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How one small step for occupational health management leads to many steps for employees – an experimental field study of incentive designs in a gamified mHealth app

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HOW ONE SMALL STEP FOR OCCUPATIONAL HEALTH MANAGEMENT LEADS TO MANY STEPS FOR EMPLOYEES – AN EXPERIMENTAL FIELD STUDY OF INCENTIVE DESIGNS IN A GAMIFIED MHEALTH APP

Research Paper

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Abstract

Physical inactivity has become one of the leading health risk factors in today's work environment, and in response, companies show increasing interest in digital health interventions to promote employees' well-being. Tools such as mHealth apps use promising approaches to encourage people to be more physically active, for example, through gamification elements combined with financial incentives. However, there is a lack of research on how these technologies and incentives need to be designed to affect employees' health behaviour positively. Based on prospect theory, this study examines the effect of gamified loss-oriented vs gain-oriented financial incentive systems with identical economic value to promote physical activity of employees. Our experiment's results showed an overall positive effect in increasing employees' physical activity (mean daily step count); more specifically, the advantage of a loss-oriented versus a gain-oriented incentive strategy compared to the control group.

Keywords: Mobile health technology, Occupational health management, Gamification, Gain- vs loss-framed incentives

1 Introduction

Life in an industrialized society is primarily sedentary. The widespread use of transport aids such as lifts, escalators, and vehicles, demands less physical effort and promotes convenience. In addition, digitalization in the workplace involves more knowledge-intensive work which requires sitting in front of a computer, resulting in long periods of inactivity. This phenomenon is known as sedentary behaviour (SB) (Tremblay et al., 2017). According to the Third European Survey of Enterprises on New and Emerging Risks in 2019, prolonged sitting is among the most frequently cited risk factors to health at work (Irastorza et al., 2020). SB is associated with numerous health risks to an individual, which can affect the productivity and performance of employees at the workplace, leading even to regular absenteeism (White et al., 2016). The COVID-19 pandemic has further exacerbated this risk through a sharp increase in remote workers (Savić, 2020) and social distancing, leading to an overall reduction in physical activity (PA), among workers and an increase in SB (Stockwell et al., 2021). Moreover, individuals often underestimate the amount of time they spend sitting during the day (Schaller et al., 2016) and overestimate the number of steps they take each day (Gaede-Illig et al., 2014), leading to a gap between subjective self-perception and actual behaviour. Insufficient PA harms not only general well-being but also causes several adverse effects on health, such as an increase in the risk of heart disease, diabetes, certain types of cancer, obesity, high blood pressure, and mortality from all causes (Ströhle, 2009). In particular, long periods of SB are a risk factor for increased mortality and cardiovascular disease (Katzmarzyk et al., 2009), as well as musculoskeletal disorders, leading to significant levels of pain and disability (Juul-Kristensen et al., 2004). In addition to these personal health consequences, insufficient PA for employees, companies, and the healthcare system must also consider the economic costs of lost productivity due to absenteeism and medical treatment costs (Pike and Grosse, 2018). In the U.S., the total cost of care for heart failure is estimated at $43.6 billion in 2020. Without improvements in outcomes, the total annual cost of care in the U.S. is expected to increase to $69.7 billion by 2030 (Urbich et al., 2020). These effects are dramatic considering that even moderate PA, e.g., brisk walking or slow cycling (Martin et al., 2000), is sufficient to minimize absenteeism and thus achieve economically positive results (White et al., 2016). Walking exercise is highly recommended for everyone as it is connected to numerous physiological health benefits addressing these stated risks and positively affecting psychological health, e.g., mood, stress relief, and enhanced cognitive functions (Kelly et al. 2017). Effective occupational health management (OHM) in companies plays therefore an important role in assuming social responsibility, keeping employees healthy in the long term, reducing absenteeism, and relieving the burden on the healthcare system.

Due to the ever-changing and emerging work models, as evidenced by the COVID-19 pandemic with a high number of remote workers, OHM offerings must be able to adapt to these types of work models. Digitization enables companies to make their existing services available as digital solutions and thus achieve independence in terms of time and location. A variety of health apps are already being deployed in the workplace, using a range of compelling features to motivate and encourage users to achieve a set health goal. The challenge with these eHealth technologies is to obtain sustained and continuous use, which is necessary to achieve positive outcomes e.g., increased PA (Teixeira et al., 2012). People tend to be intrinsically motivated whenever their actions lead to positive effects in their life (Ryan and Deci, 2000). Knowing the benefits of movement and exercising would intrinsically motivate people to continually integrate PA in their daily life. Since not every person is initially highly intrinsically motivated to engage in PA nor have they internalized PA's benefits yet, extrinsic incentives seem necessary to motivate employees to grasp the benefit of PA, and create a habit (Ryan and Deci, 2000). Several studies have investigated how eHealth technologies need to be designed to encourage continued use and consequently increased PA among primarily sedentary workers (Schmidt-Kraepelin et al., 2019; Corepal et al., 2018; Fritz et al., 2014). Some studies, particularly in health research, have examined the effectiveness of different incentives in eHealth apps. Research suggests that step and health goals, challenges, or quizzes (Dadaczynski et al., 2017), linking fitness trackers to a map-based virtual race (Gremaud et al., 2018), earning points through steps and social comparison (Haque et al., 2020), or interactive tracking and setting of goals (Zhang et al., 2021) positively influence healthy behaviours. Positive effects were also observed through social or communicative incentives such as reminders during prolonged sitting (van Dantzig et al., 2011), the combination of social step challenges and physical nudging (Mamede et al., 2021), and financial incentives (Patel et al., 2016b; Patel et al., 2016a; Patel et al., 2016c; Royer et al., 2015; Finkelstein et al., 2008). In information systems (IS) research, studies on the possibility of integrating financial incentives as extrinsic motivators in digital OHM measures are still scarce and sometimes controversial in their findings. However, especially in the case of PA, studies suggest that individuals can develop a habit of healthy behaviour through repeated practice and financial incentives can be a vehicle of ensuring that a behaviour is continuously performed before it becomes a habit (Goh and Razikin, 2015). However, it is not yet clear how the financial incentive and monetary amount should be framed and presented in an app, especially in the context of OHM (Mitchell et al., 2020). Therefore, our study addresses this research gap by conducting a randomized control trial (RCT) using two different frames for gamification and incorporating financial incentives based on the principles of prospect theory. Since the investigated design frames are easy to adopt, their ability to motivate employees towards more PA in daily life is a promising approach for digital OHM interventions.

