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The use of self-tracking technology for health

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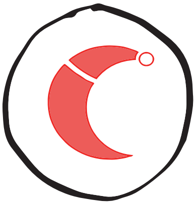
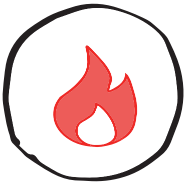
Chapter 8 |

General Discussion


Introduction

Increasing physical activity and weight management are important behaviors for the prevention of overweight and management of chronic diseases such as type 2 diabetes. A possible way for facilitating these self-management behaviors is the use of eHealth technology such as activity trackers and digital weight scales. This technology is capable of aggregating personal health data such as different indicators for physical activity, weight data, and sleeping patterns over time. As this data can be uploaded and shared with others, it is beneficial in broad applications for the individual, health care practitioners, and research. However, before this technology can be implemented within health care, certain conditions must be satisfied. For instance, the data must be of sufficient quality so that users, health practitioners, and researchers can rely on these devices. In addition, before self-tracking technology can have an impact on health behavior and health outcomes, a certain level of adoption and engagement with the device is needed. Therefore, it is crucial to know which factors determine the successful use of different self-tracking devices. Subsequently, knowledge about the actual effectiveness of this technology is also needed. Therefore, this dissertation focused on three domains: (1) the validity and reliability of activity trackers, (2) the adoption of devices that quantify physical activity, sleep and weight, and (3) the effectiveness of this technology for people with overweight and/or have type 2 diabetes as well as a general population of healthy adults.

Main findings

Reliability and validity of activity trackers

Chapter 2 and 3 focused on the reliability and validity of activity trackers. In total, 20 activity trackers, smartwatches, and apps were assessed for their reliability and validity for measuring the number of steps taken. In the first study, the Lumoback, Fitbit Flex, Jawbone Up, Nike+ Fuelband SE, Misfit Shine, Withings Pulse, Fitbit Zip, Omron HJ-203, Yamax Digiwalker SW-200 and Moves mobile application were assessed for walking at an average speed (4.8km/h) on a treadmill, and in free-living circumstances during one day. Although differences between the trackers exist, most trackers were reliable and valid in both laboratory and free-living circumstances except for the Nike+Fuelband and Moves app. The Fitbit Zip demonstrated the best validity.

In the second study, we assessed the Polar Loop, Garmin Vivosmart, Fitbit Charge HR, Apple Watch Sport, Pebble Smartwatch, Samsung Gear S, Misfit Flash, Jawbone Up Move, Flyfit, and Moves app at three different speeds on a treadmill (slow, average, and fast). We concluded that the validity depended on walking speed. Most trackers were reliable and valid at an average walking speed, with the Garmin Vivosmart and Apple Watch Sport demonstrating the best validity. At a slower speed, validity declined for most trackers except for the Gamin Vivosmart and Fitbit Charge HR. At the highest speed, the three smartwatches demonstrated the best validity.

Meanwhile, additional studies have been published about the reliability and validity of consumer activity trackers. These studies are generally in accordance with our findings for the reliability and validity of measuring steps.[1–4] However, the validity of other indicators of physical activity such as sedentary time, intensity of the physical activities performed, and the estimated amount of energy expenditure has been found to be (much) lower.[2,5–9] Consumer activity trackers tend to underestimate energy expenditure,[2,5,9] both under and overestimate time spent in low, moderate, and vigorous activity,[2,6–8] and may both over- and underestimate sedentary time.[5–7] For example, Rosenberger et al determined that different consumer activity trackers overestimated the amount of time spent in moderate-vigorous activity between 51-91%[6] whereas Gomersall et al ascertained both over- and underestimations of 46 and -50%.[8] Therefore, at the moment, most consumer activity trackers are primarily suitable for individual use but, in many cases, not appropriate for the evaluation of research outcomes concerning time spent in moderate to vigorous physical activity and energy expenditure. When consumer activity trackers are being selected for evaluation of specific research outcomes, this must be done based on existing research.[6,10]

Adoption of self-tracking technology

In **Chapter 4**, we assessed the six-month adoption of two devices that quantify physical activity, sleep, and weight. We found that the activity tracking function was used more frequently compared to sleep tracking over the six-month period, however, the use of both functions declined over time. The number of self-weighings also declined over time but stabilized from the third until the sixth month of use with over 80% of the study population weighing themselves weekly (i.e., one to five self-weighings per week) or daily (over six self-weighing's per week).

