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Does your health really benefit from using a self-tracking device? Evidence from a longitudinal randomized control trial

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ABSTRACT

The use of wearable self-tracking devices to increase health and well-being is on the rise; yet, there is a lack of scientific evidence concerning their actual benefits. This article summarizes theoretical assumptions (e.g., social cognitive theory, cognitive dissonance, conditioning, observer effects) to explore how wearables might positively affect health and well-being outcomes. A longitudinal randomized control study with a pre-post measurement design was conducted to examine the effects of wearing a fitness tracker for two weeks. Health consciousness, physical health, and indicators of psychological well-being served as dependent variables. The results suggest that wearing the fitness tracker had a statistically small but significant positive effect on users' perceived physical health and their sense of accomplishment (vs. waitlist control group), while health consciousness increased with a large effect size for all participants in the study. If users in the experimental group additionally used the accompanying app, the positive effects on indicators of self-reported health and well-being were more pronounced. Practical implications and open research questions are critically discussed.

1. Introduction

Healthy living has been identified as one of the eight megatrends through 2030 by Euromonitor International (Boumphrey & Brehmer, 2017), and wearable technologies such as fitness apps, activity trackers, or smart watches are supposed to support consumers in their aspirations towards a healthy lifestyle (Calvo & Peters, 2014). The sensor technologies installed in smartphones or wearable devices record a variety of metrics automatically and without active user engagement. This has simplified the practice of collecting data about oneself, known as self-tracking or the "Quantified Self" (QS; e.g., Swan, 2013). Online and mobile applications or other wearable devices assist consumers to track health and well-being related parameters such as activity levels, sleep quality, diet, or mood, and make a huge promise: "tracking helps you move more, feel better, and sleep better" (Nokia, 2018).

It comes as no surprise that today's society values these tools. According to a large online survey, conducted across 16 countries by GfK (2016), one in three people track their health and well-being with the help of a QS tool (i.e., online or mobile applications, activity trackers, smartwatches, or clips), and activity trackers represent more than 50% of the wearable market. Sales revenue of wearable tracking devices have increased over the past years and are expected to increase further (Tractica, 2017). And even health insurance companies have begun to incorporate activity trackers into their insurance packages (Japsen, 2016), likely in the hope of thereby combating today's major risk factors for mortality and global health burden, such as physical inactivity (World Health Organization, 2010), mental health problems (Mental Health Foundation, 2016), and poor sleep (Ferrie, Kumari, Salo, Singh-Manoux, & Kivimäki, 2011; Tang, Fiecas, Afolalu, & Wolke, 2017).

These trends seem to be based on a common lay theory that the use of technological tracking devices (e.g., activity trackers) increases health and well-being. A number of anecdotal reports may indeed support this assumption, but reliable scientific evidence is scarce and gold standard evaluations (i.e., randomized controlled experiments) are largely lacking (e.g., Hermsen, Frost, Renes, & Kerkhof, 2016; Kersten-van Dijk, Westerink, Beute, & Ijsselsteijn, 2017; Piwek, Ellis, Andrews, & Joinson, 2016). Thus, in light of the prominence that health-related QS technologies have taken on in our society and the associated expectations, it is of great importance to gain both theoretical understanding of and reliable empirical evidence on the proposed benefits of self-tracking devices on health and well-being related parameters. The present article aims to contribute to this claim in two important ways, namely theoretically and empirically. First, on a theoretical account, it addresses the question whether the use of QS technologies may have a positive impact on consumers' health and well-being, and therefore

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offers an extensive summary of potential theoretical explanations. Second and most importantly, we examined the question empirically in a longitudinal randomized control trial.

1.1. Empirical research on QS technologies

Health and well-being related self-tracking is not a new phenomenon, but its practice has changed considerably due to the advent of wearable tracking technologies. Online and mobile applications, activity trackers, or smart-watches have simplified almost all stages of the self-quantification process (Kersten-van Dijk et al., 2017; Li, Dey, & Forlizzi, 2010; Matselva & Lutz, 2018). Consumers can *collect* data about themselves automatically or with minimal effort, and their collected data is automatically *integrated* and processed into customized and visualized feedback (displayed in an online or mobile application and/or on a screen on the wearable device itself), which facilitates the interpretation of and *reflection* on the data, ultimately (supposedly) leading to behavior change (i.e., *action*).

However, QS technologies face the challenge of sustained user engagement. A commercial survey conducted in 2014 (Ledger, 2014) revealed that one third of the users abandoned their activity tracker within the first three months, and more than half of the users had stopped wearing the tracker after one and a half year (see also GfK, 2016). Thus, companies continue tweaking the design of QS technologies, particularly by considering gamification design elements such as challenges, goal setting, feedback, and rewards (e.g., virtual badges for achievements), or social interaction (Johnson et al., 2016; Piwek et al., 2016; Sardi, Idri, & Fernández-Alemán, 2017). With the help of these strategies, QS technologies can satisfy self-tracking motives (Li et al., 2010; Stragier, Abeele, Mechant, & De Marez, 2016; Swan, 2013) beyond self-improvement and personalized healthcare (Gimpel, Niβen, & Görlitz, 2013), such as hedonic (enjoyment and fun), self-regulatory (goal setting, monitoring of goal progress, and self-gratification), and social motives (community citizenship, support, and social comparison). Furthermore, like other wearable technologies, QS technologies incorporate a fashion component (i.e., "fashnology"), and wearing them may serve as a social signal for (health-identity) impression management (e.g., Hui-Wen Chuah et al., 2016; Rauschnabel, 2018). While incorporating such motivational design features may enhance persistent use, the question remains whether they are worth the effort. Do QS technologies really boost consumers' health and well-being?