2 Theoretical Background

2.1 Digital OHM

Occupational health and safety constitute a system that deals with the prevention of occupational diseases, as well as the prevention of workplace accidents and the control of company-related health risks. OHM is also responsible for the improvement of workplace health by minimizing the health-related inefficiencies of employees by developing, implementing, and coordinating specific health-promoting measures (Da Silva and Amaral, 2019; International Labour Office, 2011). Health-intervention programs are ongoing organizational activities inducing employees to adopt personal behaviours to maintain and improve their health (Wolfe et al., 1994).

The term ‘eHealth’ refers to health services and information that are delivered or enhanced through the Internet and related technologies (Eysenbach, 2001). In the past decade, mobile technologies, real-time data processing have simplified and improved eHealth technologies and activity data collection. According to Shaw et al. (2017), the term eHealth can be divided into three categories: The first category includes technological apps used to monitor and track health data and provide relevant information. The second category includes communication technologies that enable exchanges between patients and professionals. The third category includes all technologies used to collect, manage, and use health data. Mobile health (mHealth) is the use of mobile devices for health services and information (Meng et al., 2019), and can be considered as a conjunction of eHealth technologies with mobile technologies supported by apps. The apps (e.g., fitness apps) collect, analyse, process, and transmit health-related information via sensors and other systems. Self-tracking or ‘the quantified self’ describes the current trend to collect data on specific characteristics of life through mobile and wearable devices (e.g., daily activities, exercise, vital signs, symptoms of illness, or sleep) (Entreß-Fürsteneck et al., 2019).

Especially in health-promotion programs, more and more companies see promise in integrating digital technologies that aim to make their existing OHM offerings available as eHealth tools, e.g., health platforms (Duryan et al., 2020), apps (Weerasekara and Smedberg, 2019), or wearables (Khakurel et al., 2018). The collection and analysis of large amounts of health data provided by the user can help OHM to identify diseases or risks at an early stage so that appropriate and individual interventions can be taken promptly. In particular, tracking PA can encourage employees to be more physically active at work (Ilhan and Henkel, 2018; Glance et al., 2016; Rockmann et al., 2018), promoting mental well-being (Giddens et al., 2017; Henning and van de Ven, 2017) and a healthier lifestyle. However, the effectiveness of activity trackers in combination with mHealth apps needs further investigation to understand and evaluate the implementation of such strategies, especially in the work environment. From a persuasive technology design perspective (Thomson et al., 2016), the effectiveness of an mHealth app depends on the persuasive communication strategy of the system and whether it is utilized continuously by the user. The following section will discuss various incentive systems applicable in the OHM context that have already been studied in the literature.

2.2 Incentive systems in digital OHM

An emerging trend in practice to increase motivation to use and adopt a system is the application of gamification. Gamification is the use of playful thinking and the transfer of successful game mechanisms to non-game areas (Zichermann and Cunningham, 2011). Its application aims to make activities perceived as unpleasant more enjoyable by presenting them in a conducive environment and making the task more accessible and comprehensible through visualization and context, an approach that can easily be applied to the work environment (Cardador et al., 2017). To achieve these objectives, elements such as points, levels, performance graphs, and the visualization of goals work as extrinsic incentives. Points are a reward for successfully completing certain activities within the gamified environment (Werbach and Hunter, 2012). The advancements made over the course of time can be visualized through levels

(Klock et al., 2020). Performance graphs show the user's visualized progress over a specified historical period, without comparison to other players (Sailer et al., 2017). In addition, reminders or deadlines can be used to challenge users to complete a particular task (Klock et al., 2020). Especially in the task of increasing PA, gamification elements work better as incentive systems than a stand-alone tracking function or analogue measurements (Gremaud et al., 2018; Haque et al., 2020).

Another way to include an extrinsic motivator is a financial incentive. Financial incentives can be combined with other incentive systems, e.g., gamification elements. A distinction can be made here whether financial gains can be made or whether financial losses can be incurred if a set target cannot be reached. In the case of financial incentives in the form of losses, users are either first credited with a certain amount, which is reduced if the target is not achieved (Patel et al., 2016b) or provide a self-fund that will be lost if the target is not achieved (Royer et al., 2015). In the case of financial incentives in the form of gains, incentives could be paid directly or given to participants via several methods. Research suggests that it is irrelevant whether rewards are paid out directly or indirectly, e.g., in the form of a donation receipt, but that both incentives lead to an increase in the number of steps walked per week (Harkins et al., 2017).

Overall, the application of gamification and financial incentives in mHealth interventions is an emerging trend in practice and a field of research increasingly pursued in IS literature.

