited university members to share their thoughts on selected LAs (Vaghefi & Tulu, 2019). In this research, interface design was an important factor, with respondents preferring clean and simple screens and no overwhelming ads. Besides, participants expressed their preference for an easy-to-understand navigation menu and a smooth flow between screens of the app (Vaghefi & Tulu, 2019). Moreover, notifications are important, with people stating that notifications encourage users to use the app. However, participants preferred simple notifications. Also important was that the mHealth applications' data collecting tools and processes would be easy to use and take little effort. Furthermore, people mentioned that goal management features are important to them. The interviewed users wanted to be able to set goals and track their performance regarding their goals (Vaghefi & Tulu, 2019). Lastly, participants of the study mentioned freely available knowledge in apps and actionable recommendations for progress as important features of mHealth apps. Since this study was also only a qualitative study it can only give an idea of factors that are important to mHealth users, but it is not representative.

A literature review by Shabir et al. (2022) analysed factors that are important for continued use of mHealth apps. Significant factors were intrinsic motivation and extrinsic motivation. With extrinsic motivation, the study authors mean gamification elements and reward systems (Shabir et al., 2022). Also, goal setting and subsequent tracking of progress were beneficial for continued use. Lastly, supportive and active social environments were important features for users. In addition to that, the authors of the study mention that marketing and branding of LAs are crucial for people to learn about the existence of the app. Moreover, users of some mHealth apps complained about too many notifications and invasive advertisements (Shabir et al., 2022). Since the research on user experience of specific categories of health-related lifestyle apps is limited, it is important to get more data on this topic and understand how users feel about LAs.

Predictors of Use

In order to make the development of new interventions using health-related LAs more effective and in order to facilitate the development of new lifestyle apps, it is beneficial to know who the users are and what factors influence their use. Besides, it is valuable to understand which groups are not using these apps, so companies and researchers can specifically target people who have not been convinced of using mHealth apps, yet.

Demographics

One factor that is important to look at is demographics. The question is who uses mHealth apps and why. In order to answer this question, several surveys and data analyses have been conducted in the past. One characteristic that might have an influence on the use of health-related lifestyle apps, is gender. Women seem to be more likely to use mobile health apps. In a Czech study, more women than men used mHealth apps. However, the Czech study was not representative, as it only surveyed mobile app users from healthy lifestyle websites (Elavsky et al., 2017). Also, these findings stand in contrast to the studies of Bhuyan et al. (2016) and Krebs and Duncan (2015), which were nationally representative. These studies did not find differences by gender regarding the use of mHealth apps. When it comes to specific lifestyle apps, a Dutch study found that men more often used fitness apps and on the other hand women were more likely to use diet apps (Bol et al., 2018).

Another characteristic that seems to predict the use of mobile health apps is age. Younger people seem to be more likely to use health-related LAs. Krebs and Duncan (2015) found correlations between increased usage of health-related applications and younger age. Also, Bol et al. (2018) found that Dutch mHealth app users were generally younger. Older people, however, were more likely to use bodily function trackers (Bol et al., 2018). In contrast to the finding that young age predicts higher health app use, Elavsky et al. (2017) found that age did not predict a more frequent use of health-related LAs

The third factor that seems to predict health app use is income. Bhuyan et al. (2016), where data was obtained from cycle 4 of the 4th edition of the Health Information National Trends Survey (HINTS 4), and Krebs and Duncan (2015) found positive correlations between increased use of mobile health apps and income. People with a higher income are more likely to use health apps. The same correlations were also found in regard to education. The higher the education the more likely it was to use mobile health apps. This correlation was also found by Bol et al. (2018). However, Elavsky et al. (2017) found in their Czech sample that income or education did not predict a more frequent use of health-related lifestyle apps.

Other variables that might predict the use of mobile health apps are the BMI, the living area, smoking and the level of e-literacy. Krebs and Duncan (2015) found in their study, where they surveyed a representative sample of the U.S. population, that users tended to have a BMI in the obese range. Also, Bhuyan et al. (2016) found that obese people were more likely to use health apps. Moreover, they found that most mHealth app users lived in an urban area and were non-smokers. Bol et al., on the other hand, found correlations between mobile health app use and higher levels of e-literacy. Other interesting findings were that in the Czech study by Elavsky et al. (2017), excessive activity predicted the use of apps for managing sport and exercise, whereas drive for thinness predicted the frequency of use of apps for healthy eating, following a diet, and losing weight. Since there is not much previous research data on the predictors for mHealth app use and the results are sometimes contradictory, it is important to collect more data in order to better understand who uses these apps. Additionally, it is essential to collect new data about the users from 2024, since the mHealth industry has developed a lot in recent years.

Attitudes and Beliefs

Other factors that might affect the use of health-related LAs are attitudes and beliefs. In the study by Bhuyan et al. for example (2016), they found that most mHealth app users were confident in their ability to take care of themselves. In the study by Krebs and Duncan (2015) survey respondents who used mobile health apps reported that they believed the data security of their used health apps was high. Moreover, many app users claimed that the data recorded by the apps was accurate.

