Heterogeneity in physical activity behavior change – Implications for designing and evaluating digital physical activity interventions targeted at older adults

by

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List of Abbreviations

ACSM	American College of Sports Medicine
AIC	Akaike’s information criterion
aRR	adjusted risk ratio
BCT	Behavior Change Technique
BIC	Bayesian information criterion
BLRT	bootstrapped likelihood ratio test
CCAM	Compensatory Carry-Over Action Model
CG	control group
CI	confidence interval
COVID-19	Coronavirus disease 2019
DF	degrees of freedom
ES	effect size
FIML	full information maximum likelihood
GAPPA	Global Action Plan on Physical Activity
GLM	general linear model
GRoLTS	Guidelines for Reporting on Latent Trajectory Studies
HAPA	Health Action Process Approach
IG	intervention group
IPAQ	International Physical Activity Questionnaire
ISCED	International Standard of Education
LCGA	latent class growth analysis
LMR-LRT	Lo-Mendell-Rubin adjusted likelihood ratio test
LPA	latent profile analysis
MCAR	missing completely at random

mHealth	mobile health
MICE	multivariate imputation by chained equations
MMSE	Mini Mental State Examination
MMSE-2-BV	Mini Mental State Examination 2 - brief version
MoA	mechanism of action
MVPA	moderate-to-vigorous intensity physical activity
NOE	negative outcome expectancies
NOE-cost	negative outcome expectancy – too costly
NOE-long	negative outcome expectancy – takes too long
OE	outcome expectancies
PA	physical activity
POE	positive outcome expectations
SABIC	sample size adjusted Bayesian information criterion
SB	sedentary behavior
SD	standard deviation
SE	standard error
S-E	self-efficacy
US	United States
VIF	variance inflation factor
WHO	World Health Organization

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Abstract

Background: In physical activity interventions, the primary objective is to help individuals adopt or increase the levels of a physically active lifestyle, and to maintain the physical activity behavior change in the long-term. The evidence base on digital modes of delivery or digital tools in physical activity interventions is continuously growing. How their components influence complex health behavior change processes, however, has rarely been investigated in the most inactive age group: older adults. Physical activity intervention effectiveness is rarely maintained after interventions are completed and intervention benefits do not occur identically for every participating individual. Rather, acceptance, adherence, and effectiveness depend on demographic, psychological, and behavioral factors as sources of heterogeneity in health behavior change. This thesis strives to provide answers on how to identify psychological and latent behavioral factors determining the success and failure of digital physical activity interventions, and how to take these factors into account when designing digital physical activity interventions targeted at older adults. **Objective**: This thesis explores three forms of heterogeneity along the behavior change process to advance implications for future physical activity intervention development and evaluation, with a special focus on theory-based digital interventions in older adults. Applying principles proposed by social cognitive theory as well as epidemiologic considerations on missing value treatment and person-centered analyses, this thesis aims to tackle three research gaps in the form of barriers to physical activity behavior change: 1) the complexity of the behavior change process, 2) low intervention adherence and high study dropout, and 3) limited understanding of distinct unobserved subgroups within study populations. **Methods**: Study 1 covers social-cognitive mechanisms in the effect of tailored, theory-based digital interventions on movement in the physical activity stage of change in older adults. Using a chain mediation model, the intervention effectiveness via changes in social-cognitive predictors was investigated in participants of the PROMOTE I study (*n* = 351 analyzed, 59.6%). Study 2 is based on the PROMOTE I study as well (*n* = 571 analyzed, 96.9%) and focuses on the relationship between latent lifestyle profile and the risk of intervention study dropout. Lifestyle profiles consisting of six self-reported, health-related behaviors were researched using latent profile analysis. Adjusted risk ratios were calculated using Poisson regression to identify dropout-vulnerable risk profiles. In Study 3, data from the PROMOTE II study were analyzed (*n* = 215 analyzed, 88.8%). Using latent class growth analysis, latent trajectory subgroups regarding physical activity and sedentary behavior among older adults were determined and characterized by their social-cognitive predictor profile at baseline.

Results: In study 1 it could be shown that the theory-based interventions yielded the hypothesized positive effects on physical activity stage of change, partly mediated by positive social-cognitive predictor changes. Furthermore, the results indicated that there were heterogenous intervention mechanisms: While the combination of subjective and objective self-monitoring seemed to address older adults in the non-intender stage via increases in intention, subjective self-monitoring alone seemed to address individuals in the intender-stage via increases in self-efficacy. Four latent health-related lifestyle profiles were identified in study 2. Membership of the “socially inactive lifestyle” profile was associated with an elevated risk of dropping out of the study while individuals in the “slightly unhealthy lifestyle” profile had a decreased risk of study dropout. Belonging to the “highly physically active lifestyle”, and the “health-promoting lifestyle” was not associated with study dropout. Study 3 explored whether social-cognitive predictors at baseline could be used to characterize older adults who are likely to belong to distinct physical activity or sedentary behavior change trajectories over the course of a nine-month intervention. Indeed, belonging to the “stable high physical activity” trajectory was associated with higher action planning levels compared to the “stable insufficient physical activity” trajectory. Belonging to the "decreasing high sedentary behavior" trajectory was associated with higher action self-efficacy levels compared to the "increasing moderate sedentary behavior" trajectory.

Discussion and Conclusion: The studies included in this thesis show that the existence of underlying distinct subgroups can mask significant and clinically relevant changes and change mechanisms in whole sample analyses. A deeper understanding of what characterizes certain subgroups of older adults could unveil distinct needs. This thesis lays out a theoretical and methodological basis of how areas of heterogeneity in the physical activity behavior change process of older adults participating in digital interventions can be analyzed. Yet, it encountered the limitation that social-cognitive factors cannot predict latent constructs exceeding the social cognitive framework as well. Additionally, it faced the methodological issue of potentially insufficient power that accompanies exploratory subgroup analyses. Nevertheless, practical implications for designing and evaluating digital physical activity interventions targeted at older adults can be derived. Older adults' lifestyle (including but not limited to social and physical activity level), their self-rated health status, and older adults' social-cognitive mindsets are determinants of intervention success and failure. Being able to characterize distinct subgroups and their needs can advance tailoring of intervention components and behavior change strategies, and ultimately improve acceptance, retention, and long-term intervention effectiveness. This thesis provides a starting point for how future research on physical activity promotion in older adults can integrate psychological and epidemiologic principles on heterogeneity into the design and evaluation of theory-based, sufficiently powered, longitudinal, implementation-oriented, state of the art digital interventions.

Chapter 1. Introduction

1.1. Thesis Outline

This thesis pursues to generate implications for designing and evaluating digital physical activity interventions targeted at older adults by means of investigating heterogeneity in physical activity behavior change. To approach this research topic, the thesis begins with summarizing the state of the art regarding behavioral interventions for the promotion of physical activity and healthy ageing (chapter 1.2). This includes current evidence on physical (in)activity behavior in older adults as well as theory-based interventions aiming to change and promote physical activity behavior in older adults. Current research gaps are then identified by outlining barriers encountered in digital physical activity interventions targeting older adults (chapter 1.3). Afterwards, the theoretical and methodological foundations, the research in this thesis is based on, are described (chapter 1.4), leading to the research questions and objectives this thesis aims to address (chapter 1.5). Along the following three chapters, the three studies building this thesis are presented. Each study covers a different area of heterogeneity accompanying digital physical activity interventions targeted at older adults. The first study's focus lies on psychological mechanisms in physical activity behavior change and addresses heterogeneity in intervention mechanisms (chapter 2). The second study broadens its focus towards latent clusters of multiple lifestyle-related health behaviors and addresses heterogeneity in the risk of intervention study dropout (chapter 3). The third study builds on the previous studies regarding differing intervention mechanisms and latent subgroups and addresses heterogeneity in physical activity behavior change trajectories (chapter 4). Chapter 5 concludes with summarizing the results (chapter 5.1) and discussing them in the context of prior research (chapter 5.2). Limitations and strengths are addressed (chapter 5.3), followed by the implications this thesis poses for future research and practice (chapter 5.4) and concluding remarks (chapter 5.5).

1.2. Background

1.2.1. Physical Activity Behavior in Older Adults

Countless scientific publications addressing the research topic of physical activity begin with reciting the recommended physical activity levels – and so does this thesis. In an ideal world, everyone would be as physically active as recommended, or as active as their health allows. Even though this thesis emphasizes the statement that any physical activity is better than none (World Health Organization, 2020), beginning with the physical activity recommendations and their rationale shall paint a picture of the ultimate objective this thesis strives to contribute to. Building on this foundation, this section additionally summarizes the benefits of being physically active, addresses the need for increasing the prevalence of sufficient physical activity, and discusses factors that determine a physically active lifestyle – especially in the population of older adults.

Physical Activity Recommendations

The number “150” appears throughout numerous papers on physical activity, as the World Health Organization (WHO) recommends that from the age of 18 years on, and throughout adulthood and old adulthood, individuals should engage in at least 150 minutes of physical activity per week at moderate-to-vigorous intensity (World Health Organization, 2020). These international recommendations are in line with German guidelines addressing the general population (Arbeitsgruppe „Bewegungsförderung im Alltag“, 2019) as well as adults with non-communicable diseases (Geidl et al., 2020). The WHO recommendations for older adults aged 65 years or older introduced in 2020 include four physical activity components: 1) aerobic physical activity, 2) muscle-strengthening activities, 3) functional balance and strength training, and 4) sedentary behavior. The studies building this thesis mainly focus on aerobic physical activity, that is, activities like swimming, walking, dancing, or cycling. However, they consider muscle-strengthening activities (study 1, chapter 2) and sedentary behavior (study 3, chapter 4) as well.

In particular, the WHO recommendations state that for substantial health benefits, older adults should engage in at least 150 to 300 minutes of moderate intensity, or in at least 75 to 150 minutes of vigorous intensity aerobic physical activity per week, including the option to combine the two intensities equivalently. For additional health benefits, individuals are advised to perform muscle-strengthening activities targeting the major muscle groups at least twice per week. While these first two recommendations apply to adults younger than 65 years as well, the recommendation to also include functional balance and strength training on at least three days per week is unique to the age group of older adults as it is deemed to enhance functional capacity (Bueno de Souza et al., 2018) and prevent falls (Sherrington et al., 2020). Finally, older adults are recommended to reduce their sedentary time and ideally replace it by physical activity of any intensity to gain additional health benefits (World Health Organization, 2020).

Scientific Evidence for the Benefits of Regular Physical Activity

There are numerous reasons for why people should be physically active. In the editorial accompanying a series of papers published on the new WHO 2020 recommendations for physical activity and sedentary behavior, the authors refer to the effects of physical activity as an “ever-growing list of health benefits” (van der Ploeg & Bull, 2020, p. 2). These health benefits are not only relevant on an individual level, but also affect the healthcare system. This especially applies to this thesis’ target group: older adults. According to the German recommendations for physical activity promotion, physical activity counselling and exercise programs are particularly cost-effective in older adults because physical activity promotion yields health benefits faster compared to other target groups (Abu-Omar et al., 2019). In European older adults, physical activity and muscle strength are significantly associated with lower hospitalization risk and associated healthcare costs (Pardo-Garcia et al., 2021). The fact that Germany belongs to the countries with the highest hospitalization risk shows the need for physical activity promotion.

Generally, the decreased mortality risk stands right at the top on the list of health benefits due to physical activity. A recent meta-review reports that objectively assessed total physical activity (i.e., all levels of physical activity included) is a protective factor for all-cause mortality with a pooled hazard ratio of 0.33. This means that individuals in the highest category of total physical activity have a 67% lower risk to die of any cause compared to individuals in the lowest category of total physical activity (Ramakrishnan et al., 2021). A further lifestyle factor that should be considered separately from physical activity in terms of its detrimental health impact, is sedentary behavior. A comprehensive literature review concluded that there is moderate certainty evidence for a dose-response relationship between sedentary behavior and an increased mortality risk, as well as the risk to develop cardiovascular diseases, cancer or diabetes type 2 (Dempsey et al., 2020). Physical activity promotion can decrease the mortality risk associated with sedentary behavior. Firstly, substituting sedentary behavior with moderate-to-vigorous intensity physical activity is significantly associated with a lower mortality risk (Clarke & Janssen, 2021; Galvão et al., 2021). Secondly, the mortality risk due a highly sedentary lifestyle, for example because of a sedentary job, can even be eliminated if these individuals additionally engage in high moderate-to-vigorous intensity physical activity levels (Ekelund et al., 2016).

Next to the reduced mortality risk, physical activity or exercise are also associated with improved quality of life, according to a synthesis of Cochrane systematic reviews (Posadzki et al., 2020). In addition, physical activity has a positive impact on morbidity risk, including various clinical conditions such as cardiovascular and cerebrovascular diseases, type 2 diabetes, or cancer (Warburton & Bredin, 2017). Warburton and Bredin (2017) further summarize that most studies find a curvilinear dose-response relationship between physical activity and health outcomes; meaning that the highest relative benefit can be seen in inactive individuals starting to be more physically active. This has been reported by a meta-analysis on mortality risk reduction in older adults as well: They found that older adults who engaged in some moderate-to-vigorous intensity physical activity, but did not meet the recommended level, still had a by 22% reduced mortality risk compared to those individuals engaging in zero minutes of moderate-to-vigorous intensity physical activity (Hupin et al., 2015). Findings like these are particularly relevant for health education and intervention research, as they suggest that small successes in physical activity promotion can lead to clinically relevant health benefits.

Many of the described health benefits apply to the general population but there is a multitude of studies examining why specifically older adults should engage in regular physical activity. A systematic review, for example, found that exercise-related interventions can lead to immune changes that are relevant in the ageing process, possibly contributing to the prevention of disease and prolonging the health span in older adults (Sellami et al., 2018). An analysis of cohort effects in five generations of German older adults has recently shown that even if there is an association between historical context and health deficits in old age, the life choices we make along the way towards old age are the more important predictors (Stephan et al., 2020). This does not necessarily imply that these life choices need to be made early on. Rather, there is accumulating evidence suggesting that there are substantial health benefits of becoming physically active even in old age. For example, a prospective cohort study of men aged 65+ years from the United States (US) found that recent physical activity levels are better predictors of mortality risk than past engagement in physical activity (Laddu et al., 2018). These results were corroborated by a Norwegian 22-year prospective study on adults, reporting that becoming physically active can eliminate the increased mortality risk posed by previous years of not meeting recommended physical activity levels (Moholdt et al., 2021).

Prevalence of Physical (In)Activity

After having praised all the benefits of physical activity, here comes the bitter truth: Many German older adults are not sufficiently physically active on the recommended level. In fact, epidemiologic data reveal that only 36.5% / 26.4% of female and 48.3% / 32.2% of male older adults aged 65+ years perform enough aerobic physical activity / muscle-strengthening activities, respectively (Finger et al., 2017). These numbers stem from the representative survey GEDA (Gesundheit in Deutschland aktuell) 2014 / EHIS (European Health Interview Survey) 2015. Epidemiologic studies on the prevalence of physical inactivity in German older adults confirm the need for innovative and effective interventions: According to an analysis of pooled survey data on sport and physical activity participation in Germany assessed between 1998 and 2018, the prevalence of older adults (almost) never engaging in sport ranged between 60% and 85%. Not engaging in vigorous intensity physical activity was prevalent in 55% to 70% of older adults (Abu-Omar et al., 2021). Across time and datasets, the risk of not engaging in sport and vigorous intensity physical activity (Abu-Omar et al., 2021) as well as leisure-time physical activity (Linder et al., 2021) was nearly consistently associated with advanced age. With regard to sedentary behavior, data obtained by the European Commission in 2017 suggest a prevalence of 53.7% for sitting more than 4.5 hours per day in German adults (López-Valenciano et al., 2020). The authors further noted that across the European countries, the prevalence was significantly elevated in older adults aged 65 years and above. These epidemiologic studies clearly demonstrate the need for effective physical activity interventions targeted at older adults. These interventions need to be designed in a way that they attract their target group, that is insufficiently active older adults. This is a tough challenge to tackle, as generally, individuals with an already healthy lifestyle and high health literacy tend to participate in health promotion programs. This has also been observed in German older adults aged at least 65 years, with a recent study reporting that over 70% of their study participants met the WHO recommendations (Kleinke et al., 2020), clearly showing that this sample was not representative of the German older adult population.

Determinants of a Physically Active Lifestyle in Old Age

Naturally, age and accompanying ageing-related barriers are not the single determinants of heterogeneity in physical activity participation. In the contrary, numerous predictors or preventing factors of a physically active lifestyle – also within the age group of older adults – have been proposed and researched, starting with other demographic factors such as income, education, and migration background (Abu-Omar et al., 2021; Finger et al., 2017). This section focusses on two areas of determinants or contexts of physical activity participation which are relevant to this thesis: 1) the clustering phenomenon of multiple health behaviors, and 2) health-related reasons for physical activity participation. At this point it should also be noted that there are also several psychological theories which aim to explain the health behavior change process. These will be introduced in the section following this one.

Multiple Health Behaviors

A healthy lifestyle is the combination of several single health behaviors. The "big four" behaviors determining health-related lifestyle can be summarized with the acronym SNAP, which stands for smoking, nutrition, alcohol drinking, and physical activity (e.g., see Noble et al., 2015; Ratz & Lippke, 2021). A growing body of research is performed on the associations between single health behaviors. These analyses include the exploration of lifestyle clusters, that is, co-occurring health behaviors. For example, the two health-promoting behaviors physical activity and the consumption of fruits and vegetables have been consistently found to be interrelated (e.g., Tan et al., 2018). This means that individuals who are regularly physically active are generally more likely to also adhere to a healthy diet. The same co-occurrence applies to health-risk behaviors. For example, smoking is related to heavy alcohol consumption (Mudryj et al., 2019). Considering other health behaviors or combinations, the cross-behavior link is not reported as consistently, with excessive alcohol consumption and physical inactivity being an example for a lacking association (Noble et al., 2015). The complexity of health-related lifestyle poses a challenge towards its definition and exploration – and requires what Park and Park (2020) refer to as multifaceted lifestyle profiling. They utilized the Delphi survey method to develop an assessment tool for the lifestyle profile of older adults. Its reliability and validity have not been verified yet, but the initial tool contains 62 items spanning over the three categories "physical activity", "activity participation", and "nutrition". The authors argue that the lifestyle profile is highly nuanced, and that multiple health behavior research needs to go beyond SNAP in order to find more effective ways of preventing disease, prolonging healthy ageing, and improving health-related quality of life.

Back in the year 2008, multiple health behavior research has been designated as "the future of preventive medicine" (Prochaska, 2008, p. 281). In the distinct population of older adults, lifestyle is highly relevant as multiple health behaviors can be regarded powerful facilitators of healthy ageing (Franklin & Tate, 2009). According to a European prospective multi-cohort study, participants with a combination of a body mass index below 25 and at least two other healthy behaviors (never smoking, physical activity, or moderate alcohol consumption) live until the age of about 70 years on average without major chronic diseases (Nyberg et al., 2020). The authors also report that there is a significant dose-response relationship between the healthy lifestyle score (consisting of the four mentioned health indicators) and years lived free of chronic disease: The best lifestyle score was associated with over nine disease-free years compared to the worst lifestyle score. This indicates that, even though the single health behaviors have a significant impact on health outcomes, their combination multiplies the health benefits.