2.3 Behavioural economics: Insights from prospect theory applied in the health context

From a persuasive technology design perspective (Thomson et al., 2016), the question is how gamification elements in mHealth apps need to be designed to lead to an actual change in employee behaviour. When reviewing the current literature, it is noticeable that the use of different gamification elements is based on different behavioural economic theories and that their effectiveness varies depending on the context of application and their study design (Edwards et al., 2016; Villalobos-Zúñiga and Cherubini, 2020). According to Bandura (1977), the success of an intervention depends on the persuasive communication approach, which means that when the content of a message is essentially the same, different framing of the message, such as emphasizing the positive effects or negative effects, can make it more or less effective (Gallagher and Updegraff, 2012). Prospect theory from Kahneman and Tversky (1979) provides the practical and theoretical foundation for this observation: The risk-averse individual can be significantly affected by changing the value of an object to either gains or losses, therefore leading to differences in an individual's behavioural choices. Some studies have already examined these insights in the health context. For example, Lim and Noh (2017) tested the effectiveness of gain- over loss-framed performance feedback, discovering that the persuasive frame of performance feedback can influence the rate of adoption of mHealth apps and consequently PA. Thus, referring to Rothman and Salovey (1997), loss-framed appeals should be used to persuade users toward a health behaviour that involves an unpleasant outcome such as detection of illness, and gain-framed messages should be used to persuade users to engage in health-promoting behaviours, such as prevention appealing to the risk-averse mind. However, these assumptions can also be interpreted differently, depending on one individual underlying construal of behaviour.

Patel et al. (2016b) used insights of prospect theory, to demonstrate that the same magnitude of financial incentive can have a different effect on outcomes depending on the design of the incentive. The authors relied on the fact that losses are weighted more heavily by participants than gains for small or medium monetary amounts, and therefore a risk-averse person will be expected to act primarily avoid losses rather than to achieve gains (Kahneman and Tversky, 1979; Rechenberg et al., 2016). Patel et al. (2016b) showed that when differentiating between daily feedback alone or between three different financial incentives of equal value in the form of gain incentives (amount paid every day), loss incentives (amount deducted from a prepaid amount), or lottery incentives (amount could be wagered daily), only the participants in loss incentives were able to achieve a significant increase in reaching the daily step-goal of 7,000 steps. Although there is scientific and practical support of their effectiveness, behavioural theories are insufficiently considered in the development of mHealth apps today (Sullivan and Lachman, 2016). At the same time, research efforts in IS research have been limited, and their results are partly contradictory. There is still a gap in research looking at the design of mHealth technologies using gamification and financial incentives and their impact on employees' PA in the workplace context. To address this gap in research, we will subsequently formulate corresponding hypotheses.

3 Hypothesis

The object of this study is to test the effectiveness of different incentive designs in a gamified mHealth app. Based on the theoretical foundations, we derive two hypotheses. First, we hypothesize that the app's design in the treatment groups motivates employees more than the control group using the app as a simple pedometer without any incentive system.

Hypothesis 1 (H1): An incentive frame in fitness apps encourages employees to take more steps daily than simple self-tracking.

Further, we want to investigate the effectiveness of two different framings, gain- or loss-framing, with the same expected economic value. The previously mentioned studies observed that the same magnitude of incentives leads to different outcomes depending on the framing and design. Based on what we learned from prospect theory, we hypothesize that there is a difference in achieving the goal of increased activity between the two groups in favour of the loss-framed group.

Hypothesis 2 (H2): A loss-frame in fitness apps encourages employees more than a gain-frame with the same economic value.

Additionally, we are interested in whether any differences in employees' subjective self-perception towards their actual PA could be observed due to the intervention design and exposure to visual gamification elements. Considering that people often misjudge their actual PA (Gaede-Illig et al., 2014), we believe that mobile self-tracking devices can lead to a better assessment of PA. For example, the literature shows that mobile self-tracking devices can help users with health problems to manage their health more effectively on a daily basis in a paperless format (Salah et al., 2014). In an occupational context, we also believe that performance graphs help to assess better and track PA levels. Since the theoretical basis for this conclusion is still limited, we do not form a hypothesis but look at the relationship in an explorative way.

4 Experimental Approach

4.1 Game design and experimental conditions

We conducted a RCT and set up a field experiment over six weeks using a between-subjects factorial design to test our hypotheses. To evaluate the effectiveness of a gamified mHealth app on employees' exercise behaviour and motivation, we designed two experimental conditions (treatment groups) and one control group. The mHealth app used already existed and was modified and provided to the employees for study purposes only. We collected app user data and examined the number of steps taken during our intervention. We also collected survey data before and after the intervention. The experimental conditions are designed as follows:

Treatment Group 1 (TG1): Game-design elements; gain-framed incentives

Treatment Group 2 (TG2): Game-design elements; loss-framed incentives

Control Group (CG): Visualization of steps; no incentives

An overview of the gamification elements implemented in TG1 and TG2 is shown in Table 1. Since the CG served as a baseline in our experiment, the app was reduced to a simple step-display and progress bar for the day. All other functions and features such as levels, points, or financial incentives were not available to the CG user. The app in TG1 and TG2 was designed to encourage participants to exercise through a combination of gamification, collecting points (visualized by stars), reaching higher levels, and financial incentives that were paid out after the intervention. Figure 1 shows the app's design as it appeared to TG1 and to TG2 and, in comparison, the app’s design for the CG. To visually represent progress through points accumulated over the week, a performance chart was created in the form of a line graph as a subcategory of daily objectives in TG1 and TG2.