Reviewing existing studies on QS technologies, researchers (e.g., Hermsen et al., 2016; Kersten-van Dijk et al., 2017; Piwek et al., 2016) uniformly conclude that the effectiveness of QS technologies has not yet been examined sufficiently. On the one hand, case studies and user surveys suggest that QS technologies do have beneficial effects on consumers' health and well-being (Hermsen et al., 2016; Kersten-van Dijk et al., 2017). On the other hand, these cross-sectional self-reports obtained from highly selective samples (i.e., people who already use QS technologies; cf. Rapp & Cena, 2016) cannot provide reliable scientific evidence for the effectiveness of these "interventions". Rather, longitudinal, randomized controlled studies are needed. Those studies, however, are scarce. For example, Hermsen et al. (2016) reviewed 72 studies on the effectiveness of a variety of tracking and feedback technologies for behavior change (e.g., energy and water consumption, skills, weight loss, physical activity, or driving), but only three of which were controlled laboratory studies and only seven were randomized controlled field studies. Etkin (2016) and Harris et al. (2015), however, conducted controlled studies to examine the impact of pedometers. They revealed that wearing a pedometer led to a significant increase in physical activity. Taken together, these empirical findings may serve as initial reliable evidence that QS technologies can support healthy behaviors such as physical activity and may thereby improve health and well-being (e.g., Fanning, Mullen, & McAuley, 2012; Penedo & Dahn, 2005; Warburton, Nicol, & Bredin, 2006). Yet, there remains the need to advance our understanding of the theoretical foundations of these supposed effects, as well as the necessity for methodological gold standard evaluations of them.

1.2. Theoretical explanations

Although empirical evidence for the effectiveness of QS technologies on health and well-being is limited, several theoretical accounts such as self-regulation approve the proposed effects (Abraham & Michie, 2008; see also; Almaki, Gray, & Martin-Sanchez, 2016; Hermsen et al., 2016; Kersten-van Dijk et al., 2017).

Self-Regulation. Self-regulation refers to affective, cognitive, and behavioral processes to reach goals over time and across situations (e.g., Karoly, 1993). The first stage of self-regulation is *self-monitoring* (e.g., Carver & Scheier, 1982). Self-monitoring is a well-established psychological intervention technique (e.g., Knittle et al., 2018; Murawski, Wade, Plotnikoff, Lubans, & Duncan, 2018; Williams & French, 2011). It renders the monitored parameters visible and thereby increases awareness of automatic, habitual (and often undesired) behaviors and their consequences (e.g., Carver & Scheier, 1982; Karoly, 1993). Thus, the self-monitored parameters act as some sort of feedback, initiating reflection and opening up opportunities for behavior change. Importantly, QS technologies such as activity trackers support the self-monitoring process by making data tracking easier and providing customized and easily interpretable feedback on the tracked data. Kersten-van Dijk et al. (2017) refer to this as the *self-improvement hypothesis of personal informatics*: the use of QS technologies provides users with valuable information about the self, which leads to self-insights. These, in turn, drive behavior change (i.e., towards healthy behaviors). Furthermore, according to *social cognitive theory* (Bandura, 1991) or *control theory* (Carver & Scheier, 1982), individuals tend to compare monitored parameters with *goals and standards*, and, if they recognize deviations, they initiate necessary changes. Many QS tools confront consumers with some standards to be achieved (e.g., 10,000 steps or 7 h of sleep) or allow them to set their own goals. Thus, besides supporting consumers in self-monitoring, QS technologies could facilitate health-related goal setting and goal achievement.

Self-Evaluation. The feedback consumers receive from QS technologies also helps them to satisfy self-evaluation motives (Gregg, Hepper, & Sedikides, 2011). Overall, most individuals desire to have an accurate and positive view of themselves (self-assessment and self-enhancement motives), to confirm their pre-existing view of themselves (self-verification motive), or to even improve the self (self-improvement motive). Thus, it is likely that consumers will engage in more healthy behaviors, as they want to receive positive feedback from the QS technology (to ensure need satisfaction). However, it may also happen that consumers score below expectations (e.g., the QS technology revealing that they were not as active as they thought they would be), and this could cause *cognitive dissonance* (Festinger, 1957). On the one hand, the resulting state of psychological discomfort may have negative consequences. For example, consumers may experience a decrease in their self-esteem and/or abandon the tracking device (Almaki et al., 2016; Diefenbach, 2018; Lee & Drake, 2013). On the other hand, however, cognitive dissonance may encourage consumers even more to engage in healthy behaviors to resolve the discomfort and to ensure that future feedback from the QS technology will again confirm the positive self-view. Furthermore, QS technologies are fashion products and similar to other visible products serve a symbolic function (Belk, 1988; Hui-Wen Chuah et al., 2016; Rauschnabel, 2018). Wearing an activity tracker could signalize that technology and health is an important part of the person's identity. Thus, QS technology usage may make up the *extended self* of being a person with a healthy lifestyle, which "forces" the person to actually engage in a healthier lifestyle in order to maintain self-congruence. In sum, QS technologies may act as a congruence or dissonance-based intervention. Previous research has shown that such interventions are effective in changing health behavior (Freijy & Kothe, 2013).