Because of this assumption, multiple health behavior research goes beyond investigating the co-occurrence of single health behaviors. Researchers in this field also investigate the implications and possibilities of simultaneous or sequential multiple health behavior change (Prochaska, 2008). They also develop, test, and apply psychological theories such as the Compensatory Carry-Over Action Model (CCAM) to understand the mechanisms underlying the correlation between distinct health behaviors and their modification (e.g., see Lippke, 2014; Lippke et al., 2021; Salinas Martínez et al., 2021). Multiple health behavior change research assumes that changing or taking action towards changing one health behavior can increase the chance of changing a second health behavior. For example, intervention studies targeted at promoting physical activity in older adults then might also report an improvement in diet. This phenomenon coins multiple health behavior change and is known as co-variation (Prochaska, 2008) or coaction (Johnson et al., 2014). Whether this phenomenon occurs as a spill-over effect in an untargeted second health behavior, or whether both health behaviors need to be targeted directly for a multiple health behavior change to occur, has not been extensively researched and depends on the respective behavior combination and intervention components. However, if multiple health behavior change is the intervention objective, researchers are advised not to completely trust in spill-over effects on untargeted behaviors but to include intervention strategies considering both health behaviors (e.g., see Ratz & Lippke, 2021; Sarma et al., 2019).

Considering the role of digital health or eHealth in multiple health behavior change interventions: A recent meta-analysis found eHealth interventions targeted at multiple health behaviors to effectively promote physical activity and healthy eating, but not healthy weight status, in people with chronic diseases (Duan et al., 2021). Regarding the target population of older adults, a meta-analysis from 2012 aimed to compare the effects of single behavior and multiple behavior interventions, but failed to do so due to the lack of multiple health behavior change studies at that time (Nigg & Long, 2012).

Even though multiple health behavior change is still not researched enough to comprehensively claim the benefits, explain the mechanisms, and suggest state of the art intervention strategies, the research conducted so far is still promising. For example, the combination of poor sleep, physical inactivity and poor diet quality is associated with increased odds of reporting poor self-rated health in Australian adults (Oftedal et al., 2021). This finding suggests that self-rated health can be improved by changing one of these health behaviors, and even more so by changing multiple of these health behaviors. Concluding in short: Because of their co-occurrence and interrelatedness, other health behaviors can be regarded as determinants of physical activity in older adults.

Health-related Reasons for Physical Activity Participation

Why older adults perform – and maintain to perform – physical activity can have diverse reasons, even within their age group. Qualitative studies with older adults show that the most commonly reported reasons for being physically active (Franco et al., 2015), for participating in sports (Jenkin et al., 2017), and for maintaining the physical activity habit (Huffman & Amireault, 2021; Maula et al., 2019) are physical and emotional benefits (e.g., on physical status, self-confidence, independence, health, and wellbeing), being able to influence the ageing process, and the interaction or connection with peers. Important determinants include enjoyment, social aspects, affordability, accessibility, flexibility, and continuity (Blackburn et al., 2021; Boulton et al., 2018). It must be noted that older adults do not only perform physical activity for health reasons. Studies show that the sense of purpose is related to health behaviors such as physical activity, vegetable intake, and sleep quality in older adults (Hill et al., 2019; E. S. Kim et al., 2020). And yet, the desire to preserve health, as well as cognitive and executive functions, might be pronounced in older adults because this age group most intimately faces ageing-related changes, morbidity risk and mortality risk.

Higher levels of self-rated health (Kekäläinen et al., 2020), wellbeing (Buecker et al., 2020; de Souza et al., 2018; Kekäläinen et al., 2020), and quality of life (de Souza et al., 2018), are all related to physical activity in (older) adults. It is well known that an increase in physical activity leads to improved self-rated health (Opdal et al., 2020), psychological well-being (Bragina & Voelcker-Rehage, 2018), and quality of life (Elavsky et al., 2005) in older adults. In a European cross-sectional survey, physical activity was found to act as a buffer in the relationship between multimorbidity and self-rated health as well as life satisfaction (Marques et al., 2018). Health-related indicators can also be contributors of heterogeneity in physical activity participation, that is, acting as predictors of physical activity. For example, a Finnish study found good mental wellbeing at the age of 42 years to predict participation in leisure-time physical activity at the age of 50 years (Kekäläinen et al., 2020). In older adults, another study found psychological wellbeing to predict the adoption and maintenance of a physically active lifestyle over the course of eleven years (E. S. Kim et al., 2017).

Thus, high levels of health-related indicators can be the predictors enabling older adults to engage sufficiently in physical activity. On the other hand, the desire to either preserve health or increase low levels of health-related indicators can be among the reasons for older adults to become or stay physically active. And yet, even if such determinants of physical activity in older adults are known, there is still one major problem: Not every individual who wants to be physically active will actually put this intention into practice or turn it into a new habit. This is where the health psychology perspective comes into play.

Physical (In)Activity from a Health Psychology Perspective

Up to this point, it has already become evident that – even when narrowed down to physical activity behavior in older adults – health behavior change is complex and difficult to approach. For this reason, the discipline *health psychology* attempts to understand and describe health behavior change by means of psychological theories. While the distinct theories underlying this thesis are described in the theoretical framework (chapter 1.4), the factors commonly assumed to determine health behavior adoption, cessation, and maintenance, are summarized at this point.

Broadly, health behavior change can be separated into a motivational and a volitional stage. Motivational theories of behavior change aim to explain how the intention to engage in a behavior forms; for example, the intention to become regularly physically active (e.g., see Pfeffer & Wegner, 2020; Ratz & Lippke, 2021). The so-called social cognitive framework includes theories such as the Theory of Planned Behavior (Ajzen, 1991) and the Social Cognitive Theory (Bandura, 1986) which suggest that intention forms based on two determinants: outcome expectancies and self-efficacy (Rhodes et al., 2019). For example, the expectance that a more active lifestyle could decrease the risk of a heart attack and that this benefit outweighs the costs of spending time, energy, or money (outcome expectancies) could cause older adults to form the intention to start walking 10,000 steps per day. Furthermore, the intention is influenced by the perceived ability to regularly meet the daily step goal (self-efficacy), as individuals are more likely to attempt health behavior change if they believe that they can succeed (e.g., see Tang et al., 2019). According to the Health Belief Model (Becker, 1974), the fear of health impairment, loss of independence, or death (perceived threat) may determine the desire to engage in a physically active and healthy lifestyle. This may occur in a situation such as a doctor's appointment in which older adults realize that they are obese and hypertensive due to their sedentary lifestyle, increasing their likelihood to die from a heart attack (risk perception, perceived vulnerability, and severity). Furthermore, the Self-determination Theory (Deci & Ryan, 1985) proposes that the intention to perform a specific behavior can depend on how well the behavior fits the individual's universal needs (relatedness, autonomy and competence), if the individual enjoys engaging in physical activity (intrinsic motivation), and if the individual perceives the activity to have positive effects (extrinsic motivation).

Even though these mindsets, often called social-cognitive predictors of health behavior change, have been found to be related to behavior, with the relationship between intention and physical activity having a small effect size of $r = .27$ (Rhodes, Cox, et al., 2021), intention is not considered the optimal predictor of behavior. For example, a meta-analysis concluded that only 54% of the intenders in the included studies went on to reach their physical activity goals (Rhodes & de Bruijn, 2013). Motivational theories focus on explaining the formation of intention, but they do not consider what comes afterwards: that is, how the intention to change relates to the actual performance of the behavior. Thus, volitional theories build upon motivational theories and aim to explain how the intention to change a health behavior is turned into practice. This is known as "bridging the intention-behavior gap".

The factor that is commonly proposed to bridge the gap between intention and behavior is the ability to define in advance when, where and how to perform the intended behavior (known as action planning or implementation intentions). Setting a specific goal and defining how to reach it (Gollwitzer & Sheeran, 2006), being able to monitor and analyze one's own progress (self-monitoring, e.g., see Han & Rhee, 2021), to identify barriers and to plan how to overcome them (coping planning, e.g., see Degroote et al., 2021) have been proposed to facilitate successful health behavior change. Furthermore, the gap between physical activity intention and behavior has been shown to depend on social-cognitive factors such as self-efficacy, sociodemographic factors such as employment as well as personality-related factors such as conscientiousness, meaning that these factors act as moderators in the intention-behavior relationship (Rhodes, Cox, et al., 2021). In the initial phases of health behavior change, the process requires conscious decisions and the ability to withstand temptations or change of context and subsequently relapsing to old behaviors (self-regulation, e.g., see Kwasnicka et al., 2016; Leventhal et al., 2003), whereas processes become more unconscious and automatic as the new health behavior is maintained (habit, e.g., see Verplanken & Orbell, 2003). However, only recently researchers proposed a process framework targeting automatic processes to initiate health behavior change (Larsen & Hollands, 2021).

Next to the separation into motivation and volition, there is a second way of distinguishing health behavior change theories, that is, continuum and stage-based theories. Continuum theories assume that change occurs in a linear way, meaning that each increase in a social-cognitive predictor of physical activity will then increase the probability of engaging in physical activity. Stage-based theories, on the other hand, assume that individuals experiencing change move through a change process by switching from one stage of change to the next. The most commonly used stage-based theory is the Transtheoretical model (Prochaska et al., 1992; Prochaska & DiClemente, 1983). It proposes that acquiring behavioral strategies to change the health behavior determines certain processes of change, that is the movement between five distinct stages of behavior change: precontemplation, contemplation, preparation, action, and maintenance. The Health Action Process Approach (HAPA) (Schwarzer, 2008; Schwarzer et al., 2011) is a hybrid model which attempts to combine linear and stage-based behavior change processes in both the motivational and the volitional phase of health behavior change. This model will be introduced in more detail in chapter 1.4. of this thesis. At this point, the keyword tailoring and the role of health behavior change interventions come into play, as stage-based models propose that each stage is determined by different social-cognitive predictors which need to be specifically targeted by intervention components. For example, the MoVo process model was developed to propose specific intervention programs designed to bring about change in selected social-cognitive predictors in both motivational and volitional processes (e.g., see Fuchs et al., 2011; Pfeffer & Wegner, 2020).

The process within which physical activity interventions based on the above-mentioned theories lead to changes in physical activity behavior is commonly known as mediation. Shortly, this means that theory-based interventions do not only/always target the behavior itself but they target the social-cognitive predictor assumed to influence behavior change or the movement from one stage of change to the next (e.g., see Ratz & Lippke, 2021). A recent systematic review and meta-analysis has analyzed mediators of physical activity interventions in non-clinical adult populations. They found that, indeed, current psychological theories accurately predict significant mediations by theoretical constructs, but that the effect sizes are small (Rhodes, Boudreau, et al., 2021). This suggests that current theories do not cover all aspects that appear to be relevant in health behavior change. Nonetheless, physical activity interventions in general have been widely reported to successfully promote a physically active lifestyle in older adults (e.g., see Taylor et al., 2021), which is elaborated on in this next section.

1.2.2. State of the Art: Interventions to Promote Physical Activity Behavior Change in Older Adults

To summarize the state of the art for physical activity interventions targeted at older adults, this section firstly covers the current evidence on the significance and effectiveness of physical activity interventions and discusses current knowledge on the utility of theory-based versus non-theory-based interventions. Furthermore, this section will go into more detail with describing the complex components of physical activity interventions, presenting digital interventions as a promising mode of delivery, and addressing the issue of study participation and engagement.

The Effectiveness of (Theory-based) Physical Activity Interventions

The ultimate aim of physical activity promotion is the optimal gain in health benefits as recommended and synthesized by the WHO (2020). Yet, physical activity interventions do not necessarily aim to achieve perfect engagement in the recommended physical activity levels. Rather, good practice includes the assurance that any physical activity is better than none, that inactive individuals should increase their activity gradually and that everyone should only engage in the level of activity that is in accordance with their functional ability and physical fitness (World Health Organization, 2020).

With regard to the effectiveness of physical activity interventions, a myriad of syntheses such as systematic reviews, meta-analyses and umbrella reviews exists – and thus the evidence base is steadily growing. Giving the vast amount of research on physical activity interventions, many syntheses are now addressing specific populations (e.g., focusing on one age group, setting, or health characteristic), intervention components (e.g., focusing on mode of delivery, usage of certain strategies or theories), and behaviors (e.g., moderate-to-vigorous intensity physical activity, walking, or sedentary behavior). Physical activity promotion interventions can be generally described as effective. For example, a scoping review found physical activity interventions in general to be effective in older adults (Taylor et al., 2021). But as this was as scoping review, the authors only narratively synthesized the evidence and concluded that there was modest evidence for the positive physical activity intervention effect in older adults. A meta-analysis quantitatively assessing the effectiveness of physical activity interventions revealed a significant increase in physical activity levels between baseline and post-intervention with an effect size of $d = .46$ – yet this analysis was not focused on older adults (McEwan et al., 2020).

When it comes to identifying the most relevant intervention ingredients, intervention development needs to be tailored to the intervention objective, target population and setting. This requires detailed analyses of intervention components, target populations and target behaviors. For example, Di Lorito et al. (2021) conducted a meta-analysis in which they addressed the diversity of intervention components in physical activity interventions targeted at older adults and stressed the need for closing current research gaps such as studies on group interventions and the use of motivational strategies.

In general, whether theory-based interventions outperform non-theory-based interventions with regards to yielding successful health behavior change is still up for debate, with recent meta-analyses leaning towards equivalent effectiveness – for health behavior change in general (Dalgetty et al., 2019) and for physical activity behavior change in particular (McEwan et al., 2019, 2020). Furthermore, there is currently no evidence suggesting the superiority of one theory over others – rather, health behavior change theories seem to overlap and cover similar constructs (Gourlan et al., 2016). This leads to the conclusion that current knowledge is good enough to successfully understand and change physical activity behavior in older adults. Yet, this thesis addresses two areas in which physical activity promotion in older adults needs further research: understanding how interventions work and which components work best for whom; and evaluating how digital interventions can be utilized while overcoming the challenges posed for the older adult population.

The Complex Components of Physical Activity Interventions

Health behavior change interventions are complex and the components need to be considered carefully during the intervention development. As mentioned in the section above, one of these components to be considered is the target behavior. A meta-analysis from 2018 suggests that the biggest benefit with regard to an increase in energy expenditure is expected from replacing sitting time with short periods of moderate-to-vigorous intensity physical activity and frequent intervals of light intensity physical activity (Biswas et al., 2018). However, the authors note that interventions promoting such complex behavior changes are difficult to facilitate because external resources, such as time and built environment, and internal resources, such as motivation, intention, or self-efficacy, are required.

McEwan et al. (2019) concluded that the appropriate use of theory may be needed in order to foster health behavior change by means of selected health behavior change strategies. The so-called “science of health behavior change” is continuously growing, with its cornerstones being Behavior Change Techniques (BCT’s, e.g., see Armitage et al., 2021; Michie et al., 2013, 2018) and their Mechanisms of Action (MoA, e.g., see Carey et al., 2018; Connell et al., 2019).

A systematic review conducted more than ten years ago has already found internet-based health behavior change interventions to be more effective the more BCT’s they included (Webb et al., 2010). Specifically within the population of physically inactive older adults, the following BCT’s have been identified as successful: sufficient health education such as information about health consequences, demonstrating the target behavior and how to put it into practice, including providing concrete physical activity instructions, as well as individually administered strategies such as goal setting, action and coping plans, monitoring physical activity and seeking social support (Arnautovska et al., 2018). Especially when it comes to tailored interventions and providing specific combinations of BCT’s to only those who need them, digital health or m-health interventions show great advantages and unique potentials (Schroé et al., 2020). Complex physical activity interventions such as the digital aLiFE and eLiFE interventions as part of the PreventIT project are developed, incorporating theory-based constructs and mapping them to numerous BCT’s (Boulton et al., 2019).

Digital Interventions as a Promising Mode of Delivery

The mode of delivery of physical activity interventions, that is the channel through which intervention components are transmitted to study participants, can determine intervention success and failure. The choice of mode of delivery should on the one hand be oriented towards the needs of the target group; but on the other hand, the needed personal, financial and time resources play a role. For example, in the target group of older adults, physical activity is considered as a source that provides a sense of connectedness, which might be optimally achieved by addressing the social context of physical activity promotion. There is some research suggesting that group-based interventions are particularly useful for fostering long-term behavior change maintenance in older adults (Farrance et al., 2016). According to a randomized controlled trial from Canada, offering group-based interventions in the community can significantly increase adherence to physical activity recommendations in older adults – especially when all members of the group, including the instructor, belong to the age group of older adults (Beauchamp et al., 2018).

This raises the question of the age-appropriateness of digital interventions that do not include face-to-face components. In order to discuss digital interventions further, a definition of the term “digital health” shall be introduced, including an explanation of how the term relates to eHealth and mobile health (mHealth). As the WHO cites in their guideline *Recommendations on Digital Interventions for Health System Strengthening*, digital health can also be called “the use of digital technologies for health” (World Health Organization, 2019, p. ix). It further states that digital health is “a broad umbrella term encompassing eHealth (which includes mHealth), as well as emerging areas, such as the use of advanced computing sciences in ‘big data’, genomics and artificial intelligence”. eHealth is defined as “the use of information and communications technology in support of health and health-related fields”, whereas its subset mHealth is defined as “the use of mobile wireless technologies for health" (World Health Organization, 2019, p. ix). Furthermore, one can distinguish between various other terms, such as computer-based, internet-based, or web-based interventions. According to the journal JMIR's house style and editorial guidelines, "web-based intervention" is the preferred term to use, whereas internet-based should only be used if non-web-based components such as e-mails are included. The term computer-based, in turn, should be used when the interventions are only available offline (JMIR Publications, 2021).

It is evident that the use of internet-delivered, digital interventions seems more feasible and effective in digital natives compared to older adults who need to adapt to digitization. Internet-delivered interventions are not considered innovative anymore, as they have been shown to effectively increase physical activity already ten years ago (Davies et al., 2012). The use of technology in behavioral medicine even reaches back to the late 1940's with the first use of pedometers for obesity treatment (Arigo et al., 2019). However, as technology is still developing rapidly and innovations are happening within short time intervals, the use of eHealth and mHealth interventions is one of the hot topics in health promotion and prevention research. One of the advantages of digital interventions is that they offer an elegant way of integrating technology, such as wearable activity trackers. One solution for the implementation of digital physical activity interventions in older adults could therefore be the use of a blended intervention, including both face-to-face components such as group-based activities as well as digital components such as wearables.

Wearable activity trackers offer an objective way of self-monitoring daily physical activity behavior (such as step count and minutes spent exercising at a moderate-to-vigorous intensity). Even over just the last two to three years, a number of systematic reviews and meta-analyses have reported them to significantly increase physical activity participation (Brickwood et al., 2019; Chaudhry et al., 2020; Lynch et al., 2020), also in sedentary older adults (Liu et al., 2020). However, these studies generally describe findings as inconclusive when it comes to long-term behavior change sustainability and superiority over alternative physical activity intervention components.

Next to offering automated ways of self-monitoring, digital interventions have the potential to facilitate other BCT's as well, such as planning and monitoring using physical activity diaries and plans. Studies have shown that daily diaries can facilitate implementation intentions for lifestyle behaviors (Anderson, 2021). Digital interventions, moreover, have the promising potential of facilitating and enhancing BCT's and features of persuasive system design, and their effectiveness has been shown for physical activity and sedentary behavior (Direito et al., 2017), but also weight loss maintenance (Asbjørnsen et al., 2019). A newer BCT regularly found to be incorporated in smartphone mobile applications is gamification, but its effect on successful health behavior change has yet to be researched systematically (Edwards et al., 2016).