Gain-framed incentive: In TG1, users took part in a challenge with the goal to climb up levels and win the highest payout of €12 within six weeks. Level advancement was achieved by collecting daily points. The rules were as follows: Participants started in level 1 with a payout of €0. If the exercise target of 8,000 steps per day was reached, the participants received two points. If participants reached even 12,000 steps or more per day, they would receive three points. Participants were eligible for an extra point per week if the app had been synchronized on seven days of the week. In total, a maximum of 22 points per week could be achieved. If the employees reached 14 points or more before the end of the week, they moved up a level. If they were below that, the level was merely maintained. A step down was not possible in this treatment. Points could not be carried over into the next week. Each level advancement was rewarded with a financial incentive of €2. After the intervention of six weeks, a maximum of €12 could be earned. Therefore, the challenge's overall goal was to reach level 7 and receive the total payout of €12.

Loss-framed incentive: In TG2, participants also joined a challenge, but the goal here was not to climb up levels but to prevent from dropping from the highest to the lowest level and, therefore, lose the payout of €12. Participants started in level 7 with an upfront payout of €12. Maintaining the level worked similarly to the point system of TG1. If employees collected at least 14 points per week, they maintained their level. If they were below that, they dropped down one level. Again, the financial reward was linked to the level at the end of the challenge. Therefore, each level descent was punished with losing €2 of the upfront incentive. The overall goal of the challenge was to maintain level 7 and not lose any of the €12 payout.

Gamification Elements	**TG1**	**TG2**	**CG**
Visualization of steps	☐	☐	☐
Points	☐	☐	-
Level	☐	☐	-
Visualization of goals	☐	☐	-
Performance graph	☐	☐	-
Financial incentive	☐	☐	-
Frame	Gain-frame	Loss-frame	No frame

Table 1. Gamification elements according to the experimental condition.

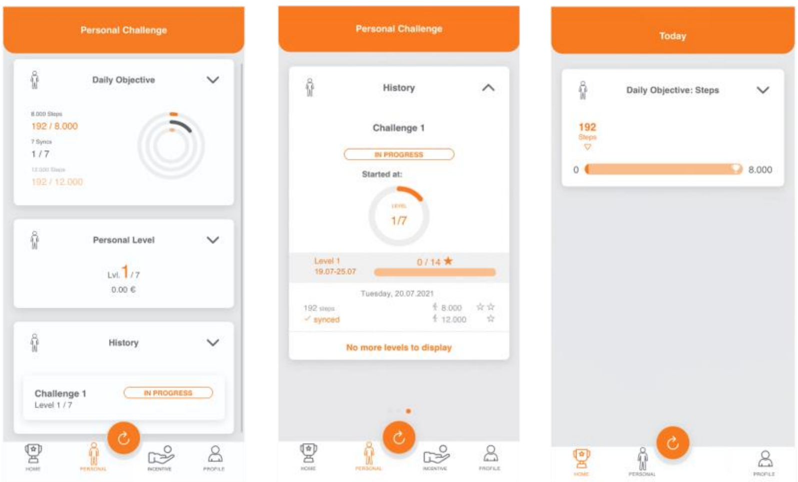

Figure 1. App design; left: TG1 overview gamification tools, center: TG1 level system, right: CG home display.

We set a target of 8,000 steps per day due to research of Tudor-Locke et al. (2011) stating that approximately 7,000 to 8,000 steps per day are a reasonable threshold for daily PA in line with current public health guidelines for the minimal amount of time that should be spent in moderate to vigorous PA. The level design was set to a weekly basis with a point reset every new week. We used this approach considering research explaining that individuals tend to be more motivated by immediate rather than delayed gratification when completing a task (Loewenstein et al., 2013; O'Donoghue and Rabin, 2000). Therefore, the weekly basis subdivided the overall goal into six small goals enabling weekly gratification and a new chance every week detached from the previous weeks' performance.

4.2 Participants and data collection procedure

The data collection took place from June until September 2021. All employees of a German university were invited via mailing lists and allowed to participate in the experiment. Interested participants were directed through an online link to the pre-questionnaire, including the registration process. The only requirements were that participants own a smartphone with the operating system (OS) iOS (Apple Inc.) or Android (Google LCC), had time to measure their daily step-count during the expected six-week period of the experiment, and consented to the use of their data for research purposes. The data collection was anonymous, with the only exception being the provision of an e-mail address, which was needed to enable contact and the allocation of data collected during the pre-, intervention, and post-phase. After registration, participants immediately completed the pre-questionnaire, using the software Qualtrics (Provo, UT). The following data were collected in the pre-questionnaire: demographics, health-related information, prior experience with mHealth apps, and information about the participants' occupation, including hours worked per week and type of occupational activity (predominantly sedentary vs predominantly standing). Individuals whose questionnaires were incomplete were excluded from the further course of the study. After the registration process, we assigned participants randomly to either TG1, TG2, or CG. We used the method of covariate adaptive randomization to ensure that the baseline characteristics were well-balanced despite the small group sizes (Kang et al., 2008). For the intervention part of the study, we asked participants to install the mHealth app and we provided instructions on how to install and use the app. Furthermore, individuals received additional information about their app's challenge and its goal depending on the experimental condition.