Operant Conditioning. From a behaviorist perspective, healthy behaviors can be *reinforced* through external incentives, but also through goal achievement, because goal achievement itself can act like rewards (e.g., Mace & Kratochwill, 1985). As outlined above, goal achievement becomes more visible with the help of QS technologies. Additionally, QS technologies often provide external incentives for goal achievement, such as virtual badges (e.g., Johnson et al., 2016). Thus, by making goal-achievement visible and by rewarding progress with incentives (cf. Barte & Wendel-Vos, 2017), QS technologies should further support the achievement of health-related goals and reinforce respective healthy behaviors, ultimately leading to increased health and well-being.

Reactivity. The proposed impact of QS technologies on health and well-being may further result from reactivity effects. First, it may be argued that consumers of QS technologies are being observed at least by themselves and by the technology (and potentially by social networks and, due to the symbolic signaling function of "fashnology", by other people in general), and may therefore adjust their behaviors to confirm with social norms (e.g., the norm to be physically active). This implies that QS technology usage could initiate socially desirable behaviors due to *observer effects* (e.g., Ball, Jeffery, Abbott, McNaughton, & Crawford, 2010). Second, self-tracking of certain health and well-being indicators and the accompanying feedback makes these parameters and associated behaviors more salient, and salient behaviors are usually maximized (Etkin, 2016; van Sluijs, van Poppel, Twisk, & van Mechelen, 2006). Thus, *measurement* itself can increase performance. A study by Etkin (2016) revealed that individuals who knew that the device they were wearing was counting their steps walked more than individuals who did not know that the device was tracking steps. This suggests that QS technologies, simply by measuring certain parameters (e.g., counting steps), can increase healthy behaviors (e.g., walking more steps).

Intrinsic Motivation. Finally, potentially negative side effects of external incentives (Cameron, Banko, & Pierce, 2001) and measurement (Etkin, 2016) on intrinsic motivation need to be discussed. Etkin (2016), for example, showed that participants in her study perceived walking to be more like work and experienced less enjoyment and well-being, if they knew that the device was tracking their steps. At first glance, this suggests that QS technologies could undermine enjoyment. However, it should also be noted that such undermining effects are usually restricted to intrinsically motivating activities that are performed without an extrinsic goal (Deci, Ryan, & Koestner, 2001). In addition, Etkin (2016) found that measurement reduced the enjoyment of reading when reading was performed without a goal, but increased enjoyment if performed with the goal to read as much as possible. Furthermore, existing evidence does not suggest that undermining effects occur for health-related behaviors. Promberger and Marteau (2013) conclude that for "health-related behaviors that rely on self-control, incentives may enhance feelings of competence and might actually increase motivation and behavior even post-incentive" (p. 954). In this respect, QS technologies may rather increase than undermine enjoyment, as goals and external incentives (e.g., receiving the badges, becoming healthier) are integral to the activity of self-tracking and may elicit feelings of competence.

In sum, there are many theoretical accounts suggesting that QS technology usage may lead to more healthy behaviors and thereby to better health and well-being. In general, we therefore propose a positive impact on QS technology usage on health and well-being. Specific predictions, as examined in the current research, are outlined in the following.

1.3. The present study

As noted above, empirical evidence concerning the effectiveness of health-related QS technologies is largely based on surveys among highly selective samples of individuals who were already "experts" in health-related self-tracking. In contrast, the aim of the present study was to examine the proposed health-related impact of wearable QS technologies by means of a longitudinal randomized controlled study among novice or "common" users (Rapp & Cena, 2016; Stragier et al., 2016). Unlike expert users, common users have fewer skills regarding all stages of the QS process (Rapp & Cena, 2016; Stragier et al., 2016); however, these are the people who are targeted by health insurances and QS technology companies as prospective users. Thus, it is especially important to examine the effectiveness of QS technologies in this less experienced group. Furthermore, the few controlled studies on health-related wearable QS technologies were usually restricted to the tracking of a single parameter, such as steps (e.g., Etkin, 2016; Harris et al., 2015). However, today's most prevalent health-related QS technologies – activity trackers (e.g., AmazFit, Fitbit, Garmin Vivofit, Huawei Band, Jawbone UP, Misfit, Nokia Steel, Samsung Gear, Xiaomi Mi Band …) – usually go beyond tracking a single parameter. In addition to counting steps, they can often automatically track heart rate, activities, or sleep quality. They implement psychological principles in the design of accompanying mobile applications (cf. gamification strategies, e.g., Johnson et al., 2016; Sardi et al., 2017) and are dedicated to foster health and well-being in a rather holistic sense (cf. Gaggioli, Riva, Peters, & Calvo, 2017). We therefore examined the impact of health-related QS technologies on several health indicators and – based on the theoretical explanations presented above – expect a positive impact of QS technology usage on these indicators. In particular, we propose that health-related QS technology usage (i.e., activity tracker, please see Method section) not only increases health consciousness (*Hypothesis 1*) and perceived physical health (*Hypothesis 2*), but also psychological well-being (*Hypothesis 3*).[1]