We found that different types of factors (e.g., personal, behavioral, and technical) are important for the adoption and sustained use of self-tracking devices. These factors were related differently to the use of different self-tracking functions.

Personal factors (age, BMI, gender, and education) were not related to the use of an activity tracker. For the use of the sleep tracker, younger people, people with a higher education, and individuals with a BMI between 25-30 used the sleep tracker more often. For the use of the weight scale, men, younger people, and individuals with a BMI between 25-30 weighed themselves more often. With regard to *behavioral factors*, the most important findings were that, in general, having a specific motive for self-tracking (compared to a general motive 'documentary', i.e., the wish to know more about own health) or having the intention to change a specific behavior (e.g., the wish to increase physical activity) help to increase adoption of a device. In addition, of the four dimensions of self-regulation used in this thesis, a higher goal-orientation at baseline contributed to the numbers of activity and sleep measurements during the study period. Also, *technical factors* are important when considering the adoption of self-tracking technology. Technical failures, battery life, the ease of use, and perceived usefulness of a device have all been found to impact adoption.[11,12] From our evaluations with the participants in both Chapters 4 and 6, participants indeed identified technical factors, such as the installation procedure and limited battery life as barriers for usage.

Our findings are mainly in line with the review of Perski et al who summarized a variety of factors associated with the engagement of digital behavioral change interventions. They determined that both individual or population based factors influence engagement (e.g., motivation, expectations, self-efficacy, and demographic characteristics), the setting (e.g., the social and physical environment such as cultural factors or access to the internet), the content of the intervention (social support features, reminders) and delivery based factors (e.g., mode of delivery, professional support features, control features, novelty, complexity, tailoring of content, and interactivity).[13] In addition, many studies point out that eHealth literacy is an important factor influencing the adoption of eHealth technology. eHealth literacy has been defined as “the ability to seek, find, understand and appraise health information from electronic sources and apply the knowledge gained to addressing or solving a health problem”.[14] Men, older people, those having less education, and people who are unemployed may have lower eHealth literacy.[15,16] People who are more experienced with using the internet and indicate a higher perceived health status show higher eHealth literacy.[16]

Effectiveness of self-tracking technology

We have examined the effectiveness of the use of self-tracking technology in three different studies. In **Chapter 5**, a systematic review and meta-analysis was conducted to determine the effectiveness of the use of activity monitors for incremental physical activity in people with overweight or obesity. We found moderate evidence that activity monitor based behavioral physical activity interventions increase physical activity in these adults and that adding an activity monitor to a behavioral physical activity intervention increases the effect on physical activity. In the studies included in this systematic review, however, primarily simple pedometers were employed with limited abilities to graphically represent individual physical activity patterns over time and limited possibilities for personalized feedback towards individual goals.

Therefore, in **Chapter 6**, a randomized clinical trial was conducted to ascertain the efficacy of a consumer level activity tracker combined with an online lifestyle program in people with type 2 diabetes. In this study, it was found that this intervention was effective for increasing physical activity. In participants who increased their steps per day with a minimum of 1000 steps (defined as responders), a clinically relevant and significant decline in HbA1c was found. Social support was found to be a significant confounder for results on HbA1c with responders exhibiting a greater social support at baseline compared to non-responders. Notably, the effect of being a responder within the intervention group was still associated with a clinically relevant lowering of HbA1c at the 12-month follow-up. Responders decreased their HbA1c, on average, with -10.7 ± 9.2 mmol/mol whereas non-responders showed a change of 0.8 ± 7.7 mmol/mol. These results suggest that, if people with diabetes initially increase their physical activity level with at least 1000 steps/d, they may have maintained these increased activity levels leading to a sustained impact on HbA1c at a one-year follow-up. These results are not displayed in Chapter 6 but do strengthen the conclusions of the study.

In **Chapter 7**, the role of self-regulation was investigated for the effect of self-tracking of physical activity and weight on BMI change in a general population. We found that BMI significantly decreased at short term (four months) and that this was maintained at long term (12 months). Change in BMI was explained by the intention to decrease weight, self-weighing frequency, and increment of self-regulation capabilities: goal orientation at short term and decision making at long term. In total, six out of ten participants indicated to have increased their physical activity behavior as a result of using the devices, and four out of ten improved their eating pattern.