Technology acceptance and age-related needs should be taken into account when developing digital health interventions that are targeted towards older adults (Nebeker & Zlatar, 2021) – for example, by adopting user-centered development methods (Langener et al., 2018). Technology acceptance and behavioral intention have been reported to predict technology adoption, but researchers also report that the self-efficacy to independently use the technology and early experience with technology predict its long-term usage (Mitzner et al., 2019). Lack of self-efficacy, knowledge or support have been reported as barriers to the use of eHealth in older adults (Wilson et al., 2021). These findings show that providing a feeling of competence at an early stage is essential. This can be a challenge when the target group is characterized by age-related physical, motor, and cognitive decline and confronted with having to get accustomed to digitization in advanced age. Lee and Maher (2021) argue that initial engagement can be more relevant than usability, as technology acceptance may depend more on the intervention being what older adults want rather than what older adults need. However, not only the attitude towards digital health can be of importance. For example, a longitudinal cohort study from the US found declining health to be accompanied by declining use of digital health technologies (Levine et al., 2018).

Summarizing, the technological realization of BCT's has been shown to be effective for several health behaviors and age groups, including physical activity promotion in older adults, but researchers need to keep in mind that participants need to receive proper training, support and tailoring to diverse wants and needs in order to ensure adherence and maintenance (Hsu et al., 2018; Kampmeijer et al., 2016).

Physical Activity Intervention Participation and Engagement

Adherence can be one of the major challenges in health behavior change interventions as it is the indicator of whether an intervention is not only effective in theory but also in practice. This does not only include the uptake of a new lifestyle or a lifestyle change, but adherence to interventions also includes sustained health behavior change and the formation of new and lasting habits. The continuous participation in physical activity interventions is of utmost importance for intervention effectiveness. For example, a Japanese study shows that only long-term but not short-term participation in a group-based exercise program could delay the deterioration in lower extremity muscle strength in community-dwelling older adults (Hayashi et al., 2021). Ensuring high and sustained study and physical activity participation starts with addressing the group-specific motives for engaging in physical activity (see also chapter 1.2.1.). Beck et al. (2016) summarized that understanding participation in older adults requires the consideration of various factors such as demographics, social context, environment, health constraints, prior knowledge and behavioral predictors such as self-efficacy. They also reported that in their study there was agreement among older adults that enjoyment was the top-ranked motive for physical activity participation, followed by satisfaction. This multitude of determining factors is corroborated by further research (e.g., see Boulton et al., 2018). With regard to maintenance motives in older adults, a meta-analysis from 2020 found that self-determination and intrinsic motivation were correlated with physical activity maintenance, whereas the evidence for an association with enjoyment and satisfaction seemed too scarce (Huffman et al., 2020).

At this point, the question is not only what determines physical activity and thus study participation in older adults, but how to incorporate existing knowledge into intervention development and evaluation. The previously mentioned PreventIT project aims to train intervention participants in specific skills such as planning and self-regulation. The theoretical model is based on the HAPA and includes an independent phase, being aware that participants will be required to maintain the physical activity on their own at one point. Furthermore, it uses digital technologies and mHealth components to tailor motivational messages to individual responses (Boulton et al., 2019). In digital health behavior change interventions, the engagement with the intervention material plays an important role and features need to be targeted towards the needs and impairments accompanying the ageing process. This can be achieved by specific design processes such as user-centered design (e.g., see Yardley et al., 2016)

The recent year, which was marked by the Coronavirus disease 2019 (COVID-19) pandemic, demonstrated the importance of effective and accepted digital lifestyle or health behavior change programs for all population groups. A recent study found that older adults were less likely than younger age groups to accept a virtual group-based weight management program during the pandemic. This highlights the need for well-designed interventions aimed at hard to reach groups such as older adults (Abbott et al., 2021). The fact that older adult engagement could not be achieved when it was really needed further marks the current research gap and leads to the barriers to physical activity behavior change that are yet to be overcome.

1.3. Research Gaps: Barriers to Physical Activity Behavior Change

The previous section served to lay out the background of this PhD thesis, summarizing the relevant concepts, assumptions, and evidence that this thesis is now expanding on. Moving along towards the research objectives and studies building this thesis, the current section aims to lay out the three research gaps which this thesis pursues to contribute to closing. In the following, these three research gaps will be introduced as barriers to successful physical activity behavior change. This thesis proposes that, on the one hand, a barrier to physical activity behavior change exists due to the lack of sufficient and extensive research of the complex underlying mechanisms of the behavior change process (research gap/barrier 1). On the other hand, it suggests that current digital physical activity intervention research suffers from a lack of knowledge on how to facilitate adherence and prevent study dropout (research gap/barrier 2), as well as on how to identify distinct subgroups and their needs (research gap/barrier 3).

Barrier 1. Complexity of the Behavior Change Process

Changing health behavior is difficult, even if the theoretical knowledge regarding the determinants and mechanisms of health behavior change is steadily growing. The science of behavior change is continuously adding evidence linking BCT's to their MoA within the Theory & Techniques of Behavior Change Project (Carey et al., 2018; Connell et al., 2019; Johnston et al., 2021). However, social-cognitive mechanisms of physical activity behavior change are not yet fully understood (Rhodes, Boudreau, et al., 2021). One reason for still limited understanding of the behavior change process can lie in the underutilization of interdisciplinarity, calling for the linkage of health psychology theory with public health interventions (Kelly & Barker, 2016). Furthermore, models and theories specific to digital behavior change interventions are scarce and need to be further researched (Hekler et al., 2016). Given that certain digital components can act as BCT’s and, thus, target specific social-cognitive mechanisms, it is critical to understand potential heterogeneity in the way intervention strategies affect individuals. How the use of digital tools can influence physical activity behavior change, for example, by targeting social-cognitive predictors, has been done before (e.g., see Petersen et al., 2020; Schroé et al., 2020). So has the evaluation of mediation in theory-based physical activity interventions in older adults (Peels et al., 2020). To what extent digital components of theory-based physical activity interventions can contribute to facilitating forward movement in the stages of behavior change via social-cognitive mechanisms in older adults, however, is a current research gap and thus needs further research.

Barrier 2. Low Intervention Adherence and High Study Dropout

Health behavior change interventions, including digital interventions, can suffer from low adherence and high study dropout. For example, in a sample of Australian adults, researchers reported attrition of more than 30% over a 100-day period from an app-based physical activity intervention (Edney et al., 2019). They also found intervention engagement to be associated with increases in physical activity levels, highlighting the relevance of both intervention adherence and continued engagement. There is research on how to improve adherence to physical activity interventions in older adults: A meta-analysis found telecommunication and the usage of technological features such as objective monitoring and motivational feedback to be among the factors that can improve adherence to falls prevention programs in community-dwelling older adults (Hughes et al., 2019). Researchers conducting a real-world randomized trial comparing two web-based walking interventions found that intervention interactivity was associated with engagement and effectiveness but described attrition in real-world trials as problematic, with only 16.9% of participants remaining at the three-month mark (Kolt et al., 2020).

Furthermore, ensuring maintenance after physical activity interventions poses a challenge. A recent study came to the discouraging conclusion that increases in physical activity are not sustained after intervention completion (McEwan et al., 2020). The physical activity level at recruitment has been shown to be the best predictor of physical activity maintenance, demonstrating that knowing and addressing the relevant baseline characteristics could improve predicting and possibly even facilitating maintenance (Kendrick et al., 2018). However, a qualitative analysis of wearable activity tracker users showed that curiosity in technology and initial positive response did not optimally predict long-term usage. Rather, digital interventions need to convince older adults of the long-term benefits (Kononova et al., 2019).

More research is required to gain a better understanding of what determines participation, adherence and study dropout in older adults participating in digital physical activity promotion interventions. As described in chapter 1.2.1., determinants of physical activity participation could be engagement in related health behaviors as well as the self-rated general health status. The knowledge of certain baseline characteristics that influence study participation and retention could be useful for tailoring interventions and participant support strategies in order to prevent selective study dropout out foster long-term intervention benefits. Thus, this is the second research gap this thesis addresses.

Barrier 3. Distinct Subgroups and their Needs are Widely Unknown

There are many factors that prevent or facilitate physical activity participation in older adults, but these factors vary across individuals (Bauman et al., 2002; Beck et al., 2016; Bethancourt et al., 2014). Therefore, the challenge for intervention research is finding ways of matching subgroups to their needs and respective intervention components. Additionally, knowledge on how to use individual data available at baseline for the identification of subgroups and considering the existence of heterogenous subgroups in analyses of change, is still limited. Health psychologists call for mediation analyses per subgroup to better understand behavior change processes based on changes in social-cognitive predictors of behavior change (e.g., see Peels et al., 2020), but there is more to heterogeneous behavior change than the psychological indicators. For example, certain accompanying lifestyle behaviors, the health status or affinity to technology could determine intervention effectiveness or the way individuals experience change.

Considering the previously mentioned factors that might influence physical activity participation and intervention engagement in older adults, it is conceivable that change in physical activity interventions occurs heterogeneously. Intervention effectiveness might me masked in the whole study population if differences within subgroups are not being accounted for. The ability to identify distinct groups of individuals can not only help to predict who is likely to benefit from interventions, but it can also contribute to predicting heterogeneous change trajectories over the course of lifestyle interventions. Both could potentially be utilized to design tailored interventions – considering and addressing the needs of certain subgroups. However, research on heterogeneous change within study populations is still scarce, making it the third research gap this thesis is targeting.

1.4. Theoretical and Methodological Framework

1.4.1. Social Cognitive Models of Health Behavior Change

The interventions that were analyzed within the three studies building this thesis were designed to promote physical activity via self-monitoring to foster self-regulation (Bandura, 1991), assuming the principles of health behavior change proposed in the HAPA (Schwarzer, 2008; Schwarzer et al., 2011). The HAPA belongs to the social cognitive framework described shortly in chapter 1.2.1. on engagement in physical activity from a health psychology perspective. Even though only one health behavior domain was targeted within the two analyzed intervention studies (i.e., physical activity in terms of aerobic activities as well as strength, balance, and flexibility training activities), several other health behaviors were assessed during the studies as well, making theories on multiple health behavior change applicable. The CCAM is also attributed to the social cognitive framework and is one of the few psychological theories on multiple health behavior change (Lippke, 2014; Lippke et al., 2021). Thus, in the following section, the two main behavior change theories building the theoretical framework of this thesis will be presented: the HAPA and the CCAM.

The Health Action Process Approach

The HAPA is a relatively young social cognitive model that has been proposed in the late 2000's (Schwarzer, 2008). It is described as a hybrid model which combines both motivational and volitional processes, thereby including determinants of behavior initiation (such as risk perceptions, outcome expectations, action/task self-efficacy, and intention) as well as maintenance (such as action and coping planning, maintenance and recovery self-efficacy, and action control). The model includes continuum mechanisms in terms of relationships between these social-cognitive predictors of health behavior change. For example, it assumes that risk perception, outcome expectancies and action self-efficacy are determinants of the intention to change the health behavior. Further, planning is proposed to bridge the intention-behavior gap. In parallel, the HAPA assumes that individuals can be attributed to three distinct stages of change which they move through one at a time during the behavior change process. For example, older adults who do not intend to engage in the recommended levels of moderate-to-vigorous intensity physical activity are categorized as being in the pre-intention stage of change. They can move to the intention stage once their risk perception, outcome expectations and self-efficacy regarding the target behavior are high enough to spark the intention to be sufficiently physically active. Moving to the action stage of change, thereby leaving the motivational and entering the volitional phase, depends on the ability to connect intentions with behavior via planning as well as the perceived capability of maintaining the behavior without relapsing to old habits (Schwarzer, 2008; Schwarzer et al., 2011).

Studies have been conducted which proposed and tested stage algorithms for correctly identifying the respective stages (Lippke et al., 2010; Schwarzer et al., 2011) as well as for verifying the proposed social-cognitive patterns within the stages of change (Wienert et al., 2019). As there are several interdependencies between the social-cognitive predictors in the proposed HAPA model, a recent meta-analysis of the HAPA accordingly reports multiple mediating and moderating mechanisms (Zhang et al., 2019). The largest effect on behavior was attributed to action self-efficacy via intentions and maintenance self-efficacy. The mediating effect of planning between intention and behavior was described as modest. The authors highlighted the importance of stage-specific self-efficacy in both motivational and volitional phases of health behavior change. This statement matches the assumption that planning mediates the intention-behavior relationship as a function of self-efficacy, meaning that self-efficacy acts as a moderator for intention and planning (Di Maio et al., 2021), or that the mediation is moderated by self-efficacy (Yeager et al., 2018). The stage-specific relevance of predictors and determinants of successful health behavior change further means, that individuals in specific stages of change will benefit the most from interventions that target the respectively relevant social-cognitive predictors. Interventions based on the HAPA, therefore, are often stage-tailored, meaning that intervention components specifically address pre-intenders, intenders, or actors, respectively.

The Compensatory Carry-Over Action Model

The CCAM is even younger than the HAPA, as it has been proposed in the year 2014 (Lippke, 2014). This model aims to address multiple health behavior change by describing the processes and mechanisms connecting one health behavior and its determinants to a second health behavior with its determinants in return. While the CCAM's origin lies in obesity and diabetes research, connecting the two energy intake and expenditure related health behaviors physical activity and diet (Lippke, 2014), its application has been extended to, for example, sleeping behavior (Tan et al., 2018) and internet use (Gao et al., 2020; Lippke et al., 2021). The model draws from existing social cognitive theories on single health behaviors such as the HAPA and rearranges them under the framework of multiple behavior change to address the carry-over mechanisms from one behavior to a second behavior. The CCAM proposes that social-cognitive predictors of one behavior, such as the intention to be physically active, can be related to the social-cognitive predictors of a second behavior, such as the intention to follow a healthy diet. This link is related to compensatory cognitions, which have been proposed in the Compensatory Health Beliefs Model and depict situations in which there is a discrepancy between intentions and the actual behavior. Furthermore, the CCAM integrates wellbeing as a higher-level goal in its model structure, proposing that health- and wellbeing-related indicators play a significant role in the psychological mechanisms underlying multiple health behavior change (Lippke et al., 2021; Tan et al., 2018). This phenomenon can be translated to the earlier mentioned assumption that striving for regaining or conserving health and wellbeing can act as a predictor of physical activity participation in older adults.

In summary, the CCAM proposes the following five axioms (e.g., see Lippke et al., 2021, p. 215): 1) different health behaviors interrelate, 2) striving for a higher level goal, such as wellbeing, influences the building and increasing of intentions to engage in health behaviors, 3) self-efficacy predicts behavior and moderates planning, and planning mediates the relationship between intention and behavior, 4) carry-over mechanisms and compensatory cognitions are pathways through which behavior-specific processes of two health behaviors interrelate, and 5) stress management and wellbeing are related to multiple health behaviors which jointly amount to a healthy lifestyle.

Social cognitive models, in conclusion, provide the theoretical framework needed in order propose and explain relationships, mechanisms and changes within older adults participating in the two physical activity intervention trials that are central to this thesis. However, this thesis does not only aim to advance the understanding of the health behavior change process (research gap/barrier 1 in chapter 1.3.). This thesis also addresses and aims to explore and provide implications on heterogeneity in digital intervention study participation, dropout, and behavior-related as well as health-related changes (research gaps/barriers 2 and 3 in chapter 1.3.). Thus, the following two sections move away from the theoretical framework and towards the methodological framework. As this thesis includes three studies on behavioral intervention trials, chapter 1.4.2. provides an overview of one important challenge to such studies: missing value treatment. Afterwards, person-centered methods for the identification of latent subgroups will be elaborated on in chapter 1.4.3. in order to conclude the methodological framework this thesis is building upon.

1.4.2. Missing Value Treatment in Intervention Studies

One of the major challenges frequently arising in clinical intervention trials is the treatment of missing information that results from loss to follow-up. The early study dropout in digital physical activity interventions targeted at older adults has therefore been defined as one of the main barriers this thesis aims to address. How to handle missing data, how to investigate selective dropout and how to utilize this knowledge to prevent loss to follow-up in future studies are questions that come up in the three main chapters of this thesis. Therefore, missing value treatment in intervention studies is a central component of its methodological framework.

Generally, there are three principles under which information can be missing according to Rubin (1976): not at random, completely at random, and at random. If data are missing not at random, this means that there is a systematic reason for the data being missing, but that researchers do not know this reason because the data predicting missingness are unobserved. In contrast, data are considered missing completely at random if the fact that they are missing is independent from both observed and unobserved data. The third mechanism, missing at random, is present when the data are missing systematically, but the missingness can be explained by observed information. In this case, existing information can be used to produce an estimate of the missing information (Rubin, 1976).

A common but bias-prone approach to handling missing values is the complete case analysis, in which individuals with missing information are excluded from analyses (also known as list-wise deletion). This approach is best to be used when data are missing completely at random, and according to a systematic review of extended follow-up studies of randomized controlled trials, complete case analysis is be the most popular approach (Sullivan et al., 2017). They further report that 60% of studies assumed that their data were missing completely at random, but only 10% of studies explicitly stated the missing data mechanism. An earlier review of randomized controlled trials reported similar findings, with complete case analysis being the most commonly used method (Bell et al., 2014). However, if there is selective dropout and/or data are missing systematically, the results of complete case analyses can be biased and lose their representativeness. Thus, the best-practice method is to align analyses with the intention to treat principle (White et al., 2011), meaning that all study participants are analyzed according to their originally planned allocation, regardless of whether they adhered to the intervention, crossed over to another intervention arm or discontinued the study.

There are several methods to include all study participants according to the intention to treat principle, such as data imputation and model-based estimation (Bell et al., 2014). Using the sample mean or the last observation carried forward are common approaches for simple imputation, which however often lead to biased results, reduced sample variance and increased alpha error rates (Bell & Fairclough, 2014). Thus, multiple imputation is commonly regarded as the gold standard of missing value treatment, even though its versatility and complexity can also increase the risk of its false use (Jakobsen et al., 2017; Sullivan et al., 2018).

Model-based approaches include maximum likelihood estimation which is used in longitudinal models such as mixed models and latent variable models. The so-called full information maximum likelihood (FIML) method is able to produce estimates as long as there is information on at least one timepoint, enabling the inclusion of participants who only completed baseline assessment and were then lost to follow-up (Bell & Fairclough, 2014). This method assumes that data are missing at random and is frequently used in person-centered methods, which are described in the next section.

1.4.3. Person-centered Methods

Person-centered analyses aim to identify associations between individuals, which separates them from the more common variable-centered analyses, which aim to identify associations between variables (Frankfurt et al., 2016; Jung & Wickrama, 2008; Lennon et al., 2018; Thompson et al., 2011). The so-called finite mixture models are utilized when researchers assume that individuals can be categorized into subgroups based on information that has not been assessed. That study populations are often heterogenous and experience intervention components as well as intervention-related change trajectories heterogeneously has been identified as one of the barriers to successful physical activity behavior change (see chapter 1.3.). In order to investigate potential underlying heterogeneity within study populations, researchers can utilize mixture modeling. Mixture modeling techniques aim to assign individuals to latent unobserved subgroups, which should be homogeneous within but heterogeneous between each other (Berlin et al., 2014). The identification of groups with shared characteristics, such as scores on risk factors, is often used to analyze change in subgroups comprising similar individuals (Thompson et al., 2011). In mixture modeling, the analyzed population may not follow a normal distribution, but is assumed to comprise a mixture of separate normal distributions.