The app needs to synchronize with either Google Fit (Google LLC 2018) for OS Android or AppleHealth (Apple Inc. 2021) for OS iOS to connect with the built-in smartphone accelerometers. The number of steps achieved for each participant throughout each whole day during the study was collected as a continuous variable. Participants were informed about the importance of carrying their smartphone with them during the intervention to count the achieved steps. Connection to a wearable was not allowed and was checked to ensure the same conditions for all participants. Nevertheless, data could be missing for a day if a participant turned off the smartphone or the app or did not carry the smartphone at all. For the primary analysis, collected data was the step-count value which was collected through the app. In case of missing data (≤ 6 days in total), we used the average step-count of all the measured steps per day on a participant level to fill the gaps. We considered this approach appropriate to minimize data bias due to the even distribution of missing data across groups. However, the percentage of participant-days on which step-count data were missing during the intervention was overall less than 5%. After the intervention phase, the participants received a post-questionnaire according to their assigned group. In the post-questionnaire, the participants' subjective PA was assessed through their estimation of PA on a working day by rating themselves on a scale from 1 to 100.

Also, a manipulation check was added to ensure that the participants of each group actively recognized the design of the group's intervention. We integrated two questions in the post-questionnaire of each TG1 and TG2 for manipulation validity: The first question aimed to see whether participants recognized the level system and the gain- or loss-frame of their intervention group. Therefore, we asked TG1 whether they could move up levels by moving enough and meeting the weekly step-goal in their game design. Most participants (n=15) confirmed that this was the case, while only a few (n=3) disagreed. However, since these three cases did not move up any level during the intervention phase, we still consider this an acknowledgment of the intervention group's gain-frame. In TG2, we asked if they would have been relegated to a lower level by not moving sufficiently to meet the weekly step-goal. Like TG1, most of the participants confirmed (n=12), while a few (n=3) disagreed due to the same reason, that they did not descend a level during the loss-framed intervention. We only identified one case of TG2 to fail the manipulation check. Therefore, we excluded this participant from further statistical analysis.

Out of the approximately 300 employees that were contacted through the mailing list, 82 (27%) individuals participated in the experiment and were assigned to groups. Across all three groups, 54 (66%) of the assigned participants completed the full six-week intervention, including both questionnaires. Table 2 shows the numbers and reasons for participants' exclusion from the study. Data collected from any participants who dropped out of the study were not included in the analysis. The reasons for withdrawing from the study were health-related issues, unsolved technical issues, or the inability or the unwillingness to carry the smartphone adequately for data collection. A total of 49 (59.75%) data sets were used for the analysis.

Assigned Group (n)		**TG1 (27)**	**TG2 (27)**	**CG (28)**
Excluded from further evaluation due to (n)	No app downloaded	2	6	2
	Dropout during the intervention phase	6	3	5
	Missing step-data exceeded six days in total	1	2	5
	Manipulation check failed	0	1	0
Sum		**18**	**15**	**16**

Table 2. Reason for the exclusion of participants.

4.3 Statistical analyses and results

We used the software IBM SPSS Statistics for Macintosh, Version 27.0 (Armonk, NY), for performing statistical analysis. Descriptive statistics are presented as mean (M) and standard deviation (SD). Results are considered statistically significant on a level of alpha of .05. All the following participant baseline characteristics are generally well-balanced across the three study groups (Table 3). Participants had a mean age of 32.43 years (SD=11.20), with an age range of 19 to 63 years. 61% identified as women and 39% as men. The average body mass index (BMI) of the participants was 22.46 (SD=3.21), while 74% of the participants have a BMI within the range classified as healthy (18.50-24.99), 18% within the overweight range (25.00-29.99) and 8% within the underweight range (<18.50). The majority (96%) defined their activity at work as mainly sedentary; the rest considered it balanced between standing and seating. Out of all participants, 57% indicated that they had previous experience with a mHealth app collecting step-data.

Group (n)		**TG1 (18)**	**TG2 (15)**	**CG (16)**
Age	mean (SD)	32.67 (11.37)	30.67 (9.37)	33.81 (12.94)
	range	22 - 63	23 - 54	19 - 60
BMI	mean (SD)	21.69 (2.48)	22.38 (2.62)	23.47 (4.31)
	range	16.98 - 26.09	18.99 - 28.73	16.36 - 29.63
Gender, n (%)	female	11 (61.11)	9 (60.00)	10 (62.50)
	male	7 (38.89)	6 (40.00)	6 (37.50)
Predominantly SB, n (%)		16 (88.89)	15 (100.00)	16 (100.00)
Hours worked per week, n (%)	< 25	4 (22.22)	4 (26.67)	5 (31.25)
	≥ 25	14 (77.78)	11(73.33)	11 (73.33)

Previous experience with mHealth apps, n (%)	yes	10 (55.56)	11 (73.33)	7 (43.75)
	no	8 (44.44)	4 (26.67)	9 (56.25)
OS, n (%)	Android	10 (55.56)	3 (20.00)	6 (37.50)
	iOS	8 (44.44)	12 (80.00)	10 (62.50)

Table 3. Characteristics of study participants.

The primary outcome variable is the mean daily step-count measured by the built-in smartphone accelerometers. Data are distributed normally for CG and TG2 but not for TG1 (Shapiro-Wilk-Test, p<.05); homogeneity of variance is assumed (Levene's test, p=.077). After inspection with a box plot, the two found outliers were not considered suspicious nor declared as measurement errors after screening the data sets (Figure 2).