Personality and Health-Related Lifestyle Apps

One aspect that has not been well researched in connection to health app use but may have an impact on the use of health-related lifestyle apps, is personality. So far, only a single study has looked at how personality affects the usage of health-related LAs. Nonetheless, having these insights is crucial to comprehending the user archetype and better meeting the demands of app users. Studies frequently include the Big Five personality traits, conscientiousness, extraversion, agreeableness, neuroticism, and openness because they provide valuable context (Aziz et al., 2023). In the study by Aziz et al. (2023), the relationship between personality features and physical health app use was examined. It was found that users who score high on conscientiousness and neuroticism use physical health apps more frequently. Next to that, a cluster analysis was conducted, where typical physical health app users were searched for. Three different archetypes were found (Aziz et al., 2023). The first one was ‘happy conscious occasional’ users. They are satisfied with life, high in conscientiousness and low in neuroticism. This group uses mHealth apps almost once every day. The second archetype was ‘happy neurotic occasional users. This group is satisfied with life, moderate in conscientiousness and high in neuroticism. They use health apps regularly. The last group are ‘neutral neurotic frequent’ users. They are neither satisfied nor dissatisfied with life and score high on conscientiousness and neuroticism. They use health-related LAs almost three times a day. Since this is the only study researching the effect of personality on health app use, more research is needed in order to confirm or reject the claims. Moreover, it has to be seen whether other personality traits than conscientiousness and neuroticism also have an effect on physical health app use.

Research Objectives and Questions

The purpose of this study is to look at how various kinds of health-related lifestyle apps are used and experienced. Next, the relationship between personality and the usage of health-related LAs will be examined, along with other background characteristics. Lastly, the relationship between mental health and the usage of health-related lifestyle apps will be analysed. The present study is centred around the following research questions:

RQ1: *To what extent are different types of health-related lifestyle apps being used and what are people's experiences with using these apps?*

RQ2: *To what extent are personality traits and background variables associated with the use of health-related lifestyle apps?*

RQ3: *To what extent is the use of health-related lifestyle apps associated with mental well-being?*

Methods

Design

Participants' usage of and experiences with various health-related lifestyle app categories, as well as the correlation between their use and person-related background characteristics, personality traits, and mental health, were assessed by a cross-sectional online survey.

Participants and Procedure

The University's Behavioural Management and Social Sciences Ethics Committee gave the study approval. The project targeted European adults, specifically in Germany and the Netherlands, of every age. Participants had to meet two requirements in order to be eligible to participate: they had to be at least 16 years old and proficient in either German or English. Two techniques of sampling were utilised to obtain the sample consisting of 111 people. Snowball sampling was used to find participants, and those the researchers knew were urged to take part and tell their friends and family about it as well. Here, participants received a link to the Qualtrics-created online survey. The poll was offered in both German and English, allowing respondents to select their favourite language. In addition, convenience sampling was employed using the University of Twente's Sona participant acquisition website. In this instance, participants were able to register using Sona in order to take part and get Sona credits as compensation. Prior to completing the survey, participants were given an information sheet with further pertinent details about the study, including its topic and significance. They were then asked to sign an informed consent form acknowledging that their participation was voluntary. See Appendix A. Participants were also told that participants may leave the research at any moment, for any reason, and that there would be no repercussions. In addition, participants were told that their answers would remain anonymous and would only be utilised for the study and that they may get in touch with any of the researchers with any queries. Participants gave their consent when their answer to the question: “Do you agree to all the above-mentioned statements?” was yes. Upon consenting, respondents could finish the questionnaire. The questionnaire was built with Qualltrics. It took about 20 minutes to participate.

Materials

Questionnaire

The online questionnaire included questions about three groups of variables: (1) person-related background variables and personality, (2) use and experience with health-related LAs and (3) mental well-being.