Health Consciousness. Health consciousness is "the extent to which health concerns are integrated into a person's daily activities" (Jayanti & Burns, 1998, p. 10). Previous research has shown that health communication in media raises health consciousness (Dutta-Bergman, 2004), and mobile wellness applications have also been found to increase health awareness (Holzinger, Dorner, Födinger, Valdez, & Ziefle, 2010). Thus, by making health-related issues subject of discussion and more salient in people's everyday lives, their health consciousness should rise (Grifantini, 2014). Similarly, we expect health consciousness to increase in response to QS technology usage, as these technologies support health self-regulation, such as the monitoring of health-related parameters throughout the day.

Physical Health. As outlined above, there are many theoretical accounts in support of the assumption that QS technology usage drives health behavior change, such as physical activity (Etkin, 2016; Harris et al., 2015), which in turn has beneficial effects on people's health (e.g., Warburton et al., 2006). Accordingly, we expect perceived physical health to increase in response to QS technology usage.

Psychological Well-Being. We also expected positive effects of QS technology usage on psychological well-being, for several reasons. First of all, there is substantial evidence that physical activity is not only beneficial for physical health, but also for psychological well-being (e.g., Penedo & Dahn, 2005). And second, health and well-being are highly valued goals in people's lives (e.g., Boumphrey & Brehmer, 2017; OECD, 2017). As QS technologies can support consumers in the progress towards and achievement of health-related goals, their usage is likely to increase experienced meaning and accomplishment. Furthermore, today's QS technologies also consider gamification principles, and initial evidence indicates that gamification can increase enjoyment as well as engagement (e.g., Looyestyn et al., 2017; Sardi et al., 2017; Suh, Wagner, & Liu, 2018). Additionally, the tracked data can be shared in social communities (e.g., Stragier et al., 2016), which may help satisfy social needs. Altogether, this suggests that QS technology usage can have beneficial effects on positive emotions, engagement, relationships, meaning, and accomplishment. According to the PERMA-

[1] This research is part of a larger project that was preregistered with www.aspredicted.org.

model (Seligman, 2011) and empirical evidence thereof (e.g., Deci & Ryan, 2008; Diener, Suh, Lucas, & Smith, 1999; Hooker, Masters, & Park, 2018; Klug & Maier, 2015; Sheldon & Elliot, 1999), these five elements are important building blocks of psychological well-being.

2. Method

2.1. Participants

Participants were $N = 105$ students enrolled in a university course on work and organizational psychology in Austria. One participant had to be excluded due to a substantial amount of missing data in the second questionnaire (i.e., more than 15%), and two participants were screened out because they had reported very low health or well-being (i.e., more than three standard deviations below the sample's mean), and thus, constituted outliers. From the remaining $n = 102$ participants, 28 (27.5%) indicated that they were currently doing some sort of self-tracking: 14 students used either an activity tracker or a smartwatch, eight students did not use specific tracking devices, but tracked their health and well-being with health apps (e.g., *MyFitnessPal*, *Lifesum*, or *SleepCycle*), and six students tracked their running with the *Runtastic* app. We excluded those 22 participants who currently used tracking devices or health apps from our statistical analyses, but retained the six participants who only tracked their running.[2] Thus, the final sample comprised of $n = 80$ (63% female) students aged 18–53 years ($M = 26.29$, $SD = 6.25$), who had not been tracking their health and well-being at the beginning of the study. The students were randomly assigned to an experimental condition ($n_E = 39$) and a waitlist control condition ($n_C = 41$). The two groups did not differ significantly in their overall attitude towards self-tracking, $t(78) = 0.30$, $p = .762$, or the dependent variables at T1, $F(7, 72) = 0.97$, $p = .461$.

2.2. Procedure

The study was conducted within a university course and used a pre-post-control design. All students in the course were invited to take part in an "activity tracker evaluation study". They were informed that participation was voluntary, would be compensated with course credit, and required wearing a new activity tracker for two weeks, as well as filling in a baseline questionnaire (at T1) and an evaluation questionnaire (at T2). We supposed that wearing the activity tracker for two weeks would be sufficient for novice users to gain experience with and get used to the activity tracker. Apart from this, the two-week interval was most appropriate to process the study within the university course.

The students were told that there was only a limited amount of tracking devices and that they would therefore be randomly split into two groups (i.e., cover story): one group would receive the activity tracker first and the other group afterwards. The activity tracker they received was the *Xiaomi Mi Band 2*, which constitutes a rather cheap water resistant wristband and ranges among the top five most sold wearables worldwide (IDC, 2018). It has long battery life and comprises an accelerometer and a photoelectric heart rate sensor. Steps and heart rate can be tracked without the usage of any accompanying mobile application; they are shown on the display of the wristband. The *Mi Fit* app further allows monitoring sleep (total sleep time, deep sleep, light sleep, and awake time), activities, distance, and calories. The students were not obliged to use the app, but 53.8% in the experimental condition did.