Latent profile analysis, for example, aims to identify these distributions by categorizing individuals into latent profiles based on similar patterns in a set of observed continuous parameters (Oberski, 2016). The process of profile assignment relies on an expectation maximization algorithm, which calculates the individual probabilities of membership in each profile, the sum of which is always one. A discrete variable indicates the latent profile which an individual is assigned to according to respective posterior probabilities. The distribution of fractional memberships across the latent profiles allows for adjustment for uncertainty (Berlin et al., 2014; Oberski, 2016). In the case of latent growth trajectories, longitudinal mixture modeling techniques facilitate the identification of latent subgroups based on similar change patterns. This way, procedures such as latent class growth analysis and growth mixture modeling enable researchers to analyze distinct subgroups within a sample population with regard to heterogenous change trajectories (van der Nest et al., 2020).

The presence of undetected heterogenous change trajectories could be one of the reasons for why physical activity interventions are difficult to design, evaluate and implement on a large scale. Physical (in)activity belongs to the health-related behaviors that are in the center of attention when it comes to global prevention and health promotion programs. Physical activity participation – and thus intervention success and failure – is very complex and thus difficult to target and to maintain. Analyzing heterogeneity in digital physical activity interventions targeted at older adults will not solve this major public health issue. However, this thesis proposes that it can provide implications for future design and evaluation of physical activity interventions, moving one step closer towards healthy ageing with the help of a physically active lifestyle.

1.5. Objectives, Research Questions and Hypotheses

Being aware of the global significance of physical activity promotion in older adults (chapter 1.2.1.), of the potential that digital theory-based interventions offer in terms of effective physical activity behavior change (chapter 1.2.2.), and of the current research gaps identified within the science of physical activity promotion (chapter 1.3.), the following research questions occurred:

1) To what extent is there a mediating effect of social-cognitive changes on physical activity stages of change resulting from web-based interventions in community-dwelling older adults?
2) To what extent does the initial health-related lifestyle profile predict study dropout from a web-based physical activity intervention trial targeting older adults?
3) To what extent do older adults participating in a physical activity intervention trial experience different short-term activity-related change trajectories and are these associated with baseline social-cognitive predictors of physical activity behavior change?

Using these three research questions as a roadmap, this thesis pursued the objective of investigating heterogeneity occurring along three levels of the health behavior change process. These three areas were labeled as 1) heterogeneity in study participation – assuming that baseline predictors can contribute to explaining why older adults drop out of physical activity intervention studies; 2) heterogeneity in social-cognitive mechanisms of interventions – assuming that digital physical activity interventions foster behavior-related changes via social-cognitive mechanisms and that these change processes can differ by certain digital components; and 3) heterogeneity in change trajectories – assuming that older adults follow distinct activity-related change trajectories during intervention studies, which could be predicted by baseline indicators. Figure 1-1 shows an overview of the three levels and the corresponding studies.

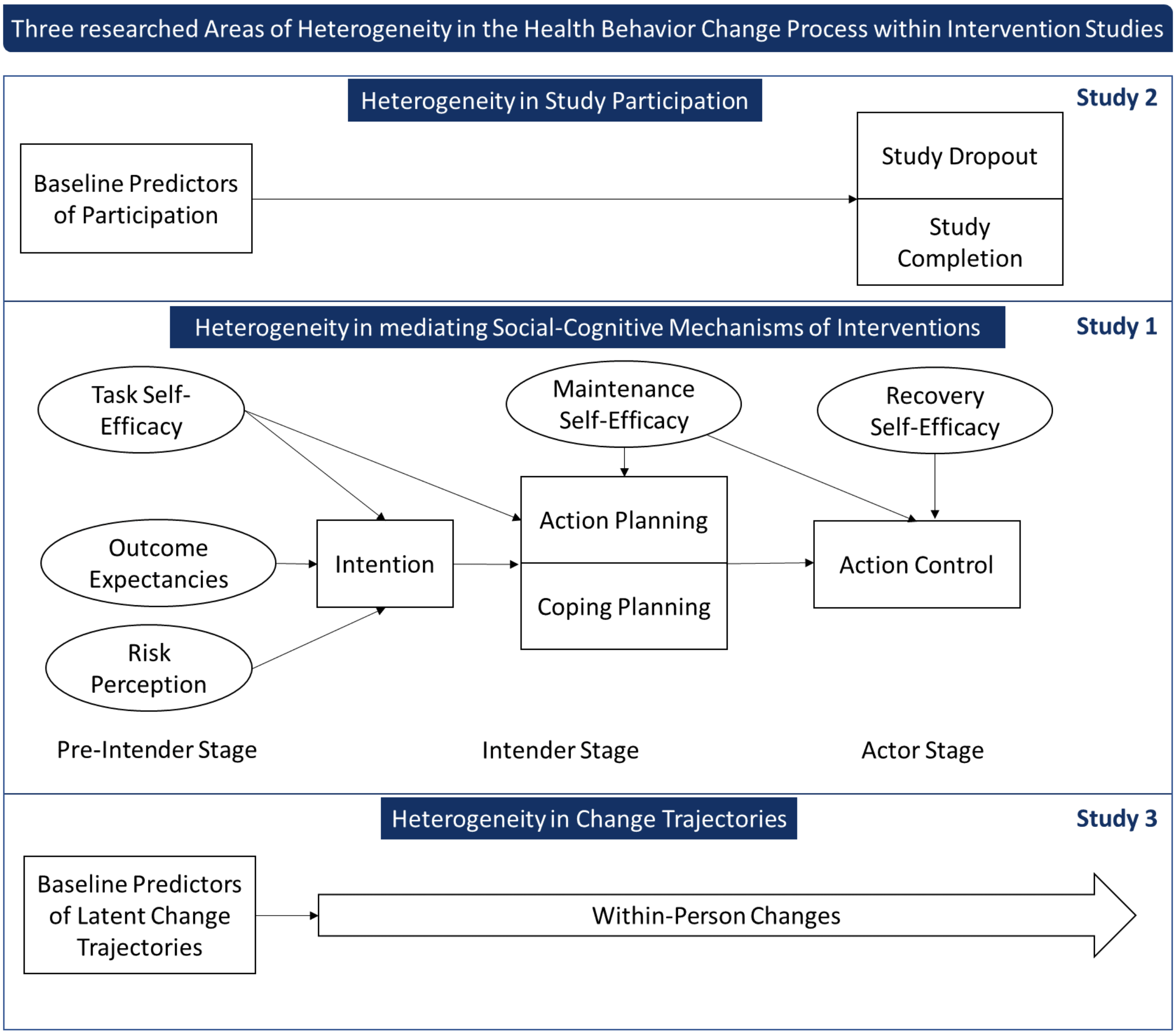

Figure 1-1. Overview of researched areas along the health behavior change process. The model for study 1 is the Health Action Process Approach, adapted from Schwarzer et al. (2011).

As depicted in Figure 1-1, this PhD thesis consists of three empirical studies aiming to address the research questions posed above. In particular, these three studies included the following objectives. Please see also Table 1-1 for an overview of research questions, objectives and hypotheses of the empirical studies within the thesis.

Study 1 aimed to investigate the effects of two ten-week web-based physical activity interventions on changes in physical activity behavior stage of change and social-cognitive predictors of physical activity in community-dwelling older adults. The second aim was to test the mediating role of the changes in social-cognitive predictors for facilitating the effect on physical activity stage of change.

Study 2 aimed to identify latent lifestyle profiles of health-related behavior and investigate the extent to which these lifestyle profiles, as well as subjective health status and satisfaction with life, predict study dropout from a web-based physical activity intervention trial targeting older adults.

Study 3 aimed to investigate latent moderate-to-vigorous intensity physical activity trajectories and associated social-cognitive factors in older adults participating in a nine-month physical activity intervention trial. The secondary objective was to identify and investigate latent change trajectories regarding sedentary behavior.

Table 1-1

Overview of empirical studies within the thesis.

Study	Research Questions	Objectives	Hypotheses
Study 1	To what extent is there a mediating effect of social-cognitive changes on physical activity stages of change resulting from web-based interventions in community-dwelling older adults?	(1) to investigate the effects of two ten-week web-based physical activity interventions on changes in physical activity behavior stage of change and social-cognitive predictors of physical activity in community-dwelling older adults (2) to test the mediating role of the changes in social-cognitive predictors for facilitating the effect on physical activity stage of change	(1) there is a significantly elevated direct effect of the two intervention groups on physical activity stage of change in comparison to the delayed intervention control group (2) this effect is more pronounced in the intervention group additionally monitoring their physical activity objectively in comparison to the intervention group only monitoring their physical activity subjectively (3) the intervention effect can be explained by a positive change in

			social-cognitive predictors for physical activity
Study 2	To what extent does the initial health-related lifestyle profile predict study dropout from a web-based physical activity intervention trial targeting older adults?	(1) to identify latent lifestyle profiles of health-related behavior (2) to investigate the extent to which these lifestyle profiles, as well as subjective health status and satisfaction with life, predict study dropout from a web-based physical activity intervention trial targeting older adults	(1) older adults can be categorized into latent subgroups based on similar patterns in lifestyle-related behaviors (2) a combination of risk behaviors is associated with an increased risk of study dropout (3) good self-rated health and satisfaction with life are associated with a decreased risk of study dropout
Study 3	To what extent do older adults participating in a physical activity intervention trial experience different short-term activity-related change trajectories and are these associated with baseline social-cognitive predictors of physical activity behavior change?	(1) to investigate latent moderate-to-vigorous intensity physical activity trajectories and associated social-cognitive factors in older adults participating in a nine-month physical activity intervention trial (2) to identify and investigate latent change trajectories regarding sedentary behavior	(1) there are latent subgroups which differ by their moderate-to-vigorous intensity physical activity and sedentary behavior change trajectory over the course of the nine-month intervention period (2) latent trajectory membership is associated with baseline social-cognitive predictors for physical activity behavior change

1.6. References

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Chapter 2. Effects of two Web-based Interventions and Mediating Mechanisms on Stage of Change regarding Physical Activity in Older Adults

Ratz, T., Lippke, S., Muellmann, S., Peters, M., Pischke, C. R., Meyer, J., Bragina, I., & Voelcker-Rehage, C. (2020). Effects of two web-based interventions and mediating mechanisms on stage of change regarding physical activity in older adults. *Applied Psychology: Health and Well-Being*, *12*(1), 77–100. https://doi.org/10.1111/aphw.12174

Abstract

Background: Web-based, theory-driven interventions effectively promote older adults' physical activity. Social-cognitive mechanisms of their effect on stage of change need to be further researched. **Methods**: Older adults were randomly allocated to intervention group 1 (ten-week online physical activity program), intervention group 2 (same program plus activity tracker) or delayed intervention control group; n = 351 were analyzed (59.6% of originally allocated individuals). Stages of change for recommended endurance- and strength training and social-cognitive predictors of physical activity were assessed using questionnaires at baseline and follow-up. Intervention effects and mediation were investigated using mixed-effects ANOVA and ordinal least squares regression. **Results**: Direct effects on stage of change were found for intervention group 1 regarding endurance training ($b_{\text{intervention group 1}}$ = 0.44, 95% confidence interval [0.15, 0.73]), and both groups regarding strength training ($b_{\text{intervention group 1}}$ = 1.02, [0.71, 1.33], $b_{\text{intervention group 2}}$ = 1.24, [0.92, 1.56]). Social-cognitive predictor changes in task self-efficacy, intention and action planning explained intervention effect on stage of change, but not to the full extent. **Conclusions**: The results indicate significant web-based intervention effects on physical activity stage, partly mediated by changes in task self-efficacy, intention and action planning.

Keywords: Healthy ageing; mediation; social-cognitive predictor; controlled intervention trial

Introduction

Physical activity (PA) can reduce all-cause mortality, prevent non-communicable diseases and improve functional status, cognition and wellbeing in older adults (Bauman, Merom, Bull, Buchner, & Fiatarone Singh, 2016; Lee et al., 2012). The good news for inactive older adults is that starting to be physically active even in late life can have significant health benefits, compared to staying inactive (Hamer, Lavoie, & Bacon, 2014). A way to address inactive older adults' PA behavior is via web-based exercise interventions, which seem to effectively increase PA levels in older adults (e.g., Alley et al., 2018; Muellmann et al., 2018) and might provide a suitable (Ammann, Vandelanotte, de Vries, & Mummery, 2013) as well as cost-effective and easily accessible alternative to traditional methods (Elbert et al., 2014; Vandelanotte et al., 2016).

According to social cognitive theory, PA behavior is determined by social-cognitive predictors (e.g., Ajzen, 2002; Maddux & Rogers, 1983). The health action process approach (HAPA) postulates that there are three stages of change: nonintention, intention and action. During the health behavior change process, individuals in one stage move to the next one, in other words "pass through different mindsets on their way to behavior change" (Schwarzer, 2008, p. 11). This theory suggests that interventions which target the relevant psychological processes in the respective mindset might yield the biggest success (Schwarzer, 2008).

The social-cognitive mechanisms through which web-based interventions might influence older adults' PA behavior change are still inconclusive. A systematic review of mainly face-to-face interventions suggests that self-regulatory techniques such as self-monitoring and goal-setting might lead to decreased PA levels and social-cognitive pathways such as self-efficacy in older adults (French, Olander, Chisholm, & Mc Sharry, 2014). Yet, self-monitoring using accelerometers/pedometers has been reported to significantly increase

PA levels in older adults (Cooper et al., 2018) and to possibly motivate participants to remain in a trial (McMurdo et al., 2010).

In general, higher self-efficacy is positively related to the degree to which an individual has set the goal to realize a specific behavior, which is referred to as “intention” in the literature; and both are in turn related to higher levels of planning (Ajzen, 2002; Schwarzer, 2008). Intervention studies in non-clinical adult populations report mixed results regarding the question, whether increases in social-cognitive predictors such as self-efficacy, intention and planning in turn might play a mediating role in promoting the change of health behavior (Rhodes & Pfaeffli, 2010). Whether interventions based on the transtheoretical model of health behavior change (Prochaska & Velicer, 1997) are matched to stages of change or not does not seem to moderate their effect on PA change in adult populations, yet the inclusion of self-efficacy in these interventions is associated with a two-fold likelihood of PA promotion, according to a recent meta-analysis by Romain et al. (2018). Mouton and Cloes (2015) have shown that a combination of web-based and center-based interventions for promotion of PA in older adults succesfully increased PA stages of change, but not the web-based intervention alone. However, they did not inverstigate potentially mediating mechanisms in this effect. While there are studies investigating the working mechanisms of web-based intervention effects on a healthy lifestyle, such as in rehabilitation patients (Duan et al., 2018), the question whether there is a mediating effect of social-cognitive changes on PA stages of change resulting from web-based interventions, has not yet been addressed in community-dwelling older adults.

The first research aim of this article was to investigate the effects of two ten-week web-based exercise interventions on changes in PA behavior stage of change and social-cognitive predictors of PA in community-dwelling older adults. The second aim was to test the mediating role of the changes in social-cognitive predictors for facilitating the effect on

PA stage of change. Both aims were investigated in community-dwelling older adults aged 62 to 78 years. The authors hypothesized that 1) there would be a significantly elevated direct effect of the two intervention groups on PA stage of change in comparison to the delayed intervention control group; 2) this effect would be more pronounced in the intervention group additionally monitoring their PA objectively by wearing an activity tracker in comparison to the intervention group only monitoring their PA subjectively; and 3) the intervention effect would be explained by a positive change in social-cognitive predictors for PA.

Method

Trial Characteristics and Setting

The PROMOTE study is a community-based intervention trial, embedded in the Physical Activity and Health Equity: Primary Prevention for Healthy Ageing (AEQUIPA) research network which was funded by the German Federal Ministry of Education and Research (BMBF) (Forberger et al., 2017). The aim was to compare the effectiveness of two individually tailored web-based interventions to promote initiation and maintenance of a physically active lifestyle in older adults aged 65 to 75 years in comparison to a delayed intervention control group (Muellmann et al., 2017). The study was approved by the Ethics Committee of the Technical University of Chemnitz (TU Chemnitz), Faculty of Behavioural and Social Sciences, on July 14, 2015 (number: V-099-17-HS-CVR-PROMOTE-03072015) and was registered at the German Clinical Trials Register on July 11, 2016 (number: DRKS00010052). All study participants were fully informed about the study and provided informed consent.

The study took place in the Bremen-Oldenburg metropolitan region in northwestern Germany from February 2015 to January 2018. A primary outcome was objectively assessed PA, results have been reported elsewhere (Muellmann et al., 2019). Secondary outcomes included social-cognitive predictors of exercise behavior and transition in stages of exercise behavior change (main aim in the current paper), usability and acceptance of the technological intervention features (Meyer, Boll, Voelcker-Rehage, & Lippke, 2016), as well as well-being, quality of life, fear of falling, physical and cognitive functioning.

A random sample of 8,299 adults aged 65 to 75 years residing in five communities in the study region was drawn from the residents' registration office and contacted via mail. Volunteering participants between the ages of 60 and 80 years could participate in the study as well (n = 175). Eligibility was determined via telephone interviews carried out by a trained study nurse. To be included in the study, older adults needed to provide informed consent and be able to live and walk as well as participate in assessments and weekly group meetings independently. Basic German language abilities and regular internet access at home or at the family's or friends' place had to be present. Exclusion criteria were a planned vacation for more than one month during the intervention period and cognitive or other permanent impairment due to stroke or neurological diseases as well as presence of other medical contraindications for participation. Older adults were further screened for cognitive impairment using the Mini Mental Status Examination (MMSE) (Folstein, Folstein, & McHugh, 1975).

All participating older adults completed a questionnaire at baseline (T0, pre-intervention) and follow-up (T1, post-intervention, twelve weeks after T0). Older adults were randomly assigned to either a delayed intervention control group or one of two intervention groups (subjective PA monitoring versus subjective and objective PA monitoring). To keep a weekly online-diary of their PA the two intervention groups received access to a website as well as printed intervention material including an exercise guide. Intervention group 1 (IG1) monitored their PA subjectively (i.e., via the online diary), while intervention group 2 (IG2) additionally received an activity tracker (Fitbit Zip, San Francisco, USA), to objectively monitor their behavior. Fitbit data of daily steps were synchronized with the online diary. The delayed intervention control group received the intervention of IG1 after the follow-up assessment and will hereafter be referred to as CG. Further study details have been published in the study protocol (Muellmann et al., 2017).