Person-related background variables and personality

Personality-related questions were incorporated to inquire about the characteristics of the participants, including age, gender, and education level (see Table 1 for specific questions and response choices). The Big Five Inventory-10 (BFI-10) developed by Rammstedt and John (2007) was used to measure personality. It is the short form of the Big Five Inventory-44, which was created in the 1980s and consists of 44 items. Ten pieces make up the BFI-10, two for each of the Big Five dimensions. The internal reliability of each of the five subscales was assessed in order to look into the reliability of the BFI-10. Participants could select their response on a five-point Likert scale that reads as follows: (1) "strongly disagree," (2) "disagree a little," (3) "neither agree nor disagree," (4) "agree a little," and (5) "strongly agree." One of the two questions for each Big Five dimension was inverted, so a greater score denoted a lesser inclination for that Big Five dimension. The following are the five subscales: 1) In the current study, extraversion (α =.46) was measured using two items: "I see myself as someone who is outgoing, sociable" and "I see myself as someone who is reserved," which reflects the contrary item. 2) Agreeableness (α =.49 in the current study) between the following items: "I see myself as someone who tends to find fault with others" and "I see myself as someone who is generally trusting." 3) Conscientiousness (α =.49 in the present research) with the items "I see myself as someone who does a thorough job" and "I see myself as someone who tends to be lazy". 4) Neuroticism (α =.55 in the present study) with the items "I see myself as someone who gets nervous easily" and "I see myself as someone who is relaxed, handles stress well" as the reverse item. 5) Openness (α =.48 in the current research), with the opposite items "I see myself as someone who has few artistic interests" and "I see myself as someone who has an active imagination". The subscales were computed despite the fact that the alphas in the current study were too low in order to compare the results with prior findings and since the scale has been verified in other studies. The scores on the two items were averaged to create a scale score after the reverse items were recoded. Stronger personality traits are indicated by higher scale scores. Overall, according to Rammstedt and John (2007), the BFI-10 is deemed valid and trustworthy.

Use of and experience with health-related lifestyle apps

The use and experience with LAs were assessed with a self-developed questionnaire, consisting of seven parts for each health-related lifestyle app category. Before the questions were displayed, there was an introductory text that explained health-related lifestyle apps. In addition, the participants were provided with examples of current apps in order to give them an idea about the different categories of health-related LAs.

The survey was designed to measure the usage of apps by asking participants to rate their frequency of use of each type of app using a four-point Likert scale: "no" (0), "yes, once" (1), "yes, occasionally" (2), and "yes, regularly" (3). Seven categories or subscales were used to divide the apps. For each category one question about the usage of apps was asked. The question was the following: “Have you ever used a XX app for/to XX (e.g. XX)?” The seven categories were: 1) Fitness apps. Here the question was: “Have you ever used a fitness app for workouts, training plans, online training etc. (e.g. Nike Training Club, FitOn, Gymshark Training or Adidas Training)?”. 2) Exercise trackers. The question was the following: “Have you ever used an exercise tracking app to keep track of your workouts/runs (e.g. Strava, FitNotes, Fitbod or Nike+ Run Club)?”. 3) Step Counters. The question was the same as the question in the previous categories, only in regard to step counters. 4) Calorie Counters. The example apps given were MyFitnessPal, YAZIO and Fddb. 5) Sleep Trackers. The example apps given were Sleep Cycle, SleepWatch and Calm. 6) Weight tracking apps. The example apps given were Withings, Monitor My Weight and WeightWatchers: Weight Health. 7) Bodily function trackers. The question was: “Have you ever used an app on your smartphone or smartwatch to track your body functions like your heart rate or level of oxygen in your blood?”. The total score ($\alpha = .86$) on the use of health-related LAs was calculated by taking the mean score of all items in the scale. The higher the score, the more a participant used different LAs.

If the response to the usage assessment item was "yes, once (1)," "yes, occasionally (2)," or "yes, regularly (3)," a follow-up question was asked. Respondents were asked if they still use the apps. For instance, they were asked: “Do you still use a weight tracking app?”. After that two more questions evaluating the user's experience with specific health-related

LAs were posed, asking "To what extent did you like the XX apps you used?" ("Not at all" (0), "Very little" (1), "Somewhat" (2), "Very much" (3)) and "To what extent was your use of this app helpful to reach your health goals?" ("Not at all" (0), "Very little" (1), "Somewhat" (2), and "Very much" (3)). For the last two subscales, the mean was calculated to see what type of LAs participants liked and perceived as helpful. The higher the mean, the higher the liking and perceived helpfulness of the health app.

Three additional researchers' questionnaires concerning mental health apps, self-tests and cyberchondria were included in addition to the self-developed one about health-related lifestyle apps; however, they were not included in the current thesis.

Mental health and well-being

Finally, Keyes' Mental Health Continuum Short Form (MHC-SF) was incorporated to assess the variable mental well-being (Yeo & Suárez, 2022). It is an abbreviation of the forty-item Mental Health Continuum-Long Form. It has fourteen questions on the participants' emotions from the previous month. A six-point Likert scale with the options "Never" (0), "Once or twice" (1), "about once a week" (2), "about two or three times a week" (3), "almost every day" (4), and "every day" (5) is available for participants to select from for each topic. Three subscales make up the MHH-SF: 1) Emotional well-being with three items measuring happiness, interest, and life satisfaction; for example: “In the past month, how often did you feel happy?” ($\alpha = .82$ in the current study). 2) Social well-being comprising five items measuring social coherence, social acceptability, social integration, social actualisation, and social contribution; e.g., " In the past month, how often did you feel that you had something important to contribute to society" ($\alpha = .81$ in the current study). 3) Psychological well-being with six items measuring self-acceptance, environmental mastery, positive relations with others, personal growth, autonomy, and life purpose; for instance, " In the past month, how often did you feel that you liked most parts of your personality?" ($\alpha = .80$ in the current study). The mean score of each item on the scale was used to get the overall MHC-SF score. Scale ratings ranged between 0 and 5, with higher numbers denoting a participant's better mental health. In the current study, the complete MHC-SF demonstrated high reliability (α =.87).