[2] In order to reduce the complexity of the statistical analyses, we decided to exclude "expert users" from our analyses rather than to control for prior tracking experience. Although not included in the preregistration, this is justifiable based on our research question. We would like to note that descriptive analyses revealed that this excluded group of "expert users" responded very differently to the intervention as compared with the "novice users".

At T1, all participants who had signed up for the study gave their informed consent and completed the baseline questionnaire at the university's lab. The baseline questionnaire included items regarding sociodemographic characteristics and prior tracking experience, as well as the measures concerning the dependent variables health consciousness, physical health, and psychological well-being (please see "Measures"). Next, participants were randomly assigned to either the experimental or the waitlist control condition. Participants in the experimental condition immediately received an activity tracker. Two weeks later (T2), all participants returned to the lab where they filled in the evaluation questionnaire. The evaluation questionnaire included the same health and well-being measures as the baseline questionnaire, but also an evaluative part, which comprised of items concerning tracker usage during the experiment and an evaluation of the tracking experience. The evaluative part was filled in only by the experimental group. Having completed the questionnaire at T2, participants in the experimental condition handed back the activity tracker (which were then reset and cleaned), while participants in the control condition received a fresh activity tracker. The control group returned the activity tracker and completed the evaluative part of the evaluation questionnaire approximately 2.5 weeks later. At the end of the course, the students were fully debriefed and informed about the study's results.

2.3. Measures

The questionnaires were administered as paper-and-pencil surveys and included the health and well-being measures (see below) as well as additional measures (e.g., self-conceptions, evaluation of the tracking experience), which, however, were not of interest concerning the current research questions, and thus, are not reported in detail. Participants were instructed to respond to the items according to their current (rather than general) experiences.

Health Consciousness was assessed with the 5-item health consciousness subscale developed by Dutta-Bergman (2004). The English items such as "Living life in the best possible health is very important to me" or "I do everything I can to stay healthy" were translated into the German language using the committee approach (Van de Vijver & Leung, 1997). The response format was a 7-point scale from 1 indicating *strongly disagree* to 7 indicating *strongly agree*. To ease interpretation, the responses were re-scaled to a scale from 0 to 10, which was the response format of the health and well-being measure (see below). The internal consistency of health consciousness was good at both time points with Cronbach's $\alpha_{T1} = 0.72$ and $\alpha_{T2} = 0.81$.

Perceived Physical Health and Psychological Well-Being were measured with the German version (Wammerl et al., 2015) of the PERMA-Profiler (Butler & Kern, 2016). This is a short self-report instrument to assess well-being in terms of Seligman's (2011) PERMA model. It includes three items for each of the five well-being components: positive emotions (e.g., "In general, how often do you feel positive?"), engagement (e.g., "How often do you become absorbed in what you are doing?"), relationships, (e.g., "How satisfied are you with your personal relationships?"), meaning (e.g., "In general, to what extent do you lead a purposeful and meaningful life?"), and accomplishment (e.g., "How much of the time do you feel you are making progress towards accomplishing your goals?"). It further includes eight filler items that measure overall happiness (1 item), loneliness (1 item), negative emotions (3 items), and physical health (3 items, e.g., "In general, how would you say your health is?"). Together, the average of the 15 PERMA items plus the overall happiness item represent the overall psychological well-being score. The responses are scored on an 11-point scale with the endpoints 0 = *never/not at all/terrible* and 10 = *always/completely/excellent*. The reliability coefficients were excellent for physical health ($\alpha_{T1} = 0.87$, $\alpha_{T2} = 0.87$) and overall well-being ($\alpha_{T1} = 0.91$, $\alpha_{T2} = 0.94$), and good for most PERMA subscales ($\alpha_{T1} = 0.87$ and $\alpha_{T2} = 0.88$ for positive emotions; $\alpha_{T1} = 0.47$ and $\alpha_{T2} = 0.65$ for engagement; $\alpha_{T1} = 0.78$ and $\alpha_{T2} = 0.84$ for

Table 1
Means (standard deviations) for the studied variables in the experimental group (n = 39) and the control group (n = 41).

Measure	Experimental group		Control group	
	T1	T2	T1	T2
Health consciousness	6.25 (1.30)	6.81 (1.32)	6.55 (1.50)	6.77 (1.51)
Physical health	6.79 (1.58)	7.21 (1.30)	7.13 (1.68)	7.10 (1.55)
Overall psychological well-being	7.47 (1.22)	7.71 (1.24)	7.23 (1.09)	7.29 (1.09)
Positive emotion	7.13 (1.66)	7.48 (1.40)	6.78 (1.42)	6.88 (1.42)
Engagement	7.35 (1.35)	7.62 (1.43)	7.09 (1.35)	7.26 (1.39)
Relationships	8.14 (1.46)	8.04 (1.55)	7.76 (1.76)	7.82 (1.42)
Meaning	7.58 (1.89)	7.76 (1.61)	7.28 (1.34)	7.21 (1.46)
Accomplishment	7.07 (1.18)	7.53 (1.26)	7.15 (1.11)	7.22 (1.18)

relationships; $\alpha_{T1} = 0.85$ and $\alpha_{T2} = 0.89$ for meaning; $\alpha_{T1} = 0.62$ and $\alpha_{T2} = 0.78$ for accomplishment).