These findings on the effectiveness of self-tracking technology accord with other studies evaluating these devices. Several studies have found positive effects of self-tracking of physical activity on physical activity behavior.[17–19] Moreover, a recent study indicated significant long-term effects of their pedometer based intervention within primary care at three and four years of follow-up.[20] However, the effect of self-tracking of physical activity on health-related outcome measures is far less certain.[21]

For the effect of self-weighing on weight outcomes, our findings are in line with the literature. Several studies also demonstrated weight loss in different populations with self-weighing frequency being the most significant predictor for weight loss.[22,23]

Clinical implications and considerations when using eHealth

This thesis showed that, thus far, eHealth interventions based on self-tracking and self-tracking devices alone have the potential to improve lifestyle behavior. Below, a number of clinical implications and considerations when using self-tracking technology in healthcare will be discussed. Thereafter, points of improvement and future directions are discussed.

Use and considerations when using eHealth technology in health care

Although a self-tracking device can already be considered as an intervention in itself, for use within healthcare, a more comprehensive approach is needed to increase the effectiveness on both behavioral as well as health-related outcome measures. Thus, within health care, self-tracking devices can best be embedded within intervention programs that are more extensive and theory based, including the use of behavioral counselling strategies. Although we studied people with overweight and/or had type 2 diabetes in this thesis, self-tracking technology can be (and already is) applied by a broad range of target groups such as patients with low back pain, COPD, or heart disease. In addition, devices may be used in a variety of settings in both primary and secondary care; e.g., within hospitals, general care practises, or paramedical care such as physical therapy practises.

The timing of health enhancing interventions is obviously important. Since the number of people with overweight, obesity, and type 2 diabetes is still expected to increase in the next decades, health enhancing interventions should ideally occur when people are recently diagnosed with type 2 diabetes or even before that. This will ultimately prevent that diabetes related complications such as feet problems or obesity related comorbidity limit physical activity at a later time. Thus, I suggest that additional emphasis should be placed on health enhancing interventions within primary care to prevent or postpone health issues that are more severe and need treatment in secondary care.

An important consideration when using eHealth technology within health care is the eHealth literacy of the user.[15,16,24] In our eHealth intervention described in Chapter 6, we noticed that a number of patients with type 2 diabetes did not want to participate because they were not in possession of a computer or smartphone or due to lack of abilities to use a computer. In addition, a number of participants in our intervention had difficulties with installing the Fitbit activity tracker and using the eHealth program. Thus, intervention designers and health practitioners should take the eHealth literacy of their target group into account and find solutions for optimizing support when needed.

Furthermore, although the use of wearable technologies was primarily studied in this thesis, the rise of mobile health applications (i.e., mHealth) may also provide opportunities for use in health care. These health apps can be downloaded on an individual’s smartphone, and many of them involve the promotion of physical activity. They use accelerometers from the smartphone to track physical activity and/or sleep levels. Important advantages of health apps are that they are highly accessible (i.e., many people currently own a smartphone), and they are associated with significant lower costs compared to wearable devices.[25] A disadvantage may be lower validity of health apps to measure physical activity parameters, as we found for one app in Chapter 2 and 3, and as was found for several apps in the research of Konharn et al.[26] Also, it may be more difficult to capture an individual’s complete physical activity pattern using an app because carrying a smartphone all day during different (exercise) activities may not always be feasible or desirable. In addition, Bondaronek et al found in their recent review into the quality of health apps that, thus far, health apps have a number of short comings such as quality of the content and safety issues.[25] Therefore, as with wearable devices, the selection of an health app for use in health care interventions should always be done carefully, preferable based on scientific evidence. In line with this, different initiatives have already begun to test both wearables and health apps systematically, for instance, within the National eHealth Living Lab (NeLL) in Leiden.

The role of the health care provider

For a successful enrolment and engagement of patients in eHealth programs provided by healthcare institutions, the role of the health practitioner is crucial. To initiate using eHealth, health practitioners will need to first invest time in order to become familiar with the new technology. Also, remote monitoring of and responding to questions or patient generated data will expend time. Therefore, health practitioners (for example, nurses) should be afforded the opportunity to fulfil this specific role. Thereby, the health practitioner should have high motivation to employ eHealth technology in order to successfully engage participants in eHealth programs. Also, for the guidance of patients (both face to face and remotely), the health care provider needs specific CANMED competences such as being a health advocate and communicator[27] and have sufficient skills in motivational interviewing principles.[28]