Data Analysis

The information gathered from Qualtrics was converted into an Excel spreadsheet so that R could be used for analysis. The absence of any missing values was examined. Eight individuals were eliminated for the related analysis because three of the participants did not complete all of the items on the BFI-10 and five of the participants did not complete all of the questions on the MHC-SF. The demographic data's means, standard deviations, ranges, and frequencies were examined through the use of descriptive statistics. Descriptive statistics were calculated to look at the use of and experience with health-related lifestyle apps. The overall score of the self-developed questionnaire and the BFI-10 subscales were subjected to Pearson correlation analysis in order to investigate the relationship between personality and the usage of LAs. Because the background factors had varying degrees of quantification, multiple correlation studies were performed to look at the relationship between them and the use of lifestyle apps. Kendall Tau correlations were computed to look at the relationship between the use of health-related lifestyle apps and age, education, employment, average daily screen time, and health. The Kruskal-Wallis test was used to investigate the relationship between nationality and app usage, while the Wilcoxon Rank sum test was employed to investigate the relationship between gender and app use. Additionally, Pearson correlation analyses were carried out on the MHC-SF subscales and total score as well as the self-developed questionnaire regarding the use of LAs in order to investigate the relationship between mental well-being and the use of particular health-related lifestyle apps.

Results

Demographics of participants

With 111 participants, the mean age was 33.4 years, and the standard deviation of 16 years indicated a wide range of ages (Table 1). There was a 16–72 age range. Of the participants, one-third were male, and two-thirds were female. Most of the participants were Dutch or German. The majority had completed high school as the highest-received diploma, although the education levels ranged from less than that to a master's degree. The participants' employment statuses varied, with almost half working full-time. Among the participants, half said they were in good health. However, of the survey respondents doing sports regularly, 57% indicated that exercise/go to the gym. 30% said that they cycle and 27% stated that they are running. Additional background factors were measured but not included in this investigation.

Table 1

Demographic Characteristics of the Participants. (N = 111)

Sample characteristic	Categories	*N*	%	*M (SD)*
Age		111		33.4 (16.1)
Gender	Female	74	66.7%	
	Male	37	33.3%	
	Non-binary	0	0.0%	
	Prefer not to say	0	0.0%	
Nationality	Dutch	22	19.8%	
	German	77	69.4%	
	Albanian	1	0.9%	
	Polish	4	3.6%	
	Greek	1	0.9%	
	German immigrant	1	0.9%	
	Colombian	1	0.9%	
	Serbian	1	0.9%	
	Ukrainian	1	0.9%	
	Other (not specified)	2	1.8%	
Highest education completed	Less than high school diploma	34	30.6%	
	High school degree or equivalent	47	42.4%	
	Bachelor’s degree	10	9.0%	

Sample characteristic	Categories	*N*	%	*M (SD)*
	Master’s degree	14	12.6%	
	Doctorate	0	0.0%	
	Other	6	5.4%	
Current employment status	Pupil	17	15.3%	
	Full time student	27	24.3%	
	Not employed (including retired, looking for employment, house mother/father)	5	4.5%	
	Part time employed or part time own business (>8 hours < 32 hours)	15	13.5%	
	Full time employed or occupied with own business (>32 hours a week)	47	42.4%	
Average screen time per day	0-2 hours	12	10.9%	
	3-4 hours	35	31.5%	
	5-7 hours	40	36.0%	
	8-10 hours	14	12.6%	
	More than 10 hours	10	9.0%	
Health	Poor	2	1.8%	
	Fair	33	29.7%	
	Good	51	46.0%	
	Very good	22	19.8%	
	Excellent	3	2.7%	

Note. *N* = number of participants, *%* = percentage of sample, *M* = mean, *SD* = standard deviation.

Participants on the BFI-10 scored lowest on the neuroticism subscale and highest on the conscientiousness subscale (Table 2). Participants on the MHC-SF rated lowest on the emotional well-being subscale and highest on the psychological well-being subscale. To compare the mean of the BFI-10 and MHC-SF from the current study with the mean of previous studies, a reference mean from other studies was used. A one-sample t-test was calculated. The present study's BFI-10 results ($p > .05$) show a substantial difference from Balgiu (2018)'s results. The respondents of the present study scored higher on conscientiousness and neuroticism and lower on agreeableness than the sample of Balgiu (2018). The extraversion subscale mean is the only one whose mean ($p = .192$) is not substantially different. The MHC-SF results in this study ($p < .05$) do not differ statistically from those of Bassi et al. (2021). However, the mean of the subscale of emotional well-being is significantly higher in the study of Bassi ($p = .01$).