3. Results

Table 1 reports the descriptive statistics of the health and well-being indicators in the two groups. Descriptively, the scales' means tended to be higher at T2 as compared with T1 in both the experimental group and the control group (with the exception of the PERMA relationships subscale), but the differences between T1 and T2 were more pronounced in the experimental group. Thus, the descriptive findings were in line with our hypothesis that the usage of QS technologies would have a positive effect on the criterion variables health consciousness, perceived physical health, and psychological well-being.

3.1. Test of hypotheses

To directly test the hypotheses, we conducted a repeated measures analysis of variance (rANOVA) with time (1 = T1, 2 = T2) and criterion (1 = health consciousness, 2 = physical health, 3 = overall psychological well-being) serving as the within-subject factors and experimental condition (1 = experimental group, 2 = control group) as the between-subject factor. The results revealed a non-significant main effect of experimental condition, $F(1, 77) = 0.01$, $p = .925$, $\eta^2 = 0.00$, but a significant main effect of time, $F(1, 77) = 15.67$, $p < .001$, $\eta^2 = 0.16$, as well as a significant interaction between time and experimental condition, $F(1, 77) = 6.76$, $p = .011$, $\eta^2 = 0.07$. Thus, there was a general increase in the criterion variables over time, and, in line with our hypotheses, this increase was significantly more pronounced in the experimental group as compared with the control group. Furthermore, there was a significant main effect of criterion, $F(1.89, 145.44) = 28.67$, $p < .001$, $\eta^2 = 0.15$, but the interaction effects criterion×time, $F(1.80, 138.24) = 2.09$, $p = .127$, $\eta^2 = 0.03$, criterion×group, $F(1.89, 145.44) = 1.48$, $p = .232$, $\eta^2 = 0.02$, and criterion×time×group, $F(1.80, 138.24) = 0.79$, $p = .443$, $\eta^2 = 0.01$, were not statistically significant at $p < .05$. This suggests that, although the three criteria differed significantly in size, these differences were rather stable over time and across conditions.

To further interpret the results, we conducted three separate rANOVAs, one for each criterion variable (i.e., including the within-subject factor time and the between-subject factor experimental condition). The results of these post-hoc analyses are reported in Table 2 and, in general, mirrored the findings of the global analysis. Physical health, however, did not show a significant main effect of time, but only a significant interaction between time and experimental condition. Health consciousness and overall psychological well-being demonstrated a significant main effect of time, but the interaction between time and experimental condition failed to reach significance at $p < .05$. Examining the five PERMA subscales individually revealed that positive emotions and accomplishment significantly increased over

Table 2
Repeated measures ANOVA predicting health and well-being indicators.

Measure	Time			Group			Time×group		
	F	*p*	η^2	*F*	*p*	η^2	*F*	*p*	η^2
Health consciousness	14.66	< .001	.15	0.18	.675	.00	2.76	.100	.03
Physical health	3.12	.081	.04	0.12	.728	.00	4.28	.042	.05
Overall psychological well-being	6.43	.013	.07	1.68	.199	.02	1.98	.164	.02
Positive emotion	5.61	.020	.07	2.24	.139	.03	1.79	.185	.02
Engagement	3.63	.060	.04	1.20	.278	.02	0.19	.660	.00
Relationships	0.02	.884	.00	0.82	.370	.01	0.65	.422	.01
Meaning	0.34	.564	.00	1.57	.213	.02	1.54	.219	.02
Accomplishment	7.45	.008	.08	0.21	.645	.00	4.38	.040	.05

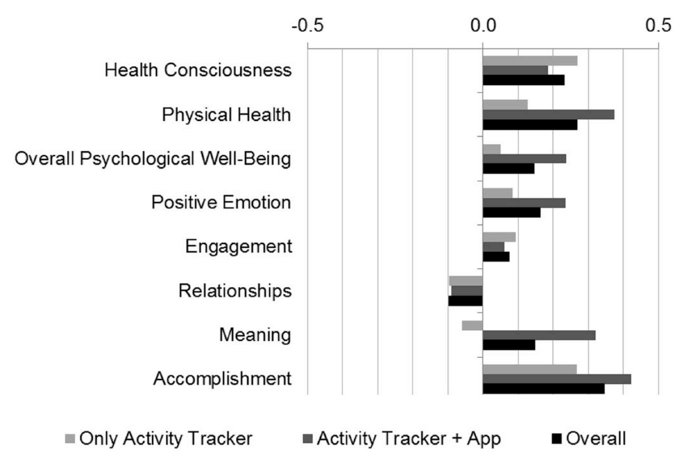

Fig. 1. Effect Sizes (Cohen's *d*) of the Activity Tracker Intervention on Health and Well-Being Indicators.

time. The increase in accomplishment was significantly more pronounced for the experimental than the control group. The other well-being components were not significantly affected by the QS technology intervention (though, descriptively, the effects were in the same direction, except for the relationships subscale; see Fig. 1, which illustrates Cohen's *d* effect sizes, Morris, 2008).