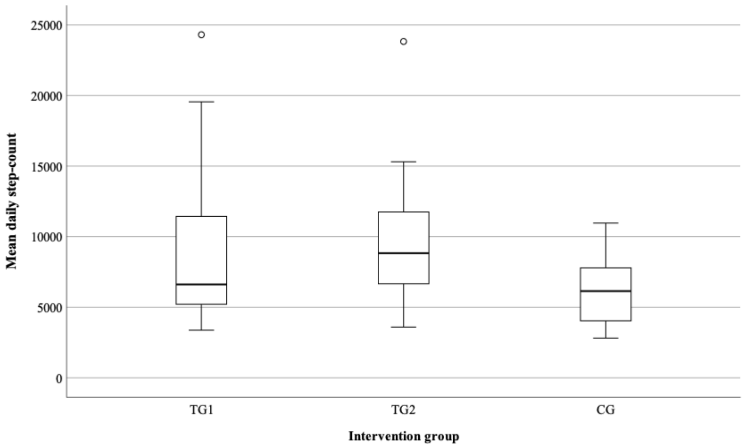

Figure 2. Box-plot mean daily step-count (Box= 25th and 75th percentiles; line in box= median; bars= min. and max. values; circles= outliers).

The average mean daily step-count of TG2 (M=9,855.33, SD=5,071.93) during intervention was 650.88 steps higher than in TG1 (M=9,204.56, SD=5,883.79) and 3,645.58 steps higher than in CG (M=6,209.75, SD=2,519.42). The median as another measuring instrument of central tendency should be considered as a robust measurement for the difference between the intervention groups characterized by a small sample size with possible uneven distribution (Habibzadeh 2017; Lavrakas 2021). The median of TG2 (8,831.00) is considerably higher than the median of TG1 (6,611.00) or CG (6,145.50). We present all results in Table 4.

	TG1 (18)	TG2 (15)	CG (16)
M	9204.56	9855.33	6209.75
SD	5883.79	5071.93	2519.42
Median	6611.00	8831.00	6145.50
95%-CI	6278.61 – 12130.50	7046.59 – 12664.07	4867.25 – 7552.25

Table 4. Outcome variable daily mean step-count.

We conducted a one-way ANOVA to assess the differences in the daily achieved mean step-count of the TG1, TG2, and CG. The ANOVA of the mean number of daily steps during the intervention phase did not deliver statistically significant results for the different groups F(2.46)=2.65, p=.082. We followed post-hoc comparisons of differences using the parametric Dunnett's test on a significance level of alpha of .05, which is especially suitable for trials using treatment and control groups (Dunnett, 1955; Lee and Lee, 2018). The loss-framed group TG2 had a statistically significant (3,645.583, 95%-CI:

lower bound: 286.16, $p<.05$) greater mean step-count than the CG. The difference between the gain-framed group TG1 and CG is not statistically significant (2,994.806, 95%-CI: lower bound: -216.88, $p=.065$). Comparing the first three weeks of the intervention with the last three weeks of the intervention, a noticeable decrease in steps for TG1 (4.63%) and CG (9.33%) can be seen, while the decline in TG2 (<0.5%) can be disregarded.

As a secondary outcome variable, we also looked at how often participants of each group met the daily step goal of ≥8,000 steps. The average mean achieved step-goal days out of 42 intervention days is highest in TG2 (M=24.13, SD=12.61), followed by TG1 (M=20.28, SD=14.38) and lowest in CG (M=12.50, SD=9.60). Also, in this case, the differences of a conducted one-way ANOVA are statistically significant for the groups $F(2.46)=3.55$, $p<.05$. The Dunnett's test post-hoc analysis reveals the statistically significant difference in TG2 (95% CI lower bound: 2.86, $p<.05$), whereas there is no statistically significant difference between TG1 and CG (95% CI lower bound: -.61, $p=.067$).

We were looking at the results from the subjective PA self-estimation on a working day correlated to the mean daily step-count of each group during the working days of the study. Participants' mean daily step-count and their self-estimation of PA on a working day correlate strongly positive for TG1 (Spearman's $\rho=.574$, $p<.05$) and TG2 (Spearman's $\rho=.635$, $p<.05$). In contrast, both variables in CG are negatively related (Spearman's $\rho=-.450$, $p=.81$).

5 Discussion

Our study provides in-depth evidence on how a combination of gamification and financial incentives can work in an occupational context. Drawing upon the perspective of prospect theory and former research on incentive systems in OHM, this RCT applied an experimental research strategy to investigate the causal link between the design of incentive systems and framing (loss-oriented vs gain-oriented) in mHealth apps and the number of steps walked daily by predominantly sedentary employees. The aim of our study is, therefore, twofold. First, we want to determine whether and to which extent gamified apps combined with financial incentives increase employees' step intensity in contrast to a simple pedometer tracking (H1). Second, we aim to investigate whether the frame, gain-oriented vs loss-oriented, impacts the number of steps walked per day while the actual rewards remain the same (H2).

The testing of H1 reveals that gamified mHealth apps in OHM combined with financial incentives increased step-counts during interventions up to 3,645.68 steps or approximately 59% compared to the CG. We see this increase in average daily step count as a considerable increase in workers' daily PA. Since the number of steps walked each day has a major impact on employee health, gamified incentive systems in mHealth applications can improve employee health in the long run. Thus, our results are consistent with previous research.