Table 2

Descriptive Statistics (means, SD), on Personality Traits (BFI-10) and Mental Well-being (MHC-SF). (N =111)

Variable	Number of items	Range	*M* (*SD*)	Reference mean [a]	*p* [b]
BFI-10 Extraversion	2	2-10	6.4 (2.1)	6.7 (1.7)	.192
BFI-10 Agreeableness	2	2-10	6.8 (1.6)	8.4 (1.4)	.002
BFI-10 Conscientiousness	2	2-10	7.2 (1.8)	6.6 (1.8)	.004
BFI-10 Neuroticism	2	2-10	6.2 (2.1)	5.5 (2.1)	.016
BFI-10 Openness	2	2-10	6.6 (2.1)	-	.023
MHC-SF total	14	0-70	40.1 (13.5)	40 (13.6)	.034
MHC-SF emotional well-being	3	0-15	10.2 (3.4)	9.3 (3.6)	.013
MHC-SF social well-being	5	0-25	11.1 (5.7)	11.2 (5.5)	.006
MHC-SF psychological well-being	6	0-30	18.8 (6.4)	19.5 (6.7)	.021

Note. M = Mean; *SD* = standard deviation; *BFI-10* = Big-Five Inventory-10; *MHC-SF* = Mental Health Continuum- Short Form;

[a] Reference means for the BFI-10 were taken from Balgiu (2018), who used the BFI-10 on a sample of 496 participants with a mean age of 19.2; reference means for the MHC-SF were taken from Bassi et al. (2021), who used the MHC-SF on a sample of 653 participants with a mean age of 42.9.

[b] Significance levels of deviation with the reference.

To what extent are different types of health-related lifestyle apps being used and what are people's experiences with using these apps?

On the self-developed questionnaire measuring the use of health-related lifestyle apps, participants indicated that their use of LAs was high (Table 3). Step counters were most often used (with around 61% of the participants responding to having some or even regular experience with such an app). Also, fitness apps and exercise trackers were very popular with around 60% and 55% respectively having used an app at least once, whereas weight tracking apps were least used (with around 24% having experience using one of these apps). Furthermore, sleep-tracking apps were also not popular with only 26% having used one of these apps at least once in the past.

Table 3

Descriptive Statistics of the Use of Health-Related Lifestyle Apps. (N =112)

Lifestyle Apps	No (0)	Yes once (1)	Yes occasionally (2)	Yes regularly (3)	*N* of participants
Fitness Apps	44 (39.3%)	18 (16.1%)	28 (25%)	22 (19.6%)	
Exercise tracker	51 (45.5%)	15 (13.4%)	22 (19.6%)	24 (21.4%)	
Step counter	29 (27.6%)	12 (11.4%)	19 (18.1%)	45 (42.9%)	
Calorie Counter	68 (60.7%)	12 (10.7%)	15 (13.4%)	17 (15.2%)	
Sleep Tracker	83 (74.1%)	7 (6.3%)	12 (10.7%)	10 (8.9%)	
Weight tracking apps	85 (75.9%)	6 (5.4%)	13 (11.6%)	8 (7.1%)	
Bodily functions tracker	76 (67.9%)	5 (4.5%)	20 (17.9%)	11 (9.8%)	
No use at all (0)					18 (16.07%)
Use (1-3)					94 (83.93%)

Note. N = Number of participants.

Of those participants who used lifestyle apps, most of them liked the apps somewhat whereas they liked step counters, fitness apps and exercise trackers the most and calorie counter and weight tracking apps the least (see Table 4). Participants liked LAs more than they perceived them as helpful. Most participants perceived exercise trackers and fitness apps as being somewhat helpful whereas sleep trackers were perceived as least helpful.

Table 4

Descriptive Statistics of Experience with Health-Related Lifestyle Apps. (N =112)

Lifestyle Apps	N participants with experience	M (SD) Like^1	M (SD) Perceived helpfulness^1
Fitness Apps	68	2.3 (0.4)	1.9 (0.9)
Exercise tracker	61	2.3 (0.7)	2.1 (0.8)
Step counter	83	2.4 (0.8)	1.8 (0.8)
Calorie Counter	44	1.8 (0.7)	1.6 (0.9)
Sleep Tracker	29	2.2 (0.6)	1.4 (0.7)
Weight tracking apps	27	1.8 (0.8)	1.7 (0.8)
Bodily functions tracker	36	2.0 (0.9)	1.8 (0.9)

Note. *N* = number of participants with experience, *M* = Mean, *SD* = standard deviation.

[1] =Answering options varied from 0= 'not at all' -- to 3= 'very much'

All participants, whether they ever used a health-related lifestyle app or not, could indicate if they would consider using an LA in the following six months. Around 55% indicated that they would not use a health-related lifestyle app and 45% would maybe or probably use a LA in the following six months.

To what extent are personality traits and background variables associated with the use of health-related lifestyle apps?