Intervention Development

The interventions contained features to promote self-monitoring of PA and incorporated self-regulation theory (Bandura, 1991; Fleig, Lippke, Pomp, & Schwarzer, 2011; Pomp, Fleig, Schwarzer, & Lippke, 2013), as well as behavior change techniques (Michie et al., 2013; Michie, van Stralen, & West, 2011), such as goal-setting, feedback, rewards, and social support. See Supplementary material 1 (Appendix) for a detailed overview of included features and behavior change techniques. The printed intervention material contained exercises tailored to individual baseline physical fitness level and feedback tailored to baseline motivational stage (nonintention, intention or action) to engage in the recommended PA. Tailoring to gender was additionally carried out using pictures of men for males and pictures of women for females. Older adults were advised to engage in moderate endurance training at least 150 minutes per week or in vigorous endurance training at least 75 minutes per week or in a combination of both training intensities. Additionally, they were encouraged to train the eight major muscle groups and their balance ability at least twice a week, as suggested by the WHO (World Health Organization, 2010) and ACSM (Nelson et al., 2007). The online-diary, which was developed using an expert-driven approach, contained and displayed information on endurance, strength and balance training, as well as daily steps for IG2 (see Supplementary material 2-3 (Appendix) for screenshots of the study website in German). The simple design of the website mostly comprised presenting the data, showing trophies as rewards for goal attainment and providing a forum for networking with other participants. The ten-week intervention was accompanied by weekly group meetings led by a trained student, where questions regarding the program were addressed, theoretical input on healthy ageing was given, and participants performed the recommended exercises together (i.e., endurance, strength and balance training), thereby supporting social networking.

Outcome Measures

Sociodemographic characteristics were collected at baseline (pre-intervention) via self-administered questionnaire in accordance to the German Health Interview and Examination Survey for Adults (Robert-Koch-Institut, 2009). Variables included sex, date of birth, country of birth, family status, living alone, number of children, education, qualification, and monthly household income. Employment was assessed using one item from a questionnaire for assessing seniors' demographic and socio-structural data in Germany (Berthelsmann Stiftung, 2018). The combination of education and qualification was coded following the 2011 version of the International Standard of Education (ISCED), resulting in a range of values from 1 to 8, higher values indicating higher educational status (Statistisches Bundesamt, 2016). It was further dichotomized into low/moderate (ISCED 1 to 4) and high (ISCED 5 to 8). Need-weighted income per capita was derived considering the monthly household income and the number of individuals living in the household according to the German Microcensus (Boehle, 2015). Age of individuals in the household could not be considered. The variable was then tertiled into low, moderate and high on a frequency-basis. The following variables were assessed at baseline (pre-intervention) and follow-up (post-intervention). Older adults were asked to rate their general health status using one item from the Short Form-36 Health Survey (Morfeld, Kirchberger, & Bullinger, 2011). Technology commitment was assessed based on three components – technological acceptance, -competence and perceived control – according to the scale developed by Neyer, Felber, and Gebhardt (2012).

Stage of PA behavior change (the transition between stages is hereafter referred to as PA change) was assessed based on items used by Lippke, Ziegelmann, Schwarzer, and Velicer (2009). During baseline and follow-up assessments, older adults completed a short questionnaire which included questions on their motivational stage of PA behavior change with regard to endurance training ("*In a typical week during recent times: Did you engage in at least 150 minutes of endurance training [e.g., fast walking, biking, swimming]?"*) and strength training ("*In a typical week during recent times: Did you engage in strength training at least twice a week [such as targeted exercises for the back, legs and abdomen]?"*). Response options were 1 = No, and I do not intend to, 2 = No, but I am thinking about it, 3 = No, but I intend to, 4 = Yes, but only since shortly, and 5 = Yes, I have been doing this for a long time. Older adults choosing options 1 or 2 are generally regarded as being in nonintender stage, those choosing option 3 are regarded as being in intender stage and older adults choosing options 4 or 5 are regarded as being in actor stage (Lippke et al., 2009).

In the baseline and follow-up questionnaires older adults were asked to rate statements concerning the social-cognitive predictors of PA on Likert-scales from 1 to 7 (1 = totally disagree, 2 = disagree, 3 = somewhat disagree, 4 = neither, 5 = somewhat agree, 6 = agree, 7 = totally agree). Since risk perception (the probability of ever getting a very serious disease) adapted from Perloff and Fetzer (1986) was only assessed pre-intervention, it was included in the description of baseline characteristics but not in further analyses. The variable measuring the intention to engage in the recommended endurance and strength training was assessed with two items (Lippke et al., 2009; Nigg, 2005). Please see Supplementary material 4 (Appendix) for further information on the specific items used for the social-cognitive predictors. Positive and negative outcome expectancies were assessed with two items, respectively (Lippke, Ziegelmann, & Schwarzer, 2004; Schwarzer et al., 2007). Self-efficacy was assessed using one item measuring task self-efficacy, two items measuring maintenance self-efficacy, and two items measuring recovery self-efficacy (Luszczynska & Sutton, 2006; Nigg, 2005). Planning was assessed using three items to measure action planning and coping planning, respectively (Lippke, Schwarzer, Ziegelmann, Scholz, & Schüz, 2010). PA habit strength was assessed using two items (Verplanken & Orbell, 2003). Cronbach's alpha for intention was .59 and .65 in the two waves. Therefore, since this was the focus of the intervention, only the variable assessing at least 150 minutes per week of endurance training was considered in analyses. Cronbach's alpha for negative outcome expectancies was .65 and .58 in the two waves. Therefore, the two items were not aggregated. From here on, the variables assessing the expectation that doing the recommended training is too costly/takes too long will be referred to as NOE-long and NOE-cost, respectively. For the remaining social-cognitive predictors, Cronbach's alpha ranged from .85 to .96. For each of these predictors, one variable was aggregated indicating the mean of the respective items; their values therefore also potentially range from 1 to 7.

Statistical Analyses

All analyses were carried out using SPSS 24 (IBM Corp. Released 2016. IBM SPSS Statistics for Windows, Version 24.0. Armonk, NY: IBM Corp.). Only cases with complete information on change in endurance- and strength training at both baseline and follow-up were included in the analyses; therefore, analyses were not intention-to-treat. The primary outcome was PA change regarding the recommended level of endurance- and strength training from pre- to post-intervention, that is, the intervention effects. The main independent variable was the group affiliation (1 = CG, 2 = IG1, 3 = IG2). The secondary outcome was a change in social-cognitive predictors from pre- to post-intervention. In order to test the third hypothesis – the explanatory potential of the change in social-cognitive predictors in the intervention effect – the changes in social-cognitive predictors were included as mediators in mediation analysis.

Changes in endurance and strength training as well as social-cognitive predictors were calculated by subtracting the value at baseline from the value at follow-up. This resulted in values ranging from -4 to 4 for PA change variables and values ranging from -6 to 6 for the social-cognitive predictors, positive values indicating a positive change. Firstly, differences between intervention groups, the CG being set as the reference category, concerning changes in social-cognitive predictors were tested using mixed-effects ANOVA via repeated measures general linear models (GLM). Then, for analysis of main intervention effects on PA change as well as mediation analysis, the PROCESS macro, version 3.0 by Hayes (2013) with a bootstrapping approach of 10,000 samples was applied. With regard to the proposed associations in the HAPA model (Schwarzer, 2008; Schwarzer et al., 2007) – an ordinal least squares regression model assuming dependent mediators was calculated, incorporating the change variables of social-cognitive predictors found to show a significant time*intervention interaction in GLM. Sociodemographic variables and subjective health status were tested for potentially confounding the mediation model beforehand. Models were adjusted for the baseline values of PA stage as well as of the social-cognitive predictors included in the model. In order to investigate whether effects differed by baseline PA stage, sensitivity analyses were conducted by calculating proportions of individuals who remained in their stage, or moved to a lower or higher stage, stratified by their baseline stage. All analyses were run separately for PA change regarding endurance and strength training. Missing values in social-cognitive predictors were not missing systematically as indicated by Little's MCAR-test (p = .212). Therefore, they were imputed using the expectation-maximization algorithm based on the variables which were identified to show significant differences in sample selectivity analyses.

For precision of effect sizes, the 95% confidence interval (95% CI) was calculated and a p-value < .05 was regarded statistically significant. In GLM the F-statistic of time*intervention interactions as calculated by the Greenhouse-Geisser method is given, including the degrees of freedom (*df*) of the interaction and error terms as well as its p-value and the global effect size as indicated by partial Eta² (η_p^2). In case the assumption of equal variances was violated, the average differences in means calculated by the Games-Howell method were considered when assessing between-subject effects. Otherwise, Tukey's post-hoc values are stated. In mediation analysis, the effect size is represented by the unstandardized regression coefficient (*b*). The HC3-option was used to calculate heteroscedasticity-robust standard errors (*se*), thereby evading the assumption of homoscedasticity in ordinal least squares regression. Multicollinearity was assessed using the variance inflation factor (VIF) in linear regression.

Results

Participant Characteristics and Flow

Participation Flow

589 older adults attended baseline assessment (pre-intervention, T0): 211 (35.8%) in IG1, 198 (33.6%) in IG2 and 180 (30.6%) in the CG (see Figure 2-1). 405 older adults completed the follow-up assessment. However, 54 older adults were consecutively excluded from this analysis because of missing data on PA change (n = 46) and due to cognitive impairment (MMSE < 25; n = 8) (Creavin et al., 2016). In total, 351 older adults (59.6% of originally allocated individuals) were included in analyses of intervention effects (see Figure 2-1).

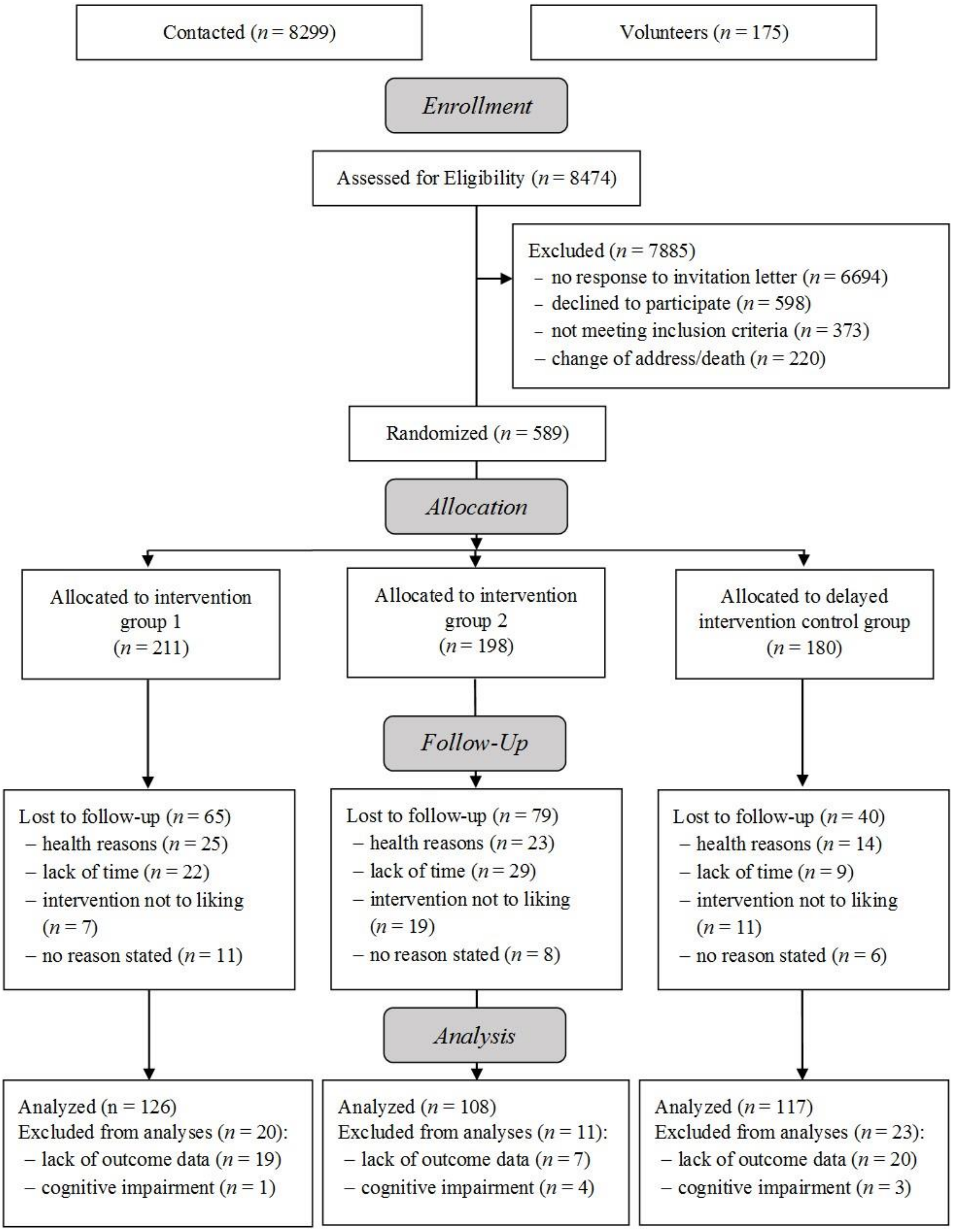

Figure 2-1. Sampling and flow of older adults through the trial.

Selectivity Analyses

The dropout rate was 31.2% and significantly higher in IG2 while significantly lower in the CG under the assumption of independence. Technology commitment, more precisely a higher level of perceived control when using technology, was associated with a decreased dropout chance in the whole sample. Stratification by group showed that this effect remained significant only in IG2 ($F[1, 184] = 4.8$, $p = .029$). Differences between the analyzed sample and the sample at baseline were evaluated by calculating the effect sizes (*ES*) as follows: $(M_{[\text{analyzed sample}]} - M_{[\text{parent sample}]}) / SD_{(\text{parent sample})}$ (Lindenberger, Singer, & Baltes, 2002; Voelcker-Rehage, Godde, & Staudinger, 2011). The analyzed sample differed significantly from the baseline sample in terms of higher proportions of older adults being male (ES = 1.13), having been born in Germany (ES = 2.66), being married (ES = 1.63), not having children (ES = 0.60), being retired (ES = 2.26), having a high educational status (ES = 2.83), having high monthly income (ES = 2.14), rating their health as excellent or very good (ES = 2.66) and reporting a low risk perception (ES = 1.63) (Cohen, 1988).

Baseline Characteristics of Analyzed Sample and Randomization Check

At baseline, the proportion of participants who stated that they had been engaging in endurance training at least 150 minutes per week for a short or long time (actor stage) was 54.4%. Regarding the engagement in strength training at least twice a week, the proportion of individuals in the actor stage was lower with 42.5%. Older adults in the analyzed sample were 62 to 78 years old (M = 70.01, SD = 3.3); one older adult did not provide information on age. Regarding sex, 43.9% (n = 154) were male, 54.1% (n = 190) were female, and 2.0% (n = 7) did not provide information on sex. The majority of analyzed older adults was retired (82.6%, n = 290), married (72.4%, n = 254), born in Germany (94.3%, n = 331), did not live alone (78.6%, n = 276), had children (84.9%, n = 298), and rated their health as good to excellent (86.3%, n = 303). Randomization was successful with regard to baseline descriptive characteristics, as well as social-cognitive predictors and PA stage, apart from a significantly elevated proportion of older adults born in a different country than Germany in the CG (8.0%, n = 9), compared to IG2 (n = 0, p = .008).

Intervention Effect on Social-cognitive Predictors of Physical Activity

Mixed-effects ANOVA revealed that across the ten-week study period, a significant time*intervention interaction was observed for intention (F[2, 348] = 6.33, p = .002, η_p^2 = .04), task self-efficacy (F[2, 348] = 4.35, p = .014, η_p^2 = .02), action planning (F[2, 348] = 4.78, p = .009, η_p^2 = .03), NOE-long (F[2, 348] = 3.14, p = .044, η_p^2 = .02), and habit strength (F[2, 348] = 14.77, p < .001, η_p^2 = .08). This finding suggests that the positive change in these social-cognitive predictors between the two timepoints was significantly higher in the intervention groups compared to the CG. These effects were not found for the remaining social-cognitive predictors. When examining the between-subjects test statistic, only changes in intention (F[2, 348] = 5.23, p = .006, η_p^2 = .03) and task self-efficacy (F[2, 348] = 5.74, p = .004, η_p^2 = .03) yielded significantly increased values for intervention groups in comparison to the CG. More precisely, the average difference between means at baseline and at follow-up was significantly higher in IG2 compared to the CG in intention (average mean difference = 0.68, 95%-CI [0.17, 1.19]). For task self-efficacy, the average difference in means between baseline and follow-up was significantly higher in both intervention groups compared to the CG (IG1: 0.61, [0.14, 1.09]; IG2: 0.50, [0.04, 0.95]). These effects were not found for NOE-long, action planning and habit strength (see Figure 2-2 for the change in means between baseline and follow-up).

Paralleling the time-effects varying by intervention groups, significant independent time effects were noted for intention, action planning, coping planning, NOE-cost and habit strength (data not shown), suggesting that significant changes over time were not exclusively observed for IG1 or IG2.

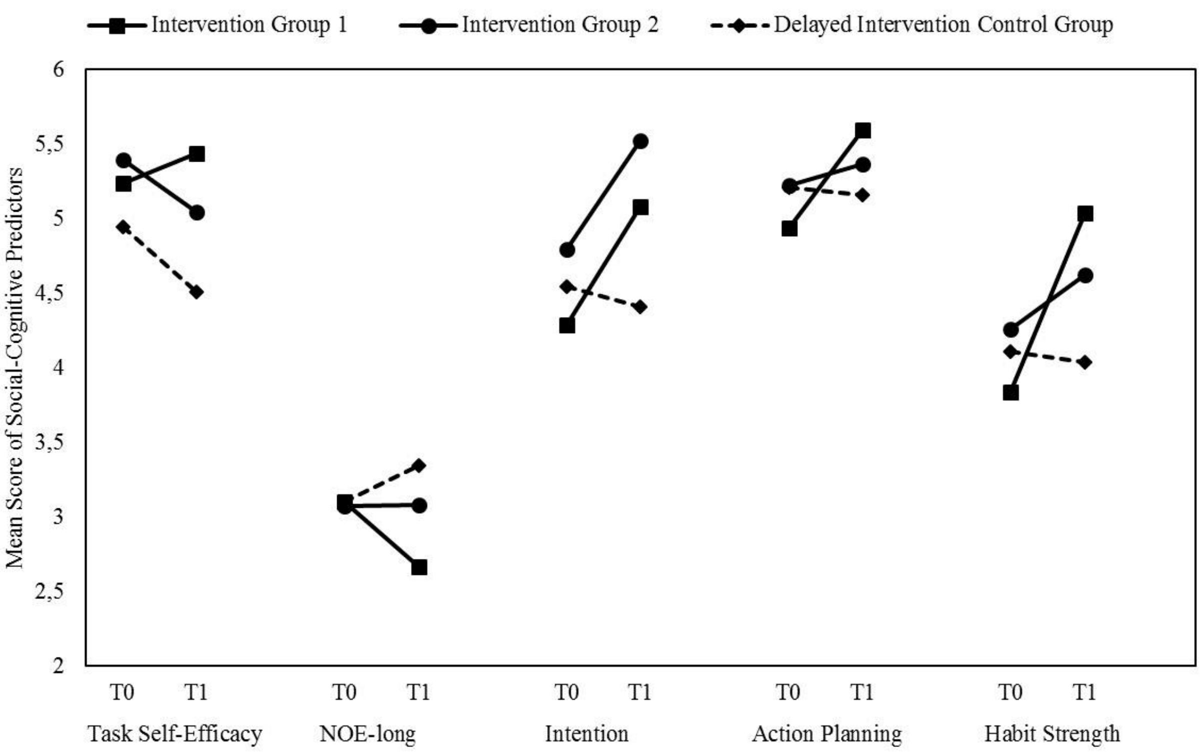

Figure 2-2. Change in means in social-cognitive predictors for intervention group 1, intervention group 2 and delayed intervention control group from baseline (T0) to follow-up (T1). Mean values can potentially range from 0 to 6. NOE-long = negative outcome expectancy – takes too long.