In conclusion, the more detailed analyses showed that health consciousness, positive emotions, and accomplishment generally increased in the course of the study, irrespective of whether the students had received an activity tracker or not. Wearing an activity tracker over two weeks had a *statistically* significant impact only on perceived physical health and accomplishment. Thus, participants in the experimental group reported a significantly stronger increase in physical health and accomplishment over the course of two weeks than participants in the control group. In sum, there was full support for Hypothesis 2 and partial support for Hypothesis 3, while Hypothesis 1 was not supported.[3] The size of the QS technology usage effects was small (see Table 2 and Fig. 1; Cohen, 1992).

3.2. Additional analyses

In the experimental group, 18 participants did not use any accompanying mobile application, and therefore, might have had a "weaker" QS experience than the 21 participants who had used the app in addition to the wristband. Consequently, we re-analyzed the data to test whether QS technology usage exerted stronger effects on the criterion variables among participants who received a more intense intervention (activity tracker plus app usage) than among those with the less intense intervention (only activity tracker usage). Fig. 1 illustrates Cohen's d effect sizes separately for the two experimental subgroups and reveals that QS technology usage tended to have stronger effects on perceived physical health and on the psychological well-being components positive emotions, meaning, and accomplishment, if participants used the accompanying mobile application in addition to the activity tracker. App usage seemed to be particularly relevant to increase meaning. Effects of the QS intervention on the meaning subscale were not statistically significant, if participants only used the activity tracker, $F(1, 57) = 0.13$, $p = .722$. However, the QS intervention significantly increased experienced meaning in the case of accompanying app usage, $F(1, 59) = 4.69$, $p = .034$.

4. Discussion

Can wearable self-tracking technologies really increase health and well-being among novice users? Our findings are in line with theoretical predictions and suggest that they do the job – although only to a limited extent. The results of the current study suggest that wearing a technological device to track one's activity and other parameters has a statistically small but significant effect on users' perceived physical health and their sense of accomplishment. The more intensely users engaged with the tracking, as indicated by their additional use of the accompanying app, the more pronounced were the positive effects on indicators of self-reported health and well-being. In particular, the additional use of the accompanying app resulted in stronger increases in self-reported physical health, positive emotions, as well as experienced meaning and accomplishment. Considering the stages of the self-quantification process (e.g., Li et al., 2010), only wearing the wristband without using the mobile application allows users to collect data about themselves and to get feedback (on the wristband). The wristband itself does not provide any information on the interpretation of the data to facilitate reflection, and thus, does not support deeper cognitive processing of the information. This, however, is required for most theoretical explanations, as outlined above (e.g., self-regulation, self-evaluation), and seems to be supported by the accompanying app: using the app in addition to wearing the wristband provides users with more information about their data, as it visualizes the data, puts it into context, and thus, facilitates interpretation. Having clear goals and standards, and getting feedback on goal accomplishment increases self-regulation mechanisms. Further, seeing one's own data in comparison to general standards or other users' data might intensify the experience of cognitive dissonance, and therefore, drive behavior change. Thus, in line with previous research on online interventions, which showed that more extensive use of theory in intervention design led to increased health behavior change (Webb, Joseph, Yardley, & Michie, 2010), our findings support the assumption that interventions that incorporate more behavior change techniques and, thus, consider more of the theories presented above, might be more effective.

In addition to the statistically rather small benefits of using a tracking device, the results indicate a consistent effect of time on health consciousness, overall well-being, positive emotion, and accomplishment, independent of the experimental condition. Particularly health consciousness increased from T1 to T2 with a large effect size. This raises the question whether simply asking questions about people's health and well-being can increase their health awareness and, potentially, their health behaviors? Our results suggest that it may do, which in the literature has been referred to as the *question-behavior effect* (e.g., Wood, Conner, Sandberg, Godin, & Sheeran, 2014). One explanation thereof might be the increased attitude accessibility (cf. Wood et al., 2013) towards relevant health goals. Both the experimental and control group answered questions about their current health and well-being; besides, the treatment (activity tracker) was obvious for the waitlist control group. Thus, all participants may have been more aware of their health behaviors, which by itself might be sufficient to improve certain health and well-being outcomes, at least in the short term.

Taken together, the current study sheds light on the potential benefits of using QS technologies to improve health and well-being outcomes. Considering the rather small effects, the promises made by QS technology companies should be regarded with caution. However, as health and well-being are generally quite stable (e.g., Diener et al., 1999) and need time to change, it could also be that stronger effects of QS technology usage unfold over a longer period of time only. Still, the significant main effect of time, irrespective of the use of a tracking device, suggests that reactivity effects might contribute to better health and well-being even to a greater extent than the genuine characteristics of a tracking device.