To date, wearable activity trackers and associated apps or websites already contain a variety of behavioral change techniques (BCTs).[29,30] BCTs that are currently the most frequently applied are related to behavioral goals, monitoring and feedback, social support, and rewards/prompting cues on past success.[31–33] However, for the application in health care, the question is whether the patient will optimally benefit from these device features or BCTs. Support from the health care professional is most likely necessary for this purpose. Therefore, I next recommend a few specific actions for the health care provider when using activity trackers in healthcare. Within the entire process, it is vital that individual needs for autonomy, competence/self-efficacy, and relatedness are respected.[34] Hereby, health care providers should begin with exploring personal *motivation* (including intrinsic motivation, attitude, outcome expectations and self-efficacy towards physical activity), exploring individual *capability* (e.g., knowledge with regard to physical activity or self-regulation capabilities) and *opportunity* of engaging in physical activity (e.g., one's environmental context and social support).[30] In this session, outcome goals may already be formulated to enhance motivation and the use of the device may need to be explained.

In a next session, the health care provider may offer support in the formulation of feasible goals based on one's baseline activity pattern, ensure a gradual building up, offer support with plan-making, and discuss barriers for reaching personal goals. Also, it is recommended that health care providers discuss and facilitate social support for their patients, e.g., by connecting patients or by facilitating walking groups. Many devices already offer the possibility for social support through the device app or platform, however, as discussed in Chapter 6, additional actions are needed for patients to benefit from these social support functions. Lastly, a health care provider should think about and agree with the patient on how the personal health data is monitored, how and when feedback is provided, and when evaluation sessions will be held. Figure 1 illustrates all of these recommendations for health care professionals when using consumer activity trackers.

Figure 1.
Practical and counseling recommendations for health care professionals when using consumer activity trackers.

Data security, privacy and ethics

Finally, the use of wearable devices to gain personalized health data from citizens, including patients, has also raised concerns with regard to data security, privacy, and ethics.[35,36] Data security and privacy is especially a current major topic with the introduction of the General Data Protection Regulation (GDPR) law and since the recent revelations about privacy breaches from large companies such as Facebook. Questions like 'what happens to our data' are asked more and more often. Many researchers and privacy organisations already pointed out the need for privacy policy regulations including public and citizen engagement, clarity and transparency, and even a new regulatory framework in which the user sells personal data back to the company.[35]

Privacy regulations differ between the European Union and the United States. With the EU-U.S. Privacy Shield, US companies processing data from EU citizens are obliged to provide a privacy policy in which they inform their users about what type of personal data they process and why, the reasons why these data are being processed, whether they intend to share data to other companies, and reasons for this. In addition, a Privacy Shield company can process the data only for the initial goal for which it was collected, they are obligated to minimize the amount of data that is gathered, keep the data only for the time needed, are required to secure the data for misuse, and are obligated to provide users access to their own data and the ability to change, correct, or delete personal data.[37] It is recommended that health care providers and researchers are aware of the privacy statement of the wearable products they utilize for their patients, and, since many digital health care products are developed in the United States, whether they are registered with the EU-U.S Privacy Shield.

Next to privacy and security related concerns, there may also be ethical concerns with regard to the use of eHealth and wearable technologies. Sharon (2017)[36] discusses a number of those concerns with regard to autonomy, solidarity, and authenticity. One concern is that self-tracking may be more or less imposed, e.g., in working environments, creating the emergence of a surveillance culture which may diminish an individual's autonomy. In addition, concerns have been expressed about a decrement of solidarity due to a shift from a collective towards an individual responsibility for health. With regard to authenticity, concerns have been raised that self-tracking may lead individuals to alienation of their own feelings and intuition, by simplifying complex phenomena, such as health, towards numbers and categories created by other people. On the other hand, advocates of self-tracking technologies point out that the act of self-tracking has the ability to improve autonomy, solidarity, and authenticity. For instance, self-tracking may help individuals to engage in personal experiments which enables them to find out 'what works for *me*'. By sharing their data and experiences, they may help others thereby increasing solidarity. With regard to authenticity, Sharon points out that that the quantified self-community does not intend to carelessly trust their data but intend to go beyond their data by linking them to subjective experiences and feelings. In this, the data is more or less a natural phase towards a richer feeling about the self. For health care providers, this may imply that they discuss the act of self-tracking with their patients and encourage them to link their data to other experiences and feelings.