Intervention Effect on Physical Activity Change

Based on significant time*intervention interactions in GLM, task self-efficacy, NOE-long, intention, and action planning were considered for inclusion in mediation analysis. According to the VIF there was some indication of multicollinearity for habit strength (VIF > 3.5). Therefore, it was decided not to include habit strength in the mediation model. According to the HAPA model, task self-efficacy and outcome expectancies predict intention and planning bridges the intention-behavior gap (Schwarzer, 2008). Consequently, the regression model to investigate the intervention effect on PA change and the mediating effect of changes in social-cognitive predictors in this process included dependent mediators (chain mediation). None of the tested variables (sociodemographic variables and subjective health status) were identified as confounders. However, mediation analysis was statistically adjusted for the baseline values of PA stage and social-cognitive predictors. The mediation analysis results are depicted in Figure 2-3.

Independent Intervention Effects

The independent intervention effect on PA change in endurance training was still significant in IG1 (relative direct effect: b_{IG1} = 0.44 [*se* = 0.15, [0.15, 0.73]]), whereas inclusion of the mediators diminished the prior significant effect of IG2 (relative direct effect: b_{IG2} = 0.28 [*se* = 0.15, [-0.02, 0.58]]). Regarding strength training, there was an independent significant positive effect of both interventions on PA change (relative direct effect: b_{IG1} = 1.02 [*se* = 0.16, [0.71, 1.33]]; b_{IG2} = 1.24 [*se* = 0.16, [0.92, 1.56]]).

Dependent Mediator Relationships

Four dependent mediator relationships were detected: 1) a positive change in task self-efficacy interrelated with a significant positive change in intention, 2) NOE-long, and 3) action planning and 4) a positive change in intention was associated with a significant positive change in action planning. IG1 showed a direct positive intervention effect on task self-efficacy and a decrease in NOE-long while IG2 showed a direct positive intervention effect on intention.

Mediation Effects in the Intervention Effect on Physical Activity Change

For endurance training there was a mediating effect through change in intention in IG2: $b_{\text{IG2}\rightarrow\text{intention}\rightarrow\text{endurance PA change}}$: 0.83 * 0.09 = 0.08 and through a chain-mediation of task self-efficacy and intention in IG1: $b_{\text{IG1}\rightarrow\text{task self-efficacy}\rightarrow\text{intention}\rightarrow\text{endurance PA change}}$: 0.92 * 0.42 * 0.09 = 0.04. Regarding strength training, a positive change in action planning was significantly associated with PA change. Therefore, two dependent mediating relationships were found: $b_{\text{IG2}\rightarrow\text{intention}\rightarrow\text{action planning}\rightarrow\text{strength PA change}}$: 0.84 * 0.25 * 0.10 = 0.02; and $b_{\text{IG1}\rightarrow\text{task self-efficacy}\rightarrow\text{intention}\rightarrow\text{action planning}\rightarrow\text{strength PA change}}$: 0.93 * 0.43 * 0.25 * 0.10 = 0.01. The proportion of explained variance by the model was high with 50% for endurance and 57%, which was due to the inclusion of baseline values of PA stage. Sensitivity analyses without inclusion of baseline values as covariates revealed that the direct intervention effects were marginally higher, but none of the mediating effects were significant (see Supplementary material 5 (Appendix)).

Baseline Stage-specific Intervention Effects

Compared to the CG, there were significantly elevated proportions of individuals in nonintender stage at baseline who had progressed to the actor stage at follow-up in the intervention groups (endurance training: 70.4% in IG2 vs. 25.0% in the CG; fisher's exact = 16.775, $p < .01$, Cramer's $V = .30$; strength training: 64.2% in IG1 and 83.0% in IG2 vs. 8.9% in the CG; fisher's exact = 61.936, $p < .001$, Cramer's $V = .44$; see Table 2-1).

In the baseline intender stage, the elevated proportion of older adults which had progressed to the action stage at follow-up was only significant for IG1 regarding strength training (85.7% in IG1 vs. 20% in the CG; fisher's exact = 22.078, $p < .001$, Cramer's $V = .45$). In baseline actor stage for strength training, there were significantly fewer individuals who had moved to a lower stage in IG1 at follow-up (3.8% moved to nonintender stage and 0% to intender stage) compared to the CG (28.8% moved to nonintender stage and 11.5% moved to intender stage; fisher's exact = 23.845, $p < .001$, Cramer's $V = .29$). The differences between IG1 and IG2 were not statistically significant in either activity.

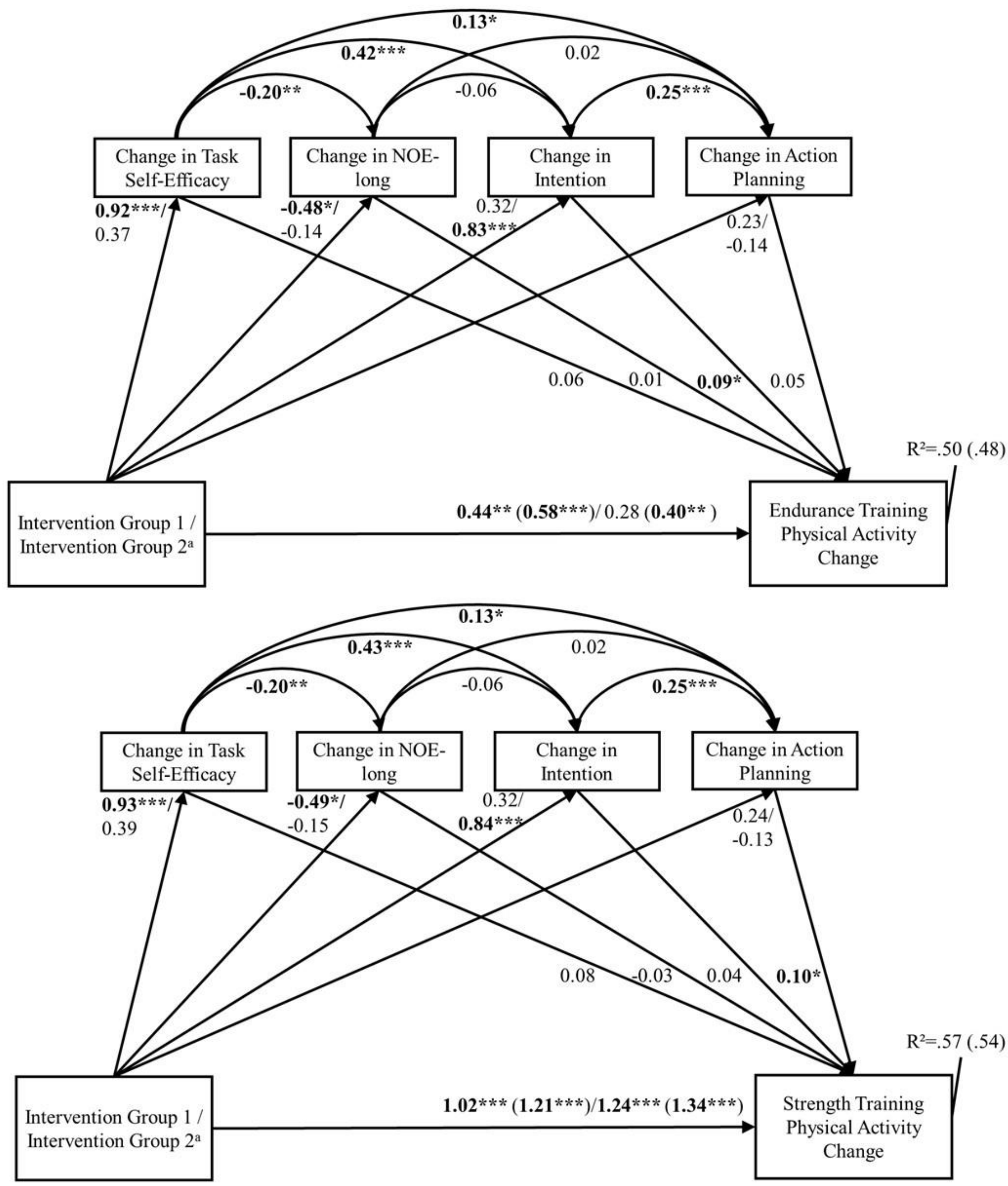

Figure 2-3. Dependent mediator model for intervention effects on endurance/ strength training physical activity (PA) change. Social-cognitive predictors were defined as dependent mediators. Unstandardized regression coefficients indicate the intervention effects (first coefficient for intervention group 1 and second coefficient for intervention group 2) and the social-cognitive predictor effects on endurance/ strength training PA change. Total effects are given in parentheses. Mediating effects can be determined by multiplying the intervention effects on social-cognitive predictors with the social-cognitive predictor effects on PA change. Analyses were adjusted for endurance/ strength training stage of change at baseline and social-cognitive predictor values at baseline. Significant regression coefficients are in boldface. NOE-long = negative outcome expectancy – takes too long.

[a]Delayed intervention control group was set as reference.

* *p* < .05. ** *p* < .01. *** *p* < .001.

Table 2-1

Endurance and strength training stages of change at baseline (T0) and follow-up (T1) by group in n (%).

		Delayed Intervention Control Group			Intervention Group 1			Intervention Group 2		
		Nonintender T1	Intender T1	Actor T1	Nonintender T1	Intender T1	Actor T1	Nonintender T1	Intender T1	Actor T1
Endurance Training	Nonintender T0	**16 (50.0)**	8 (25.0)	***8 (25.0)***	7 (20.0)	6 (17.1)	22 (62.9)	7 (25.9)	***1 (3.7)***	**19 (70.4)**
	Intender T0	5 (22.7)	5 (22.7)	12 (54.5)	***0 (0.0)***	4 (17.4)	19 (82.6)	4 (19.0)	2 (9.5)	15 (71.4)
	Actor T0	**7 (11.1)**	1 (1.6)	***55 (87.3)***	1 (1.5)	1 (1.5)	66 (97.1)	2 (3.3)	0 (0.0)	58 (96.7)
Strength Training	Nonintender T0	**32 (71.1)**	9 (20.0)	***4 (8.9)***	13 (24.5)	6 (11.3)	**34 (64.2)**	***4 (8.5)***	4 (8.5)	**39 (83.0)**
	Intender T0	**7 (35.0)**	**9 (45.0)**	***4 (20.0)***	2 (9.5)	***1 (4.8)***	**18 (85.7)**	2 (12.5)	1 (6.3)	13 (81.3)
	Actor T0	**15 (28.8)**	**6 (11.5)**	***31 (59.6)***	***2 (3.8)***	***0 (0.0)***	**50 (96.2)**	3 (6.7)	2 (4.4)	40 (88.9)

Note. Numbers and proportions are given in n (%). Proportions by group are given as row percentages. Fisher's exact test was used to test for significant differences within baseline stages (nonintender, intender and actor stage). Significant low proportions under the assumption of independence (corrected residual ≤ -2) are in boldface and italic. Significant elevated proportions under the assumption of independence (corrected residual ≥ 2) are in boldface.

Discussion

Summarizing, 351 older adults were included in the analyses for this article. Positive social-cognitive predictor changes in task self-efficacy, intention and action planning explained the intervention effect on PA change. However, they did not fully mediate the intervention-PA change relationship, but independent intervention effects were found. Comparing the intervention groups, the effect on PA change was only significant for IG1 regarding endurance training, whereas it was significant for both intervention groups regarding strength training. IG2 was not found to outperform IG1 because coefficient confidence intervals of the two intervention groups overlapped.

The results suggest that participation in a web-based intervention for PA promotion directly influences social-cognitive predictors for PA as well as the stage of change regarding PA in community-dwelling older adults. This is in accordance with research in middle-aged (Lippke et al., 2010) and older adults (Irvine, Gelatt, Seeley, Macfarlane, & Gau, 2013). However, stage-specific analyses revealed that the intervention solely involving subjective monitoring (IG1) seems to have been more effective in those who had already developed the intention at baseline, whereas additional objective monitoring (IG2) seems to have been more successful in the baseline nonintender stage.

In parallel, especially the intervention in IG2 was successful in increasing the social-cognitive predictor intention (goal-setting), which is generally suspected in baseline nonintender stage (Schwarzer, 2008). IG1 seemed to have higher intervention effects in terms of lowering negative outcome expectancies and increasing task self-efficacy. Next to the mediating effects for task self-efficacy and intention in endurance training, two underlying dependent mediator relationships were detected for strength training: By successfully increasing task self-efficacy, the intervention in IG1 had an indirect effect on PA change through increases in intention and action planning. In IG2, significant intervention effects on intention promoted PA change through a positive change in action planning. These findings suggest that objective and subjective self-monitoring exercise interventions can effectively promote transition to higher PA stages of change in older adults. Yet it should be noted that they work through different social-cognitive mechanisms (e.g., the combination of objective and subjective monitoring works via increases in intention versus subjective monitoring alone works via increases in self-efficacy) and their effect differs depending on the baseline stage of change. Therefore, the type of self-monitoring can be used as a further mode of tailoring interventions to individual needs in future research and practice.

For outcome expectancies, planning and habit strength, non-significant between-subject effects in analyses might be explained by ceiling effects (Wang, Zhang, McArdle, & Salthouse, 2008) or extreme baseline values and regression to the mean (Yu & Chen, 2014). Even though baseline values of PA stage were not significantly different, significant mediation effects were found only after adding the baseline variables to the model. Sensitivity analyses indicated that the baseline variable of PA stage was the reason for the high proportion of explained variance, which is reasonable since the value in PA change was dependent on the baseline value (e.g., individuals in the nonintender stage can automatically have higher change values than individuals in the intender stage).

Several observed associations corroborate previous findings, such as the relationship between increases in task self-efficacy, intention and action planning (Lippke et al., 2010; Paech, Luszczynska, & Lippke, 2016). Self-efficacy has been shown to moderate the mediation between intention and planning on behavior (Luszczynska et al., 2010). These observed increases in social-cognitive predictors suggest that use of intention implementation strategies, such as in form of if-then-plans in group meetings, were successful in narrowing the intention-behavior gap (Hagger & Luszczynska, 2014). Yet, there is no information on long-term maintenance of the observed effects. There was no intervention-dependent increase in coping planning, which has been shown to be associated with maintenance (Luszczynska, Schwarzer, Lippke, & Mazurkiewicz, 2011). However, some studies report coping planning to have adverse effects on self-efficacy and motivation for health behavior maintenance (Inauen, Stocker, & Scholz, 2018; Williams & French, 2011). There is research on significant mediating mechanisms in the web-based intervention effect on exercise as well as fruit and vegetable intake through change in social-cognitive predictors, for example in rehabilitation patients (Duan et al., 2018) and the general population (Lippke, Corbet, Lange, Parschau, & Schwarzer, 2016). The current study suggests that previous findings also apply to PA stage in older adults. Implications for practice in terms of how to provide support for older adults to become and remain physically active can be drawn from these insights: Effective interventions work through increases in social-cognitive predictors. Therefore, next to appropriate monitoring, key aspects such as self-efficacy and planning should be addressed. Positive effects in individuals in the nonintenders stage even in the CG additionally suggest that any attention might already pay off to some extent.

Our study has several limitations. The dropout rate in IG2 was almost twice as high as in the CG (40% vs. 22%); whereas the rate in the group without objective monitoring (IG1) was 31%. Retention rates of other digital PA intervention trials in older adults are ranging from 49% to 100%, however, there are several studies reporting dropout rates of less than 10% (Stockwell et al., 2019). The recruitment strategy attracted mainly already active, health-conscious and science-interested individuals. Hence, the high baseline actor stage rates point towards selection bias and limited external validity. This homogeneity in participant characteristics as well as systematic dropout as indicated by selectivity analyses limits the analyzed sample's representativeness of community-dwelling older adults, which should be carefully considered when interpreting the results. The short intervention and follow-up period might explain small effects in addition. Long-term behavior maintenance and habit formation had only limited possibility to manifest.

Nevertheless, apart from successful randomization and the inclusion of a delayed intervention control group, several strengths of this study should be noted. According to the evidence on promising features of behavioral interventions (Kohl, Crutzen, & de Vries, 2013), the intervention material in this study was tailored to personal fitness level, motivational stage and sex, was based on social cognitive theory and included behavioral change techniques. In addition, face-to-face components were included, enabling older adults to ask questions directly and exercise in groups under supervision of trained students, thereby ensuring a high service approach.

Concluding, this article adds to the knowledge base of web-based interventions on PA promotion successfully encouraging PA change in exercise behavior change in community-dwelling older adults and is novel in investigating mediating mechanisms of social-cognitive predictors in the intervention effect on PA change. These insights provide several implications for future research. Inclusion of objective monitoring possibilities might lead to dropout in older adults, when needs and demands are not sufficiently met, because there was a higher proportion of discontinuing older adults with low perceived control when using technology in IG2. Objective monitoring might address individuals affine to technology, while it might overwhelm the technologically-nonaffine. This analysis found mediating intervention effects via social-cognitive predictors. Future research is needed to investigate the underlying mechanisms of PA change in web-based interventions further in order to develop appropriate and effective interventions. Additionally, different types of exercise should be clearly differentiated, because in this study the need for strength training PA change in older adults seemed to be higher but also more responsive to web-based PA interventions, compared to endurance training. Upcoming studies should consider individual limitations and barriers in intervention development to prevent dropout and encourage behavior change, and adapt their recruiting strategies to vulnerable populations, such as inactive and socioeconomically worse situated older adults with health impairments. Researchers should also assess the long-term intervention effects.

Declarations

Supplementary Material

Supplementary material is available at Applied Psychology: Health and Wellbeing online.

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Authors' Statement of Conflict of Interest

Authors TR, SL, SM, MP, CRP, JM, IB and CVR declare that they have no conflict of interest.

Author's Contributions

All authors significantly contributed to the manuscript by drafting the manuscript, conceiving and designing the study, detailing the study design, supervising the collection of data and the implementation of the intervention as well as processing and conducting the statistical analyses. All authors read, critically revised and approved the final manuscript.

Ethical Approval and Trial Registration

This study was approved by the Ethics Committee of the Technical University of Chemnitz (TU Chemnitz), Faculty of Behavioural and Social Sciences, on July 14, 2015 – number V-099-17-HS-CVR-PROMOTE-03072015. All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. The study was registered at the German Clinical Trials Register on July 11, 2016 – number DRKS00010052.

Informed Consent

All study participants were fully informed about the study and provided informed consent.