4.1. Limitations and future research directions

Despite the contributions of this research to the still underexplored field of QS technologies in health and well-being, there are several limitations that need to be noted. These limitations might serve as inspiration for future research to get a clearer picture of the impact of emerging and quickly developing QS technologies. First, health and well-being were only assessed via self-report questionnaires. We did not ask participants to share their tracked data with us, as this would have potentially reduced commitment to the study due to worries about data privacy. This limited us to subjective data, as we could neither analyze app use intensity as indicated by user metrics (e.g., time in the app), nor could we include actual health behavior (e.g., steps per day objectively assessed via the tracking device). However, self-reported health and well-being outcomes have been shown to be valid and good predictors of actual health outcomes (Miilunpalo, Vuori, Oja, Pasanen, & Urponen, 1997). Except for engagement, our measures showed good reliability. Therefore, we argue that our findings still provide insight into the impact of self-tracking devices on health and well-being outcomes. Yet, we acknowledge that subjective data have their shortcomings. For example, participants in the experimental group might not actually have experienced an increase in their health and well-being, but rather have made more positive responses in order to maintain cognitive congruence after having invested effort in using the activity tracker or having engaged in health-identity impression management through wearing the activity tracker (cf. Rauschnabel, 2018). Assessing more objective measures such as weight or BMI could provide valuable insight that goes beyond self-reports of health and well-being, which might be biased due to various reasons. Therefore, we recommend future research not to limit itself to self-reported data, but also to assess valuable information through QS technologies. Naturally, this needs to be done in compliance with rigorous data protection policies.

Second, despite our longitudinal study design, the current research

[3] Excluding five age-outliers in our sample (≥39 years) from the analyses did not significantly change the results.

only examined the effect over a duration of two weeks. Opting for two weeks for the experimental treatment restricts the generalization of our findings to the very beginning of the use of wearables and may be influenced by start-up difficulties as well as the "honeymoon" effects of using the new tracking device (e.g., Dunn, Andersen, & Jakicic, 1998). Habituation as well as wear-out-effects, which may play a considerable role in real life regarding the use of wearables, may have been neglected in our study. However, as previous research has shown that a third of all users stops tracking within the first three months, it seems to be crucial that users experience the benefits of tracking health-related behaviors early on. If they do not perceive an immediate impact on their health or well-being, they might be more likely to put the tracker aside.

Third, our sample size was sufficient to detect the effects as reported above, yet it can still be considered rather small, and it consisted of university students only. Besides the obvious sociodemographic particularities of student samples, a more severe problem may arise from the motivational background of our participants. In contrast to individuals who make a conscious choice to purchase and use a tracking device in order to increase their fitness and health, in our sample, the use of the tracking device was initiated by the experimenters. Thus, the students may have had various reasons to participate in our study: the attempt to reach individual fitness goals, a general interest in new technologies, in order to support research, or simply to gain course credit. It should be noted, though, that despite this motivational variability, our findings revealed positive effects of wearables on health. This may emphasize that, even for individuals who may not be highly committed to the use of tracking devices and/or fitness goals, positive effects on health can be expected. In sum, we acknowledge that – due to these methodological limitations – the current study only provides a glimpse into the large field of behavior change effects of QS technologies and limits generalizability of our findings. Future research is encouraged to conduct randomized control studies with larger and non-student samples over a longer period with multiple measurement occasions, in order to reveal (potentially non-linear) trends.

Last, our study focused solely on the main effect of using QS technologies on health and well-being outcomes. Neither mediators (to examine potential mechanisms) nor moderators (to examine potential predictors or individual differences) were included in the study design. Thus, we cannot draw any conclusions about effect mechanisms. However, as to date there is only limited experimental research examining whether the use of technological self-tracking devices (e.g., activity trackers) increases health and well-being, it is advisable to first focus on getting reliable scientific evidence for the existence of such an effect, before turning to mechanisms and conditions. While our empirical results do not provide contributions concerning explanatory mechanisms, our summary of theoretical explanations does (see Section 1.2). Thus, the theoretical explanations outlined above offer a good starting point for theoretically grounded research to examine person variables (e.g., motivation), factors associated with the tracking process (e.g., enjoyment), and factors associated with the QS service (e.g., gamification elements, provision of health standards and norms). This might provide valuable insight into what exactly drives the effect and how different factors covary in the tracking process. In turn, this knowledge could then inspire QS technology companies to build products that are more effective in changing health-related behaviors.

4.2. Conclusion and practical implications

Looking at the use of QS technologies not as an outcome (i.e., who uses tracking devices?) but as a predictor (i.e., what happens to the user when using QS technologies?) is still a rarely researched domain. The present article contributes to this field in two important way. First, it offers an extensive summary of theoretical explanations on why the use of QS technologies may have a positive impact on users' health and well-being, and thereby provides a theoretical basis for future research. And second, it examines the question whether the use of QS technologies does have such an impact in a longitudinal randomized control trial, which constitutes the methodological gold standard, and goes beyond current research findings, which mainly rely on cross-sectional and correlational data. Does the promise given by QS technology companies that "tracking helps you move more, feel better, and sleep better" (Nokia, 2018) hold true? Our findings indicate that it does to some extent, yet not with the large impact that is sometimes implied by marketing campaigns. In general, we suggest that the contested market of QS technologies might benefit from more rigorous scientific research, which examines outcomes, process variables, and mechanisms more closely, in order (1) to substantiate the claims, and (2) to build better products. This seems particularly indicated if health insurance companies wanted to implement QS technologies, for example as health prevention tools.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2019.01.018.

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