Correlation between personality and the use of health-related lifestyle apps

When looking at the total LA use, most lifestyle apps were significantly associated with higher scores on conscientiousness and neuroticism (Table 5). When looking at the correlation between personality traits and the different types of app use, separately, the results revealed that for fitness apps, users tend to be more conscientious and neurotic. Users of exercise trackers and step counters were on average also more conscientious. Users of sleep trackers and weight trackers on the other hand were more neurotic in the sample.

Table 5

Correlation (Pearsons r) Between Personality (BFI-10) and the Use of Health-Related Lifestyle Apps. (N = 108)

Apps	BFI-10 Extraversion	BFI-10 Agreeableness	BFI-10 Conscientiousness	BFI-10 Neuroticism	BFI-10 Openness
Total score LA use	-.12 (.233)	-0.15 (.342)	.24 (.012*)	.34 (.037*)	.23 (.056)
Fitness apps	.31 (.144)	-.23 (.484)	.22 (.001***)	.26 (.002*)	-.36 (.128)
Exercise trackers	-.00 (.132)	.04 (.387)	.26 (.024*)	.06 (.003*)	.19 (.017)
Step counter	.04 (.021*)	.09 (.052*)	.15 (.044*)	-.02 (.012*)	.01 (.180)
Calorie counter	.01 (.655)	.05 (.241)	-.08 (.277)	-.04 (.165)	.06 (.263)
Sleep tracker	-.08 (.287)	-.03 (.379)	-.03 (.178)	.18 (.004**)	.11 (.154)
Weight tracker	.06 (.356)	-.04 (.198)	.05 (.066)	.26 (.024*)	-.12 (.242)
Bodily functions Tracker	-.15 (.187)	.21 (.565)	-.05 (.057)	.23 (.064)	-.16 (.146)

Note. *BFI-10* = Big Five Inventory-10, the values in brackets show the p-value for each correlation, p-value is significant if p < 0.05 *p< 0.05. **p< 0.01. ***p < 0.001.

Correlation between background variables and the use of health-related lifestyle apps

Kendall Tau correlations were performed between different types of LAs and different background variables (Table 6). When looking at the total LA use, more health-related lifestyle app use was significantly positively associated with the average screen time and negatively correlated with age. When looking at the correlation between background variables and the different types of LAs used**,** separately, the results revealed that for fitness apps, there is a significant negative correlation with age and highest education completed. Apart from that no strong significant relationship was found.

Table 6

Kendall Tau Correlation Between Background Variables and the Use of Health-Related Lifestyle Apps (N=111).

Apps	Age	Highest education completed	Current Employment	Average screen time per day	Health
Total score	-.24 (.002**)	-.03 (.620)	-.07 (.022*)	.21 (.006**)	-.07 (.431)

Apps	Age	Highest education completed	Current Employment	Average screen time per day	Health
Fitness apps	-.33 (.003***)	-.11 (.037*)	-.13 (.081)	.03 (.134)	-.03 (.623)
Exercise trackers	-.10 (.277)	.11 (.180)	-.03 (.743)	.33 (.098)	-.09 (.257)
Step counter	-.03 (.036*)	-.06 (.045*)	-.04 (.003)	.03 (.004**)	.02 (.178)
Calorie counter	.00 (.764)	-.01 (.568)	-.05 (.349)	.23 (.102)	-.12 (.146)
Sleep tracker	-.12 (.143)	.23 (.378)	-.02 (.121)	.13 (.133)	-0.21 (.244)
Weight tracker	-.04 (.052)	-.01 (.108)	-.07 (.060)	-.05 (.864)	-.06 (.421)
Bodily function tracker	-.02 (.031)	-.04 (.228)	-.03 (.072)	-.05 (.382)	-.04 (.221)

Note. The values in brackets show the p-value for each correlation, p-value is significant if $p < 0.05$
$^{*}p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

To what extent is health-related lifestyle app use associated with mental well-being?

The total score on LA use did positively correlate with psychological well-being and the total score of well-being (Table 7). Moreover, fitness apps had a positive correlation with emotional well-being. Exercise trackers were positively correlated with all well-being scales except emotional well-being. Calorie counters on the other hand were negatively correlated with psychological well-being. For the other health-related lifestyle apps no significant results were found.