Future directions of eHealth and related research

Within this thesis, many points for improvement of eHealth technology have emerged. In order to further increase the adoption of wearable devices, it is vital that technical abilities of consumer level self-tracking devices are being improved. Thereafter, developments in behavioral design are also needed to improve effectiveness of eHealth. Based on our results and other eHealth related research, recommendations are next provided for future directions in eHealth and research.

Improvement of technical abilities of self-tracking devices

First, overall user experience may be enhanced by ensuring a user-friendly installation procedure in an individual's native language and by addressing battery limitations in order to avoid data loss and non-wearing time.

Second, the reliability and validity of activity trackers should be further improved. In the event of step counting, this is especially necessary for activities that take place at a slower walking pace. As older adults and people with overweight exhibit a different, slower walking pattern compared to people without overweight,[38,39] it is important that their physical activity efforts can still be captured by consumer level activity trackers. In addition, validity of physical activity measures such as sedentary time, time spent in moderate to vigorous physical activity (MVPA), and energy expenditure should also be enhanced. Sedentary behavior is an independent risk factor for adverse health outcomes[40,41] and, therefore, may be a unique target within health promoting interventions. In addition, the amount of time spent in MVPA is the primary physical activity measure used in physical activity guidelines.[41,42] Also, energy expenditure (EE) is an important physical activity measure, especially in weight loss interventions that aim to increase EE and decrease caloric intake. Recent research has shown that GPS provide the most valid method for estimating EE[43] compared to heart rate combined with accelerometry measurements. Therefore, combining both accelerometry with heart rate and GPS may be a viable option for improving validity of EE that is measured by consumer activity monitors. In addition, there is an ongoing need for research into the validity and reliability of newly developed consumer activity trackers. This need is parallel to the nature of consumer technology since the market of consumer wearable technology continues to expand.

Third, to increase experienced usefulness of the data and thereby adoption, a device should measure what the individual really wants to know.[44] Therefore, more different types of activities may be implemented in self-tracking technology such as cycling, swimming, or performing exercises at the gym. It would be most useful for users to know how much time they spent (or how many repetitions they made) when performing these specific activities and at which intensity. Although there are already developments in the measurements of these different activities, a single device that is able to capture all of these activities is not yet available.

Lastly, users will benefit from increased possibilities for data integration. Generally, an individual does not just want to measure or change a single behavior or health outcome. Instead, people would like to gain insight into how several aspects of health, health behavior, and personal daily habits such as ‘what did I do today’ are related to each other. Thus, ideally, different types of data should be integrated into single apps or graphs in order to increase meaningful interpretations of accumulated data.

With all of the above mentioned improvements, self-generated health data will gain certain ‘valances’, such as self-evidence (accuracy of the data with regard to technical abilities), truthfulness of the data (accuracy of the data with regard to user behavior, such as wearing time), data transparency and discovery (i.e., being able to analyse relations between different types of data and discover patterns in the data), and actionability.[45] These are important conditions for people to gain insight into their actual lifestyle habits and possibility to engage in personal experimentations (e.g., finding out which individual lifestyle changes are needed to lose weight), and consequently being able to act upon this personal data.[45] This will both enhance overall user experience and motivation when using self-tracking technology.

Improvement of effectiveness of eHealth technology

As mentioned above, wearable activity trackers already contain a number of behavioral change techniques. However, there are also a number of BCTs that have been associated with increment of physical activity or self-efficacy for exercise that are currently rarely applied within self-tracking technology. Table 1 provides an overview of these BCTs. When these BCTs are further included within wearable technology (or associated programs), the potential of these interventions to further increase physical activity behavior -also in more vulnerable populations such as sedentary individuals, older adults, or people with a low social economic status (SES)- may increase greatly.[31–33] Therefore, these BCTs are discussed below using the categorisation of BCTs by Michie et al.[30]

Table 1.
Overview of BCTs that are not yet present in most consumer activity trackers.

Category	Behavioral Change Techniques
Goals and planning	-Goal setting of outcomes -Barrier identification/problem solving -Action planning -Prompt review on outcome goals
Shaping knowledge	-Provide instruction on how to perform the behavior
Natural consequences	-Provide information on consequences of behavior in general
Repetition and substitution	-Behavioral practice -Generalization of the target behavior
Antecedents	-Restructuring the physical environment
Reward and threat	-Self-reward
Self-belief	-Self-talk
Covert learning	-Prompt use of imagery

Advances in *goals and planning* within activity tracker-based interventions may help users to increase their self-regulation abilities such as increasing their goal orientation and decision-making capabilities. Goal setting of outcomes, problem solving, and action planning have found to be rarely applied in consumer activity trackers. [31–33] This may be improved by providing formats into apps or internet platforms associated with the device, to help users to select both behavioral and outcome goals, as well as making a plan on how to achieve those goals. Offering sufficient meaningful choices is hereby crucial to support autonomy.[34] In addition, users may get the possibility to select individual barriers for physical activity which are most common (e.g., lack of time, tiredness, lack of knowledge how to be active), and subsequently be prompted to think about ways to overcome those barriers. The app may also provide advices based on these barriers. Research is needed in this area to design these suggested behavioral strategies, for instance using focus groups.