Literature suggests that extrinsic motivators, such as gamification elements or financial rewards, are sufficient to stimulate health-conscious behaviour (Giddens et al., 2017; Zhang et al., 2021; Crawford, 2015; Ajunwa et al., 2017). Therefore, they are often used to initially extrinsically motivate people to engage in beneficial behaviour, grasp its meaning and value and finally internalize it to become intrinsic (Ryan and Deci, 2000; Goh and Razikin, 2015). Especially with PA in the workplace, awareness of the behaviour and its positive effects must first be created. Extrinsic motivators can contribute toward initiating an initially unfamiliar behaviour, such as taking a walk during lunch or standing up briefly between appointments, and eventually becoming a habit. In our study, we chose gamification in combination with financial incentives as extrinsic incentives to trigger a certain behaviour. Points as a gamification incentive can be viewed as virtual rewards delivering immediate positive reinforcement (Sailer et al., 2013). According to Cugelman (2013), however, one cannot simply rely on the motivational effects of points but must distinguish between the motivation triggered by collecting points and the value assigned to points by the context that makes them interesting to collect. We have given context to points and linked them to a specific level system, which in turn is linked to a financial incentive. Therefore, a monetary value was attributed to the collection of points in our study design. The monetary value should be small from a business perspective, but tangible to employees and frequently delivered to attribute meaning to the points and thus influence users' behaviour (Volpp et al., 2011). Although, regarding the economic value of financial incentives without gamification elements, the literature has been controversial so far. While in a non-work-related context, a study showed that small amounts of less than a dollar per week are sufficient to engage more movement (Mitchell et al., 2018), another study showed that small amounts are insufficient to change behaviour (Harinck et al., 2007). However, the results of our study suggest that at least the combination of gamification with small financial incentives per week (€2) is sufficient to achieve higher PA levels compared to a control group that does not receive any extrinsic incentives. Our findings indicate that gamification elements increase the economic value of financial incentives because gamification elements can transform obstacles to behaviour change into positive, even joyful, experiences. Activities that might otherwise be perceived as less exciting or strenuous are perceived as pleasant and enjoyable , such as PA, especially in sedentary jobs, where it is often connected to barriers (Planchard et al., 2018; Trost et al., 2002). In the context of OHM, the scalability of the incentive size makes a significant difference in the overall costs of such interventions, especially for large companies with many employees. Therefore, we align with Cugelman (2013), emphasizing that incentivised interventions require a deep understanding of the environment in which it is implemented to be successful. In summary, the results show that gamification in combination with small financial incentives increase PA at the workplace, therefore we confirm H1.

When testing H2 we find a significant difference in the daily mean step-count between the loss-framed intervention group and CG, whereas the difference between the gain-framed intervention and CG is not statistically significant. There was no statistically significant difference between the two intervention groups' daily mean step-count. However, the statistical significance of TG2 compared to the CG and the lower median of TG1 compared to TG2 indicate that a loss-frame, where rewards were allocated upfront and reduced weekly when the step-target was not met, works better in incentivizing employees than a gain-frame, where employees received a fixed amount when the weekly step-target was met. This is also supported by the number of days when the step-goal of 8,000 steps was fulfilled which were on average 24 out of 42 days in TG2 and therefore 20% higher than the average of 20 out of 42 days achieved in TG1. These findings are in line with the research of Patel et al. (2016b), finding that loss-incentives are superior to gain-incentives or lottery-incentives. Our results stand in contrast to the study of Lim and Noh (2017), who stated that gain-frame feedback works better in a health prevention context. Also, from the box plots (Figure 2), we recognize that the variance for the intervention groups is larger than in CG, concluding that incentives work but are dependent on the individual. Our results indicate that any OHM measures must be tailored to the individual to be effective (Rothman and Salovey, 1997). Considering the regulatory focus of an individual (prevention vs promotion focus), a strong match between orientation to a goal and the frame increases task engagement (Higgins, 1998). Although both forms (prevention vs promotion focus) can contribute to goal achievement, the likelihood of achievement depends on an individual's preferred frame. Thus, whether the individual perceives the frame as motivating or demotivating depends on his or her underlying construal behaviour (Rothman and Salovey, 1997). In other words, the regulatory focus of an individual might influence how strongly people respond to the framing, either loss-oriented vs gain-oriented, of a system (Kay and Grimm, 2017). This can influence the adoption of an incentive system (Nieroda et al., 2015), showing again that a deep comprehension of the context is vital when designing health interventions.

Some studies showed that the effects of interventions often start diminishing already during the intervention (Mitchell et al., 2020). One of the explanations for this decrease is the novelty effect of gamification (Herrmann et al., 2019). It simply explains that the high usage at the beginning of new technology decreases with time, due to a loss of curiosity and attractiveness. Therefore, gamification strategies should be designed to engage the user in the long run and achieve sustainable health outcomes. In our study, we could observe this decline in TG1 and the CG. In contrast, TG2 did not show noticeable differences during the intervention period. The loss-frame engaged the participants consistently throughout the whole study period. Overall, we conclude, when testing H2, that there is a superiority of a loss-frame compared to a gain-frame in mHealth apps to encourage employees toward more PA.

Further, we were interested in whether any differences between the intervention groups in the subjective self-perception of an employee towards their actual PA could be observed due to the intervention design and the exposure to performance visualized through the gamification elements. Research suggests that the physical self-concept correlates positively to one's PA level (Strong et al., 2005). After the intervention, the self-assessment of the employees PA in the intervention groups correlated positively with their actual data, while the CG had a biased perception of their physical movement. We therefore assume that the extended visualization aspect due to the implemented gamification elements, especially a greater visualization of PA performance through different graphs, points, and levels, helped participants to better estimate their current state of PA due to the more quantified reflection of their movement (Sailer et al., 2013). This awareness will improve employees' underestimation of the amount of time spent sitting during the day (Schaller et al., 2016) and overestimation the number of steps they take each day (Gaede-Illig et al., 2014).