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Chapter 3. Health-related Lifestyle and Dropout from a Web-based Physical Activity Intervention Trial in Older Adults: A Latent Profile Analysis

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Ratz, T., Voelcker-Rehage, C., Pischke, C. R., Muellmann, S., Peters, M., & Lippke, S. (2021). Health-related lifestyle and dropout from a web-based physical activity intervention trial in older adults: A latent profile analysis. *Health Psychology*, *40*(8), 481–490. https://doi.org/10.1037/hea0001091

Abstract

Objective: Selective study dropout limits manifestation and detection of intervention effects and is a major challenge in behavioral intervention studies. Engaging in health-risk behaviors might make individuals especially dropout-vulnerable. Thus, this theory-based study's aim was to identify health-related lifestyle profiles affecting dropout in a web-based physical activity intervention trial targeting older adults. **Methods**: The twelve-week intervention trial was conducted between 2016 and 2018 in Germany. Baseline lifestyle profiles consisting of self-reported physical activity, sedentary behavior, alcohol consumption, fruit and vegetable intake, nocturnal sleep and social activity were assessed with questionnaires and investigated in *n* = 589 individuals. The risk of study dropout related to health-related lifestyle profile was tested with Poisson regression in *n* = 571 individuals (96.9%). **Results**: Latent profile analysis identified four latent health-related lifestyle profiles: socially inactive (*n* = 23, 3.9%), slightly unhealthy (*n* = 449, 75.2%), health-promoting (*n* = 81, 13.8%), and highly physically active lifestyle (*n* = 36, 6.1%). Profiles differed significantly by sex, stage of behavior change, and subjective health. Compared to the average of all profiles, statistically significant study dropout adjusted risk ratios (aRR) were aRR = 1.91 for the socially inactive lifestyle, and aRR = 0.73 for the slightly unhealthy lifestyle. There were no statistically significant effects for the highly physically active lifestyle (aRR = 0.94), and the health-promoting lifestyle (aRR = 0.76) on study dropout. **Conclusions**: This study highlights the relevance of accounting for the correlation between health-related lifestyle profiles and study participation of older adults in physical activity interventions.

Keywords: latent profile analysis; dropout analysis; intervention trial; health-related lifestyle; physical activity

Introduction

Even in late life, physical activity adoption and maintenance have the potential to improve health outcomes (Hamer et al., 2014; Moreno-Agostino et al., 2020), highlighting the relevance of effective physical activity interventions for older adults. Digital physical activity interventions have been shown to be successful in older adults (Buyl et al., 2020; Stockwell et al., 2019), but especially in older age groups the issue of low technology adoption can arise (Hawley-Hague et al., 2014). Respective studies report retention rates between 100% and 48.7% (Stockwell et al., 2019). Ageing-related limitations and low perceived value for improved health or quality of life are known barriers to both older adults' physical activity participation (Bethancourt et al., 2014; Macniven et al., 2014) and technology usage (Berkowsky et al., 2017; Wildenbos et al., 2018). However, why older adults drop out of digital physical activity interventions still needs to be better understood so that future interventions can address individual needs within a heterogeneous study population appropriately to ensure intervention adherence and avoid selective study dropout. This is on the one hand relevant because attrition of study participants can lead to biased results (Bell et al., 2013; Michelet et al., 2014). On the other hand, early discontinuation limits intervention effectiveness and thus represents a major challenge to all behavior-based intervention studies (Burgess et al., 2017; Donkin et al., 2011). Those participants who report multiple risk behaviors or a low health status might be vulnerable to study dropout. For example, a web-based multiple-lifestyle intervention for adults reports that study dropout was related to a combination of unhealthy lifestyle behaviors (Schulz et al., 2014). Therefore, the purpose of this article is to investigate whether the initial health-related lifestyle profile predicts study dropout from a web-based physical activity intervention trial targeting older adults.

That health-risk behaviors, such as smoking and alcohol consumption, and health-promoting behaviors, such as fruit and vegetable consumption and physical activity, typically co-occur in clusters has for example been reported for adults (Mudryj et al., 2019), and older adults (Liao et al., 2019). Also, there seems to be an association between different combinations of diet- and activity behavior types and successful multiple health behavior change (Schneider et al., 2016). Theory suggests that successful single behavior interventions might impact the readiness to change a second behavior, for example, by increasing social-cognitive predictors such as self-efficacy or planning (Compensatory Carry-Over Action Model, see Lippke, 2014). Promoting a healthy lifestyle combining several health-related behaviors is an important component of behavioral medicine, because poor health and psychological wellbeing are associated with engaging in a combination of health-risk behaviors (Dohle & Hofmann, 2019; Oftedal et al., 2019), as well as with a decreased likelihood of physical activity maintenance and uptake (Kim et al., 2017), and study dropout (Cramer et al., 2016).

Understanding how lifestyle profiles and self-rated health status correlate with study dropout can provide essential insights for future intervention development and tailoring of intervention content to participants’ individual needs. This may, in turn, lead to the prevention of study dropout and biased results as well as enable dropout-vulnerable groups to benefit from physical activity interventions. The research objectives were to 1) identify latent lifestyle profiles of health-related behavior and 2) investigate the extent to which these lifestyle profiles, as well as subjective health status and satisfaction with life, predict study dropout from a web-based physical activity intervention trial targeting older adults.

Method

Procedure

The study under investigation was the PROMOTE intervention trial. Being a subproject in the Physical Activity and Health Equity: Primary Prevention for Healthy Ageing (AEQUIPA) research network (Forberger et al., 2017), it aimed to investigate the effectiveness of two tailored web-based interventions to promote physical activity in older adults aged 65 to 75 years in comparison to a delayed intervention control group (Muellmann et al., 2017). The study was funded by the German Federal Ministry of Education and Research (BMBF), approved by the Ethics Committee of the Technical University of Chemnitz (TU Chemnitz), Faculty of Behavioural and Social Sciences, on July 14, 2015 (number: V-099-17-HS-CVR-PROMOTE-03072015). All study participants were fully informed about the study and provided informed consent. Older adults were randomly assigned to either a delayed intervention control group or one of two web-based intervention groups which included weekly group exercises and subjective self-monitoring of physical activity with a web-based diary (intervention group 1) and additional objective self-monitoring with a physical activity tracker (intervention group 2). The interventions were based on the Health Action Process Approach (Schwarzer et al., 2008, 2011). Further study details, including the study flow chart, and first results of confirmatory analyses have been published in the study protocol (Muellmann et al., 2017) and recent articles (Muellmann et al., 2019; Ratz et al., 2020). Exploratory research on the relationship between lifestyle and study dropout was not previously performed or published.

Measures

Health-related Lifestyle Indicators

Six health-related lifestyle behaviors (i.e., physical activity, sedentary behavior, sleep duration, fruit and vegetable consumption, alcohol intake, and social activity) were included in the analysis of baseline latent lifestyle profiles. To ensure consistency in measurement and interpretability of the latent profile construct, it was decided to only use self-reported data, even though objectively measured data would have been available for physical activity and sedentary behavior. The International Physical Activity Questionnaire (IPAQ) was used to assess daily sedentary behavior by asking participants to indicate the average daily hours and minutes they spent sitting during the last seven days (Craig et al., 2003). Weekly duration of moderately exhausting physical activity was assessed by asking participants how many hours and minutes they spent being moderately physically active during an average week. The Food Frequency Questionnaire was used to measure fruit and vegetable intake (Gallois et al., 2013). Response possibilities ranged from 1 (*four or more times per day*) to 7 (*never/less than once per week*). To enable the inclusion of fruit and vegetable consumption in latent profile analysis (LPA), which required the variable to be continuous, the categories were converted into portions a day. Therefore, all categories indicating “X times per day” were interpreted as “X portions per day”. The category *four to six times per week* was recoded into *0.7 portions per day*, and *one to three times per week* was recoded into *0.3 portions per day*. Alcohol consumption was measured using three items of the Alcohol Use Disorders Identification Test, including frequency of alcohol consumption and number of alcoholic drinks consumed on a typical day of drinking (Saunders et al., 1993). The sum score ranges from 0 to 12, a value of 8 or higher is considered hazardous alcohol consumption. A modified version of the Florida Cognitive Activities Scale with 29 items was used to assess social activities by asking older adults how often in the last four weeks they had engaged in specific activities on a five-point scale from 0 (*never/less than once a week*) to 4 (*several times a week*). The sum score ranges from 0 to 116 (Jopp & Hertzog, 2010; Schinka et al., 2005). For nocturnal sleep duration, participants reported the average hours and minutes typically slept per night.

Self-Reported Health and Satisfaction with Life

Subjective general health was assessed with one item from the Short Form-36 Health Survey (Morfeld et al., 2011) and categorized into *poor/less good* general health, *good* general health and *very good/excellent* general health. Satisfaction with life was measured using the Satisfaction With Life Scale (Diener et al., 1985). The score ranges from 1 to 7, higher values indicating higher life satisfaction.

Covariates

Sociodemographic characteristics, including sex, date of birth, family status, and monthly household income, were collected at baseline (pre-intervention) in accordance with the German Health Interview and Examination Survey for Adults (Robert-Koch-Institut, 2009). Body fat percentage was measured using a bioimpedance scale during baseline physical examinations. Technology commitment was assessed using the construct proposed by Neyer et al. (2012). The score ranges from 1 to 5, higher values indicating higher technology commitment. Cognitive state was measured using the Mini Mental Status Examination (MMSE) (Folstein et al., 1975). Stage of physical activity behavior change (*nonintender*, *intender* or *actor* stage), specifically, spending at least 150 minutes per week moderately to vigorously exercising, was assessed based on one item used by Lippke, Ziegelmann, Schwarzer, and Velicer (2009).

Statistical Analyses

Latent Profile Analysis

To identify latent profiles based on the set of continuous lifestyle indicators, LPA was carried out using Mplus version 8 (Muthén & Muthén, 2017). LPA belongs to the person-centered methods and mixture modeling techniques and aims to identify a mixture of separate normal distributions within the not necessarily normally distributed whole sample population by categorizing individuals into latent unobserved subgroups based on similar patterns in a set of observed continuous parameters (Berlin et al., 2014; Oberski, 2016). In the process of profile assignment, the individual probabilities of membership in each profile are calculated, the sum of which is always one. LPA results in a discrete variable indicating the latent profile which an individual is assigned to according to respective posterior probabilities (Berlin et al., 2014; Oberski, 2016).

Estimates were calculated for one profile at first and then profiles were consecutively added until the model best fitting the data was identified. Model selection was based on the four-step procedure proposed by Ram and Grimm (Ram & Grimm, 2009). The fit statistics log likelihood, Bayesian information criterion (BIC), Akaike's information criterion (AIC), and sample size adjusted BIC were investigated to identify the model best fitting the data. Entropy was regarded as indicator of classification accuracy. The p-values obtained from the bootstrap likelihood ratio test (BLRT) and the Lo-Mendell-Rubin adjusted likelihood ratio test (LMR-LRT) were used to examine whether the respective model offered a significantly better fit for the data than the previous model with one profile less. The default parameterization model with equal variances and covariances fixed to zero was chosen. Full information maximum likelihood estimation was used, enabling the estimation of missing values during LPA.

Dropout Analysis

The effect of latent lifestyle profile membership, subjective general health status and satisfaction with life on study dropout on a multivariate level was analyzed using Poisson regression with robust standard errors to obtain adjusted risk ratios, as suggested by Knol et al. (2012). In accordance with the intervention study's exclusion criteria and the cut-off suggested by Creavin et al. (2016), older adults with an MMSE-score of less than 25 were excluded from the dropout analysis (n = 17). Analyses were adjusted for group assignment, technology commitment, stage of physical activity behavior change, MMSE-score and percentage of body fat. Deviation contrast was chosen for latent profiles and health status, so regression coefficients for each category indicated the relative deviation from the unweighted mean of all categories.

Analysis of Imputed Data

Once the latent profile membership variable was identified, the dataset was exported from Mplus to R for further analyses, which were conducted via RStudio, version 1.2.5001 (RStudio Team, 2019). Missing baseline values were imputed using multiple imputation with the package MICE, which stands for multivariate imputation by chained equations (van Buuren & Groothuis-Oudshoorn, 2011). The significant association between missing baseline values and observed data indicated that values were missing at random, therefore it could be expected that multiple imputation would produce valid results (van Buuren & Groothuis-Oudshoorn, 2011; van Ginkel et al., 2020). The average proportion of missing values per variable was 5%. Complete information was available for stage of change and social activity as well as the latent profile, group assignment and dropout status. Five complete datasets were created using 20 iterations. A set of predictor variables was defined to be always used for prediction of missing values, consisting of group assignment, sociodemographic information, various health behaviors, health indicators, body fat percentage, technology commitment and stage of behavior change. The average number of predicting variables per predicted variable was 15. Continuous variables were imputed using predictive mean matching. When applying multiple imputation, the multiple complete datasets need to be analyzed separately, followed by pooling the estimates and standard errors based on Rubin's rules (Rubin, 1987). Because frequencies and proportions do not include the necessary estimate and variability measures according to Rubin's rules, frequencies were averaged across complete datasets and, for easier interpretation, are reported with rounded values.

Results

Participant Characteristics

The study included *n* = 589 individuals. The mean age was 70.02 years (*SD* = 3.30, range = 62 to 78), *n* = 10 older adults (1.7%) did not provide information on age. A slightly higher proportion of participants was female (*n* = 325, 55.2%), and 19 (3.2%) individuals did not provide information on sex. The dropout rate was 31.2%, that is, *n* = 184 participants were lost to follow-up. Further details on participant characteristics have been reported elsewhere (Muellmann et al., 2019; Ratz et al., 2020).

Latent Lifestyle Profile Identification

Following the four-step model selection procedure for LPA described in the method section (Ram & Grimm, 2009), investigating potential software warnings indicated that the models had successfully converged. Because the model fit criteria as indicated by log likelihood, AIC, BIC and SABIC kept decreasing with profiles being added (see Table 3-1), the elbow plot of the fit statistics was used to identify at which point they became stable, even if more profiles were added (see Figure 3-1).

The elbow plot visualized that the values became stable around three or four profiles. Entropy was above .800 for all models. The p-value for LMR-LRT became insignificant at three profiles, suggesting that the model did not significantly improve the fit compared to the model with only two profiles. However, both the elbow plot and the BLRT indicated that additional profiles would improve the fit. In fact, the BLRT was still significant for the model with six profiles. Because the proportion in the smallest profile changed from 3.9% to 1.9%, the four-profile solution was chosen. This was in accordance with the LMR-LRT, which suggested that the four-profile solution significantly improved the fit compared to the model with three profiles (see Table 3-1).

Table 3-1

Latent profile analysis fit statistics.

Profile	Log Likelihood	AIC	BIC	SABIC	Entropy	Smallest Class	LMR-LRT	BLRT
1	-13237	26498	26551	26512	1	-	-	-
2	-13050	26138	26221	26161	1	0.0391	< .0001	< .0001
3	-12930	25913	26027	25944	0.956	0.0391	.1036	< .0001
4[a]	-12865	25797	25941	25837	0.884	0.0391	< .001	< .0001
5	-12821	25721	25897	25770	0.868	0.0391	.0770	< .0001
6	-12795	25684	25890	25740	0.853	0.0192	.0768	< .0001

Note. Profiles were consecutively added until the best fitting model was identified. AIC = Akaike's information criterion; BIC = Bayesian information criterion; SABIC = sample size adjusted BIC; LMR-LRT = *p*-value of Lo-Mendell-Rubin adjusted likelihood ratio test; BLRT = *p*-value of bootstrap likelihood ratio test.
[a]The selected model.

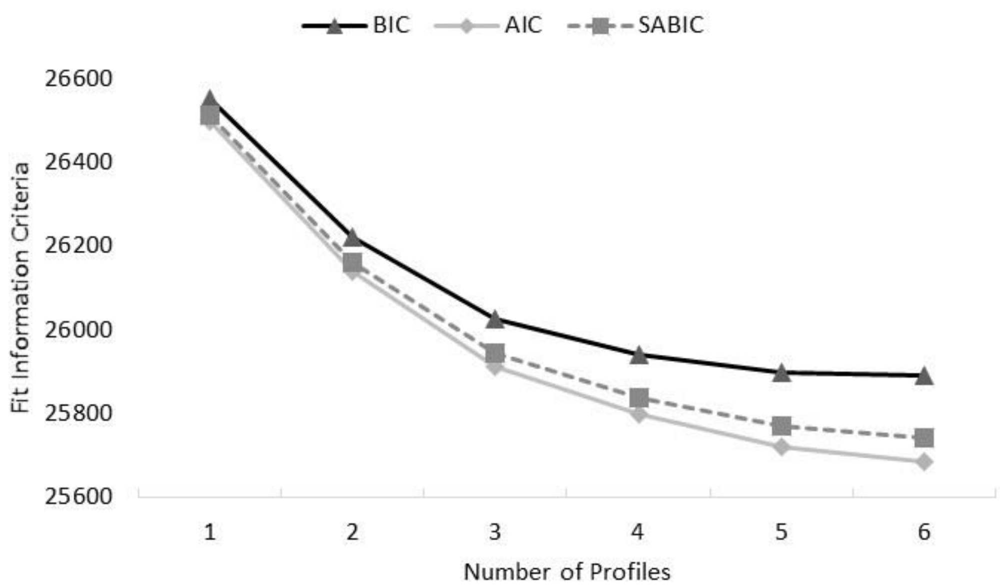

Figure 3-1. Elbow plot of information criterion values from latent profile analysis. Estimates were generated in Mplus assuming equal variances and covariances fixed to zero. The point at which the information criterion value becomes stable, even if more profiles are added, is used as indication of the profile solution best fitting the data. AIC = Akaike's information criterion; BIC = Bayesian information criterion; SABIC = sample size adjusted BIC.

Latent Lifestyle Profile Characterization

The four-profile solution contained one large profile which was labeled “slightly unhealthy lifestyle” (*n* = 449, 76.2%) and three smaller profiles which were labeled “highly physically active lifestyle” (*n* = 36, 6.1%), “socially inactive lifestyle” (*n* = 23, 3.9%), and “health-promoting lifestyle” (*n* = 81, 13.8%). Table 3-2 shows the average classification probabilities per profile as well as the proportions per profile. The distributions within the four profiles largely seemed normal according to histograms. The exception was physical activity, for which the median was consistently lower than the mean, suggesting the presence of high outliers. Also, many older adults in the profile characterized by low social activity had a score of zero.

Table 3-2

Average classification probabilities of latent profiles.

			Probability			
Latent profile	*n*	Proportion	Profile 1	Profile 2	Profile 3	Profile 4
Profile 1	36	.061	.853	.141	.000	.006
Profile 2	449	.762	.008	.964	.000	.028
Profile 3	23	.039	.000	.000	1.000	.000
Profile 4	81	.138	.006	.197	.000	.797

Individuals assigned to the latent profile “highly physically active lifestyle” on average estimated their weekly duration of moderately exhausting physical activity to exceed ten hours (*M* = 876.08 minutes, *SE* = 99.10), according to the estimates obtained from LPA in Mplus. Individuals in the latent profile “socially inactive lifestyle” scored very low on the social activity scale with a mean of *M* = 6.26 (*SE* = 2.07). Membership of the profile “health-promoting lifestyle” was found in individuals demonstrating the lowest alcohol consumption score (*M* = 2.35, *SE* = 0.20), highest fruit and vegetable intake (*M* = 4.83, *SE* = 0.30), and highest social activity score (*M* = 86.47, *SE* = 1.44). The majority of older adults was assigned to the profile “slightly unhealthy lifestyle”. This profile was the one closest to average compared to the other three profiles, which were all characterized by markedly pronounced mean values in specific lifestyle indicators (see Figure 3-2 for the distribution of lifestyle z-scores by latent profile). Slightly lower values were observed for, for example, fruit and vegetable consumption (M = 1.98, SE = 0.08) and physical activity (M = 141.76, SE = 11.61).