Table 7

The Correlation Between Mental Health (MHC-SF) and the Use of Health-related Lifestyle Apps (N = 106)

Apps	MHC-SF Emotional well-being	MHC-SF Social well-being	MHC-SF Psychological well-being	MHC-SF Total score well-being
Total score	-.02 (.013*)	-.01 (.320)	.14 (.012*)	.12 (.005**)
Fitness apps	.13 (.023*)	-.01 (.047*)	.23 (.081)	.15 (.134)
Exercise trackers	-.01 (.137)	.12 (.040*)	.24 (.043*)	.17 (.038*)
Step counter	.03 (.016*)	.05 (.035*)	.02 (.003**)	.03 (.004**)
Calorie counter	-.12 (.644)	-.04 (.438)	-.21 (.049*)	.14 (.02*)
Sleep tracker	-.02 (.163)	.13 (.178)	-.04 (.141)	.09 (.173)
Weight tracker	-.02 (.072)	-.06 (.168)	-.05 (.040)	-.04 (.234)
Bodily function trackers	.12 (0.23)	-.03 (.121)	.11 (0.24)	-.08 (.235)

Note. MHC-SF= Mental Health Continuum- Short Form; the values in brackets show the p-value for each correlation, the p-value is significant if $p < 0.05$, *$p< 0.05$. **$p< 0.01$. ***$p < 0.001$.

Discussion

In the present study, health-related lifestyle app use was not common for most lifestyle apps, only fitness apps, step counters and exercise trackers were at least occasionally used by half of the participants of the study. The reported experience of the LAs was mostly positive and the apps were mostly perceived as helpful. The majority of participants using health-related lifestyle apps were young and had high average screen time. Regarding personality traits, the average survey respondent using LAs scored high on conscientiousness and neuroticism. Moreover, this study found a positive correlation between the use of health-related lifestyle apps and psychological well-being and well-being in general.

The first research question was '*To what extent are different types of health-related lifestyle apps being used and what are people's experiences with using these apps*?' The present study revealed that the use of LAs in a mostly Dutch and German sample is not common for most app categories. Sleep trackers, weight tracking apps, bodily function trackers and calorie counters were only rarely used by the survey respondents. Only fitness apps, exercise trackers and step counters were used by approximately half of the sample. These apps were interestingly also the most liked and most helpful apps. This study shows that the use of mobile health apps is still limited. That is in line with previous research by Bol et al. (2018), where 29% of the sample actually used health apps, even though 37% had downloaded mobile health apps. Also, similar to the results of Bol et al. (2018), fitness apps were the most popular category of lifestyle apps. Interestingly, however, nutrition apps were also very popular in recent studies among mobile health apps (Bol et al., 2018; Krebs & Duncan, 2015). Also, weight tracking was an important reason for U.S. adults in the study by Krebs and Duncan (2015) to use mobile health apps. Weight tracking and diet tracking seem not to play an important role in our sample, as most participants did not use weight-tracking apps and calorie counters at all. Reasons for the differences found between this study and previous research might be that the study of Bol et al. was comprised of a representative Dutch sample of the general population with a mean age of 50.32. Also, the gender ratio was almost equal. The sample of Krebs and Duncan (2015) also had a very equal gender ratio. Our sample, on the other hand, was overwhelmingly female and also quite young. Another reason for the difference might be the year the data was collected. The app market is a fast-moving market with new health apps being offered and old ones being deleted. There is a difference between six to nine years between the year the current data was collected and the years the previous data was collected. In general, there were some major differences found in this study regarding mobile health app use compared to previous studies. Therefore, more research with representative samples about the use and experiences with specific categories of health-related lifestyle apps is needed to get a better picture of usage and experiences.

The second research question was '*To what extent personality traits and background variables are associated with the use of health-related lifestyle apps*?'. This study found that users of LAs were on average more neurotic and conscientious. Examining the relationship between personality characteristics and the use of the different health-related lifestyle app categories independently, the findings showed that users of fitness apps tended to be more neurotic and conscientious. Step counter and workout tracker users were also more conscientious on average. In contrast, the sample's users of sleep trackers had higher levels of neuroticism. With regard to background variables, lifestyle app use was negatively correlated with age and positively correlated with average screen time. Moreover, there is a substantial negative link between age and fitness applications. Also, the present study found a negative correlation between using fitness apps and the highest education completed. Other than that, no substantial and strong relationship was discovered. The results found in this study in regard to personality characteristics were similar to the results found by Aziz et al. (2023). People who score high on conscientiousness and neuroticism are more likely to use health-related lifestyle apps. The results found for the specific categories of LAs can not be compared to previous studies, as this was the first study examining this link. However, the correlations found were also concerning the personality traits conscientiousness and neuroticism, with some categories correlating with only one of the personality traits and others with both. Apparently, these are the traits having the strongest correlation with health app use. However, future research is needed in which a representative sample is selected and where the sample size is big enough to find more significant results, as the sample of this study was not representative, and many results were insignificant. Regarding background variables, the results of the present study confirmed previous results. In previous research age was a significant predictor of health app use, with younger people being more likely to use mobile health apps (Bhuyan et al., 2016; Bol et al., 2018). Interestingly, however, health-related lifestyle app use in this study was for some categories of apps negatively correlated with education. This stands in contrast to the results of Bol et al. (2018), where higher education predicted mHealth app use. Reasons for these differences can only be assumed. Therefore, and also to find more background variables contributing to the use of health apps, future research is needed. It still has to be found out which background variables predict the use of specific health-related lifestyle apps.