Although *monitoring and feedback* related BCTs are mostly present in consumer activity trackers, there is room for improvement in the delivery of feedback trough digital devices.[46] The Feedback theory emphasizes that feedback should be aimed at task motivation or task learning processes.[47] Ideally, feedback content should be tailored as much as possible to individual users (e.g., based on age, gender, activity level, health beliefs, personal goals, self-efficacy expectations, barriers, or goal progression) and facilitate learning about an individual's own behavior.[48,49] Learning can comprise gaining knowledge about which specific routes in a person's environment or actions are needed to reach a step goal or how to cook a healthy meal. In concrete learning situations, positive outcome expectations about the undesired behavior (e.g., having lunch at the computer saves time), should be replaced with positive outcome expectations about the desired behavior (e.g., taking a walking lunch break is feasible and makes me feel fit). This will enable people to learn about the changes they make in their daily habits and how these changes are related to goal progression and personal perceptions. In addition, the tone of the feedback should be empathic, positive, and always be aimed at increasing the self-efficacy of the user for engagement in the target behavior.[50,33] This may, for instance, be accomplished by providing success stories of peers. In addition to personalized or goal-orientated feedback (based on personal characteristics, personal data and individual goals), normative feedback (comparing an individual's own data with others), iterative feedback (comparing own data with data from the past), and actionable feedback should also be considered.[48,51] Actionable feedback includes feedback that provides multiple cues for action, i.e., when, where, and how to engage in a goal-directed behavior. This type of feedback was found in only 15% of the reviewed studies by Schembre et al,[51] and, therefore, affords an opportunity for the improvement of feedback content in future programs. In addition, next to the content of the feedback, efforts may be made to enhance the presentation (i.e., attractiveness), timing, frequency, and duration of feedback.[46,52] For instance, providing real-time feedback that accords with the context of the user will likely be more beneficial, e.g., a truck driver will benefit more from encouragement to increase activity levels during a break than receiving activity reminders while driving.

With regard to '*shaping knowledge*' and '*natural consequences*', the BCTs 'providing instruction on how to perform the behavior' and 'providing information about health consequences of performing the behavior' were found to be present in some, but not all activity trackers reviewed in Lyons et al. Both BCTs have been determined to influence physical activity behavior.[32] Therefore, additional efforts should be made to include information on benefits of physical activity and ways to increase it. These actions correspond with providing actionable feedback as described above.

Also, '*repetition and substitution*' and *'antecendents'* related BCTs (e.g., behavioral practice, generalization of the target behavior, and restructuring the physical environment) have been suggested as important BCTs to integrate within consumer technology.[31–33] This may be done by prompting users to perform certain exercises with detailed instructions through an app or including maps of suitable walking routes within the own area of the user. In addition, *'reward and threat'*, *'self-belief' and 'covert learning'* related BCTs (i.e., self-reward, self-talk, and use of imaginary) may be integrated within associated apps of activity trackers by including messages or notifications in which users are, for example, prompted to reward themselves or tell themselves that a walk will be energizing.

Concluding remarks

eHealth, including the use of self-tracking technology, offers potential for improving quality of health care and self-management of patients. In this thesis it was found that effective use of an activity tracker may significantly reduce the progression of diabetes, by lowering HbA1c both at short term and after one year. For the design of future interventions, it is vital that co-creation occurs with all of the relevant stakeholders in order to successfully implement eHealth innovations within healthcare.[53] In addition, the selection of appropriate intervention functions and behavior change techniques is crucial in order to optimise intervention effects.[30] All stakeholders (e.g., patients or end-users, health care providers, small and medium enterprises, researchers, and policy makers / health care ensures) should work together to create a viable eHealth product. This includes a product that offers added value for the patient and health care provider, includes a positive business case for the small and medium enterprises, and is cost-effective for the health care insurer.[24,53]

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