6 Contribution

6.1 Theoretical contributions

This study makes an important theoretical contribution to the scientific literature by integrating behavioural economic approaches into IS research. First, our study is one of the first RCTs to examine the effects of gamified financial incentives based on insights from prospect theory to increase PA in the workplace context. Since gamified apps combined with financial incentives are a practical approach in increasing the PA of employees, this study highlights furthermore that the mere framing of these incentives plays a role in the effectiveness of this OHM measure. We were able to demonstrate that a moderate financial incentive of €2 per week, combined with elementary gamification elements (TG1 and TG2), lead to higher PA compared to the CG with a simple step-pedometer. In addition, we have proven that loss-framed incentive systems are more effective than gain-framed incentive systems in increasing the PA of employees, expanding current research on the effectiveness of incentive systems in digital OHM with unique insights from prospect theory.

Moreover, results show not only that the loss-framed design led to an overall increase in daily step count over the time of use, but also that the daily step counts were consistent over a period of at least six weeks. We attribute this to the fact that not only are incentive systems a motivator in mHealth apps for continued use, but that also their framing of gamification elements (e.g., levels and points) make a difference in the motivational effect and can mitigate the negative influences of the diminishing 'novelty effect,' such as declining curiosity and waning interest in gamification (Thorsteinsen et al., 2014; Katule et al., 2016).

Finally, given the high variance in the intervention groups in relation to PA, our findings imply that the regulatory focus of an employee might influence the response and thus the effectiveness to certain incentive systems. Personalized incentives are needed instead of a 'one size fits all' approach. Collected data from mHealth technologies can therefore be used by OHM to extract valuable information so that specific interventions can be offered or recommended to each individual based on their condition and behaviour (Shackleton, 2021). The individual can thus be brought closer into focus (Abolhassan, 2017).

6.2 Implications for practice

For app developers, OHM managers, employees, and various stakeholders within the healthcare system (e.g., insurance companies) the results of our study provide numerous implications. In summary, the results add to the current state of the literature showing that mHealth incorporating incentive strategies is a promising approach in digital OHM.

First, app developers and OHM managers should be aware that the choice of the appropriate setting for a challenge can have a significant impact on the success of the intervention. When implementing an OHM intervention aiming to increase employees' PA, the best possible health outcome should be targeted. This is particularly important as the global decline in PA during the social isolation introduced to mitigate coronavirus disease in 2019 (COVID-19) has increased the risk of cardiovascular disease in the population (Peçanha et al., 2020). Since many chronic diseases are related to increasingly sedentary lifestyles, PA in everyday life can promote employee health and thus increase overall productivity and economic value (Hall et al., 2022). Studies indicate that even a 1,000-step increase in daily step count reduces the risk of all-cause mortality about 6%-36% and of cardiovascular disease morbidity or mortality about 5%-21% (Hall et al., 2020). Thus, our results indicate that employees benefit greatly from the use of extrinsic incentive systems in mHealth apps within the workplace context. Our study underlines that even the motivational frame (loss-framed vs gain-framed) of such incentive systems can impact motivation for continued usage. In contrast to the gain-framed group (TG1) and CG, it is noteworthy that often effects of digital health interventions decline during time of the intervention (Mitchell et al., 2020), where else we did not detect a decline in PA among subjects in the loss-framed group (TG2). We conclude that loss-framed incentive schemes can change employees' PA even in the longer term compared with other system designs (e.g., gain-framed). Long-term engagement is both the goal and the issue for most gamified mHealth apps (Bandura, 2004; Klasnja et al., 2009; Mettler, 2015). However, to exploit the full potential of these technologies in terms of profitability, OHM measures must be targeted to the needs of the employees and must be within a cost-benefit ratio (Michie et al., 2017). In this sense, our study has shown that even minor changes in the design can influence its effect on the individual and thus the relationship between the costs of implementation and its positive effects on employee health.

Second, since the scalability of the incentive size influences the overall costs of such interventions, it is important to know that even small financial incentives (€2 per week) in combination with the right gamification approach can achieve a sufficiently high increase in PA. Participants in the loss-framed condition were able to reach the daily goal of 8,000 steps on 24 out of 42 days, e.g., twice as often as the CG, which on average only reached the daily target on 12 out of 42 days, and 20% more than in TG2 with 20 out of 42 days.

6.3 Limitations and future research

Like most studies, our research has limitations, which could be targeted in future research. First, our study was not well-populated (N=49), and therefore, the results depend partly on the representativeness of our sample. This is a limitation that many between-subjects studies have, as a group assignment requires a larger number of participants than within-subjects studies. However, due to the between-subjects design, our study is less susceptible to external bias. Nevertheless, we assume that our study results can be supported by further longitudinal studies in which PA before and after the intervention can be compared individually.

Second, our study aimed to investigate the impact of combining gamification with financial incentives. However, we cannot directly infer the extent to which gamification or financial incentives lead to increased PA. Future studies should include a 2x2 between-subjects design to test for possible interaction effects. Moreover, participants did not lose their own money but a previously promised payout. This could be a lesser incentive than the loss of one's own money.

Third, it is not directly evident from the study results to what extent specific individual mediators, such as enjoyment of PA or employees' regulatory focus, led to a difference in mean daily step count. Future studies should therefore assess subjects' regulatory focus or motivational factors to increase the power of the results. Moreover, we advocate follow-up studies that examine the long-term effects of incentive systems after they have been removed.

Fourth, it was beyond our reach to ensure that there was no exchange between study participants about the study's design, collected points, or different incentive systems that may bias the results. Moreover, the results could be skewed through moments when participants were not actively carrying their smartphone and therefore not collecting step-data; thus, the captured step-data likely is lower than the actual step count.

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