The third research question was '*To what extent is the use of health-related lifestyle apps associated with mental well-being*?'. This study found that psychological well-being and the overall well-being score did positively correlate with the total score on LA use. Additionally, there was a positive association between emotional well-being and fitness apps. All well-being scales, with the exception of emotional well-being, showed a positive correlation with exercise trackers. Conversely, there was a negative correlation found between calorie counters and psychological well-being. There were no noteworthy findings for the other health-related lifestyle applications. Apart from calorie trackers, there seems to be no indication that mobile health app use leads to worse mental health. When it comes to the correlation between general health app use and well-being, similar results were found in comparison to the Chinese sample by Lee et al. (2024). The usage of health apps is positively correlated with general well-being. However, the Chinese sample also showed positive correlations with all three subcategories of well-being. It has to be mentioned, that it might be difficult to compare Chinese with European samples because of the difference of cultures (Lee et al., 2024). The studied U.S. sample by Lee et al. (2024) showed also similar results to the ones presented in this study. In the U.S. sample mHealth app users showed higher psychological well-being. In the sample of this study, the same correlation was found. However, the present study is the first to examine the effects of using specific lifestyle apps on mental health. Thus, a comparison to previous results is not possible. Future research is needed to see if the results of this study can be replicated and what effects mobile health app use has on mental health in other parts of the world. Researchers are advised to do a longitudinal study to compare mental health before and after using health-related lifestyle apps in order to see whether any differences can be observed. Understanding mental health is crucial since the goal of physical health applications is ultimately also to enhance mental well-being.

Strengths and limitations

There are strengths and limitations to the present study. One of the studies' strengths, for instance, is that participants in this study ranged in age from 16 to 72. The broad age range made it possible to examine the use and experience of health-related LAs in greater depth and to draw broad conclusions about them. Moreover, the self-developed questionnaire by the researcher showed a high reliability, indicating that the survey is a valid tool for examining the use of and experience with various health-related lifestyle app categories. There is a dearth of research on the classification of various lifestyle app categories. As a result, this study advances our understanding of the different categories of health-related LAs.

There are limitations to the current study as well. First off, the BFI-10 had a poor degree of reliability. Because of this, it was challenging to examine the relationship between personality and the usage of LAs because the findings were mostly unreliable. It's possible that the results of the second study question are less insightful and inconsistent. Future research is advised to use the BFI-44 since it has more questions that assess a subscale, increasing the likelihood of an accurate assessment. Second, because the survey was cross-sectional, the findings offer no significant new information on the causality of the correlations under investigation. In order to determine if using lifestyle apps affects mental well-being, future research should carry out a longitudinal study. Thirdly, the sample of this study was not representative, as snowball sampling and convenience sampling technique was used to acquire the sample. This led to a sample that was predominantly female and of young age. Moreover, the sample size of 111 was rather low considering that some lifestyle apps were only used by a few people in the sample. Therefore, it is difficult to generalise the findings. Finally, the fact that the questionnaire was created in both German and English does not guarantee its validity. There may be discrepancies between the German and English versions of the questionnaire because the researchers translated it themselves. To guarantee authenticity, expert translation is advised for future study.

Conclusion

In conclusion, study participants rarely used health-related lifestyle apps, except for fitness applications, step counters, and activity trackers. The LAs' reported experiences were largely positive, and most people found the apps helpful in achieving their health goals. Users of these apps were likely to be conscientious and neurotic, which confirms previous research and the study found that psychological well-being and the overall well-being score did positively correlate with the total score of LA use. With the cross-sectional design of the study, the rather small sample size and the unrepresentative sample in regard to the general population, future research that uses a longitudinal design to test the effects of health-related lifestyle apps on a representative and sizable sample is recommended.

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Appendix

Appendix A

Informed Consent

Thank you for your participation in this research study. Please read the following information carefully.

The data collected during the study will be used solely for research purposes and is only available for the research team. The data will be stored anonymously to protect your privacy. It will not be possible to trace the answers back to you.

For this study, ethical approval has been gained by the Ethics Committee of the Faculty of Behavioural and Management and Social Sciences at the University of Twente.

Your participation in this study is voluntary. If you decide to participate, you have the right to withdraw from the study at any time without naming a reason and without any consequences. The responses recorded before withdrawal may still be used in this study.

If you have any questions, feel free to contact one of the researchers for this study:

- g.trompramirez@student.utwente.nl
- a.freier@student.utwente.nl
- m.a.maurer@student.utwente.nl
- r.koch-1@student.utwente.nl

- I have read and understood the information provided

- I consent voluntarily to be a participant in this study and understand that I can withdraw from the study at any time, without having to give a reason and without any consequences

- I am aware I can contact the researchers in case I have any questions

- I understand that my answers will be saved and used for the research

- I understand that my responses will be anonymous

- I give my consent to participate in this study

Do you agree to all the above-mentioned statements? (yes/no)