To investigate differences between the latent profiles, ANOVAs and chi-square tests were performed on data after multiple imputation (see Table 3-3). Significant differences by lifestyle indicators were found for fruit and vegetable intake, physical activity and social activity with large effect sizes between $\eta_p^2 = .53$ and $\eta_p^2 = .65$. The latent lifestyle profiles did not differ significantly by the remaining lifestyle indicators which were marked by very low effect sizes of $\eta_p^2 = .01$ and $\eta_p^2 < .01$. In terms of covariate associations, there appeared to be more females in the "health-promoting lifestyle" profile (small effect size with Cramer's V = .15) and more nonintenders in the "slightly unhealthy lifestyle" profile (large effect size with Cramer's V = .12). The MMSE score was lower in the "socially inactive lifestyle" profile (small effect size with $\eta_p^2 = .01$), and body fat percentage appeared to be lowest in the "highly physically active lifestyle" profile (small effect size with $\eta_p^2 = .01$). There was a large effect size with Cramer's V = .14 for self-reported health, indicating that in the "slightly unhealthy lifestyle" and the "socially inactive lifestyle" profiles there were lower proportions of individuals rating their health as excellent or very good. No significant differences were observed for the other covariates (see Table 3-3).

Adjusted Risk Ratios for Study Dropout

Dropout differed significantly between latent profiles with a moderate effect size (Cramer's V = .21). The dropout rate was highest in the "socially inactive lifestyle" profile with 81.0% (n = 17). The proportions of participants lost to follow-up were similar in the other three profiles: 30.6% (n = 11) in the "highly physically active lifestyle" profile, 28.7%

(*n* = 125) in the "slightly unhealthy lifestyle" profile, and 29.5% (*n* = 23) in the "health-promoting lifestyle" profile (see Table 3-4).

In the full multivariate Poisson regression model, the direct effects on study dropout were only slightly decreased in magnitude compared to the total effects (see Table 3-4). "Socially inactive" older adults were at a 1.91-fold risk to drop out compared to the mean of all latent profiles (adjusted risk ratio [aRR] = 1.91). On the contrary, older adults in the profile "slightly unhealthy lifestyle" had a by 27% reduced risk to drop out compared to the mean of all profiles (aRR = 0.73). Less good/poor subjective health (aRR = 1.48) and very good/ excellent subjective health (aRR = 0.67) significantly predicted study dropout. There were no significant effects on dropout for the latent profiles "highly physically active lifestyle" (aRR = 0.94) and "health-promoting lifestyle" (aRR = 0.76) or for satisfaction with life (aRR = 1.08).

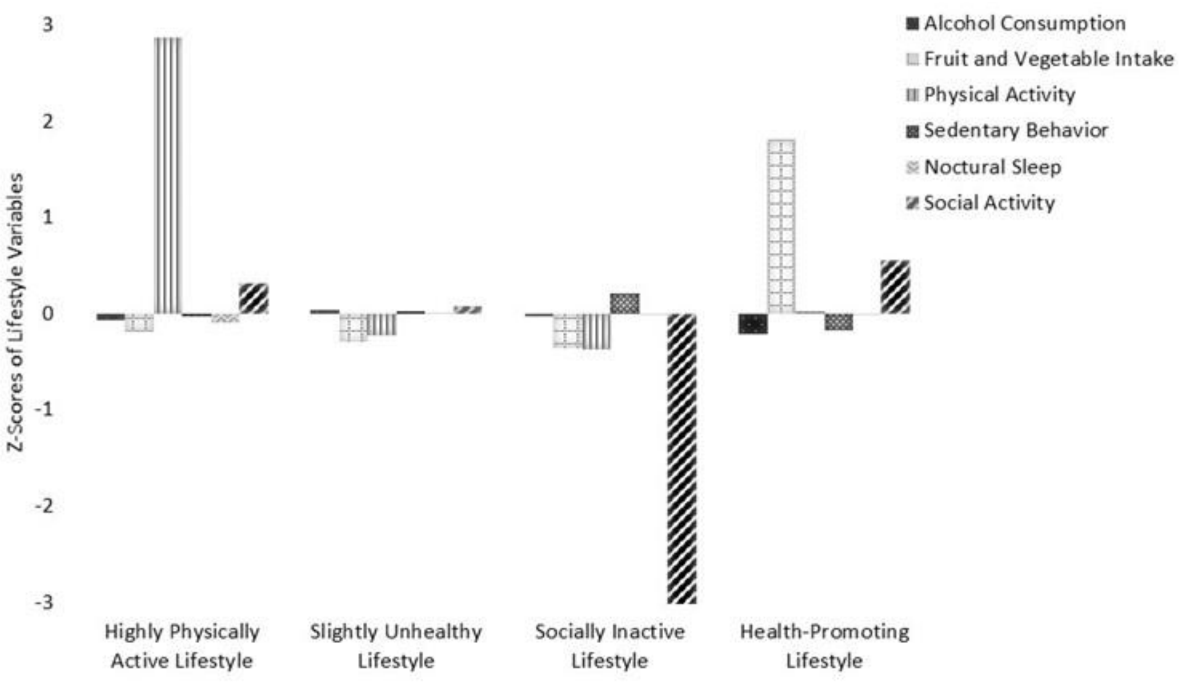

Figure 3-2. Pooled mean lifestyle z-scores by latent profile. Mean social activity z-score in the latent profile "socially inactive lifestyle" is -3.90.

Table 3-3

Latent profile characteristics.

Characteristic	Latent lifestyle profiles: Highly physically active lifestyle	Slightly unhealthy lifestyle	Socially inactive lifestyle	Health-promoting lifestyle	p	V	η_p^2
Categorical (n, %)							
Female	18 (50.0)	244 (54.3)	12 (52.2)	61 (75.3)	.004	.15	
Married	25 (69.4)	331 (73.7)	16 (69.6)	51 (63.0)	.545	.07	
Subjective health					.005	.14	
Very good/excellent	17 (47.2)	102 (22.7)	2 (8.7)	26 (32.1)			
Good	16 (44.4)	275 (61.2)	12 (52.2)	43 (53.1)			
Less good/poor	3 (8.3)	72 (16.0)	9 (39.1)	12 (16.0)			
Stage of change					.016	.12	
Nonintender	5 (13.9)	141 (31.4)	2 (8.7)	17 (21.0)			
Intender	6 (16.7)	95 (21.2)	8 (34.8)	17 (21.0)			
Actor	25 (69.4)	213 (47.4)	13 (56.5)	47 (58.0)			
Continuous (M, SD)							
Age	69.41 (3.40)	70.06 (3.31)	69.87 (3.73)	70.24 (3.19)	.645		<.01
Income	1833.68 (667.47)	1826.85 (592.37)	1652.54 (598.37)	1918.52 (657.84)	.325		<.01
Satisfaction with life	5.57 (1.20)	5.52 (1.03)	5.08 (1.11)	5.73 (0.86)	.152		.01
Body fat percentage	30.84 (8.45)	33.27 (7.78)	34.25 (8.79)	35.28 (8.26)	.033		.01
MMSE score	28.39 (1.23)	28.31 (1.54)	27.10 (6.05)	28.27 (1.66)	.037		.01
Technology commitment	3.63 (0.73)	3.43 (0.66)	3.11 (0.57)	3.49 (0.61)	.140		.02
Alcohol consumption	2.56 (1.63)	2.73 (1.60)	2.63 (1.72)	2.33 (1.61)	.183		.01
Fruit and vegetable intake	2.16 (1.08)	2.00 (0.91)	1.92 (1.14)	4.93 (1.10)	<.001		.53
Physical activity	856.67 (261.28)	134.59 (144.52)	110.43 (133.83)	200.57 (148.34)	.002		.55
Sedentary behavior	927.89 (542.06)	951.57 (450.46)	1035.48 (492.32)	860.35 (408.05)	.722		.01
Nocturnal sleep	419.50 (70.58)	425.51 (64.07)	424.96 (54.45)	424.56 (66.06)	1		<.01
Social activity	83.03 (14.52)	78.56 (10.53)	6.26 (10.15)	87.25 (10.94)	<.001		.65

Note. Estimates after multiple imputation reported. Pooled frequencies are rounded. p = p-value of between-group difference, V = Cramer's V, η_p^2 = partial eta-squared.

Table 3-4

Dropout numbers and proportions and adjusted risk ratios (aRR) for study dropout.

	Dropped out of the study		Model 1		Model 2		Model 3		Full Model[a]	
Predictor	*n*	Proportion	aRR	*p*	aRR	*p*	aRR	*p*	aRR	*p*
Latent lifestyle profile										
Highly physically active lifestyle	11	30.6	0.80	.265					0.94	.771
Slightly unhealthy lifestyle	125	28.7	0.75	.004					0.73	.001
Socially inactive lifestyle	17	81.0	2.13	<.001					1.91	<.001
Health-promoting lifestyle	23	29.5	0.77	.089					0.76	.064
Subjective health										
Very good/excellent	28	19.4			0.64	<.001			0.67	.002
Good	105	31.2			1.01	.878			1.01	.948
Less good/poor	43	47.8			1.54	<.001			1.48	<.001
Satisfaction with life							0.95	.445	1.08	.238

Note. Results are reported for $n = 517$ individuals, excluding individuals with a Mini Mental State Examination score of less than 25. Proportions represent the percentage of individuals who dropped out within groups. Adjusted risk ratios for dropping out of the study were derived using Poisson regression with robust standard errors. Total effects are shown in models 1 to 3, direct effects are shown in the full model. Adjusted risk ratios for latent profiles and subjective health indicate the relative deviation from the unweighted average of all categories.

[a] The full model was adjusted for group assignment, stage of change, technology commitment, body fat percentage and cognitive state.

Discussion

In this study, the presence of latent lifestyle profiles was investigated based on theory and the profile membership effect on study dropout from a web-based physical activity intervention trial targeted at older adults was analyzed. Four latent lifestyle profiles emerged. Membership of the "socially inactive lifestyle" profile was associated with an elevated risk of dropping out while individuals in the "slightly unhealthy lifestyle" profile as well as those reporting a very good to excellent subjective general health had a decreased risk of study dropout.

Social engagement has recently been found to be inversely associated with multiple health-risk behaviors and low levels of subjective wellbeing in older adults (Luo et al., 2020). These findings can be translated to our results which are corroborated by a longitudinal study reporting that high comorbidity and low social activity scores predict attrition in older adults with, as well as without, mild cognitive impairment (Facal et al., 2016). Furthermore, a large physical activity intervention trial in older adults found social participation to modify the long-term intervention effect on major mobility disability (Corbett et al., 2018).

Researchers investigating the association between health and lifestyle behaviors in older adults in their first decade after retirement found risky alcohol consumption and disturbed sleep duration to be associated with impaired self-rated health and life satisfaction (Storeng et al., 2020). In our study, alcohol consumption and sleep did not significantly differ between lifestyle profiles. However, with a large effect size the results indicated that self-rated general health differed by latent lifestyle profile: A higher proportion of self-rated healthy older adults was observed in the health-promoting and highly physically active lifestyle compared to the socially inactive and slightly unhealthy lifestyle. Yet, there is conflicting research on this association, as an LPA of physical activity, sleep and sedentary time did not find significant differences between latent lifestyle profiles regarding self-rated health status (Full et al., 2019). Also, satisfaction with life did not seem to play a role in neither lifestyle profile, nor in study dropout.

About 75% of this study population was assigned to the same profile, which, however, was not particularly characterized by a specific lifestyle pattern. A study from the US analyzing latent lifestyle behavior patterns also reports that the largest identified profile was not characterized by particular differences from the other profiles but rather represented the moderate version of included lifestyle indicators (Davis et al., 2019). One explanation for our finding is that the study sample was very homogenous with only a quarter of participants differing from the mean. A further explanation might be that the expected occurrence of health-related behavior clusters was only present in a specific subset of study participants rather than the whole study population. It was hypothesized that a combination of risk behaviors would be associated with an increased chance of study dropout. However, within LPA no such lifestyle profile was identified. The profile labeled "slightly unhealthy lifestyle" even showed decreased dropout chances compared to the mean of all profiles. An objective for subsequent research would be to investigate the intervention effect on a possible transition from one latent lifestyle profile to another. It could be assumed that the change of one behavior (in this case, physical activity) leads to increases in the likelihood of changing another behavior. Such a mechanism is known as coaction in the literature (Johnson et al., 2014) and could impact the transition in latent lifestyle profiles as well.

Study Strengths and Limitations

One of the strengths of this study was the sample size, as research recommends a sample size of at least 500 individuals for latent analyses (Finch & Bronk, 2011). Additionally, a variety of lifestyle parameters were assessed, enabling the inclusion of more than five indicators in latent analyses, as suggested by Wurpts and Geiser (2014). A set of covariates was included in univariate as well as multivariate analyses, showing that the latent lifestyle profile was associated with study dropout which was independent of other relevant factors such as self-rated health, technology commitment and stage of behavior change.

Yet, not every determinant known to be associated with physical activity participation has been considered in these analyses. For example, it has been shown that the built environment has an impact on physical activity and related psychosocial mechanisms in older adults (Fleig et al., 2016). Furthermore, it should be acknowledged that the socially inactive lifestyle and highly physically active lifestyle profiles both consisted of a low frequency of individuals. Profiles containing less than 5% are argued to potentially result from extracting too many profiles due to outliers rather than valid subgroups (Hipp & Bauer, 2006). Even though the BIC and BLRT have been shown to reliably identify the best model in sample sizes of n = 500 or above (Nylund et al., 2007), and the posterior probability was larger than .800, significant numbers should not overshadow interpretability and prior knowledge. However, the socially inactive lifestyle profile was regarded as a qualitatively valuable addition to the results. One methodological limitation, however, is that no measure of precision could be provided for the adjusted risk ratios, as no procedure in RStudio could be identified which allows for pooling confidence intervals for adjusted risk ratios obtained in Poisson regression.

The analyzed dataset contains a large ratio of initially active older adults (Meyer et al., 2019; Muellmann et al., 2019). In the study enrollment procedure, older adults were not screened for need of a physical activity intervention as the intervention study was not specifically targeted towards initially inactive older adults. Therefore, it is likely that rather healthy, active, and interested older adults were included in the study. This supports the notion that the study population was homogenous in terms of health indicators, such as lifestyle, self-rated health, and willingness to participate in a physical activity program. There is still a need for further research to discuss the association between enrollment criteria and homogeneity of the study sample, as well as how enrollment criteria might affect study dropout. Former analyses confirmed that the study participants were prone to overestimating their levels of physical activity (Meyer et al., 2019). Thus, the validity of self-reported physical activity is discussed in general (Lee et al., 2011; Panter et al., 2012), and the data presented in this study require careful interpretation. Nevertheless, this study focused on lifestyle based on individual perceptions, deliberately choosing self-reported over objectively measured physical activity and sedentary behavior data to ensure consistency in measurement and interpretability of the latent profile construct.

Study Implications

Latent lifestyle profiles consisting of a combination of health behaviors were found to be present in the analyzed sample and to significantly predict study dropout from a twelve-week web-based physical activity intervention trial. Future physical activity behavior change interventions should emphasize the relevance of social participation and foster the formation of sustained social networks. However, the question remains as to whether this is relevant for everyone or only those who are socially isolated. This study’s findings suggest that it is important to identify at-risk populations and to address specific barriers rather than to provide general recommendations. Such an identification of at risk-populations could be realized by using baseline data on health indicators (e.g., health-related lifestyle, self-rated health). However, there is a need for additional experimental and longitudinal research on strategies which can be utilized to identify dropout-vulnerable groups and address specific barriers.

Accounting for the correlation between health-related lifestyle and study participation in physical activity interventions is recommended for future behavior change trials. The mechanisms underlying the observed associations, as well as how to prevent study dropout in dropout-vulnerable groups, should be further investigated in future research.

Declarations

Trial Registration

This study was registered at the German Clinical Trials Register (Identifier DRKS00010052).

Conflicts of Interest

We have no known conflict of interest to disclose.

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Authors' Contributions

Tiara Ratz served as lead for writing—original draft, writing—review & editing, and formal analysis, and served in a supporting role for data curation. Claudia Voelcker–Rehage served as lead for funding acquisition, conceptualization, project administration, resources, and supervision, and contributed equally to methodology and writing—review & editing. Claudia R. Pischke contributed equally to writing—review & editing, conceptualization, funding acquisition, investigation, methodology, project administration, resources, and supervision. Saskia Muellmann contributed equally to writing—review & editing, and served in a supporting role for conceptualization, investigation, methodology, project administration, and supervision. Manuela Peters contributed equally to writing—review & editing, and served in a supporting role for investigation, project administration, and supervision. Sonia Lippke served as lead for conceptualization, contributed equally to investigation, methodology, funding acquisition, project administration, supervision, and writing—review & editing, and served in a supporting role for writing—original draft.

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Chapter 4. Distinct Physical Activity and Sedentary Behavior Trajectories in Older Adults during Participation in a Physical Activity Intervention: A Latent Class Growth Analysis

Ratz, T., Pischke, C. R., Voelcker-Rehage, C., & Lippke, S. (2022). Distinct physical activity and sedentary behavior trajectories in older adults during participation in a physical activity intervention: A latent class growth analysis. *European Review of Aging and Physical Activity, 19*, 1. https://doi.org/10.1186/s11556-021-00281-x

Abstract

Background: This study aimed to identify latent moderate-to-vigorous intensity physical activity (MVPA) and sedentary behavior (SB) trajectories in older adults participating in a randomized intervention trial and to explore associations with baseline social-cognitive predictors. **Methods:** Data were assessed at baseline (T0, participants were inactive or had recently become active), after a ten-week physical activity intervention (T1), and a second 24-week intervention phase (T2). Latent class growth analysis was used on accelerometer-assessed weekly MVPA and daily SB, respectively (n = 215 eligible participants). Activity changes within trajectory classes and baseline social-cognitive predictor differences between trajectory classes were analyzed. **Results:** A “stable insufficient MVPA” (n = 197, p for difference in MVPA level at T0 and T2 ($p_{T0\text{-}T2}$) = .789, effect size (Cohen’s d) = .03) and a “stable high MVPA” trajectory (n = 18, $p_{T0\text{-}T2}$ = .137, d = .39), as well as a “slightly decreasing high SB” (n = 63, p for difference in SB ($p_{T0\text{-}T2}$) = .022, d = .36) and a “slightly increasing moderate SB” trajectory (n = 152, $p_{T0\text{-}T2}$ = .019, d = .27) emerged. Belonging to the “stable high MVPA” trajectory was associated with higher action planning levels compared to the “stable insufficient MVPA” trajectory (M = 5.46 versus 4.40, d = .50). Belonging to the “decreasing high SB” trajectory was associated with higher action self-efficacy levels compared to the “increasing moderate SB” trajectory (M = 5.27 versus 4.72, d = .33). **Conclusions:** Change occurred heterogeneously in latent (not directly observed) subgroups, with significant positive trajectories only observed in the highly sedentary.

Trial registration: German Registry of Clinical Trials, DRKS00016073, Registered 10 January 2019.

Keywords: exercise, sitting, trajectory, mixture modeling, health behavior change

Introduction

If every inactive individual became as physically active as recommended by the World Health Organization (World Health Organization, 2010), this elimination of physical inactivity could lead to a gain of roughly half a year in life expectancy and to a reduction of all-cause mortality by 7.5% in Germany (Lee et al., 2012). Yet, Germany belonged to the five countries with the largest increases in the prevalence of physical inactivity from 2001 to 2016 among 65 countries worldwide (Guthold et al., 2018). The prevalence of sedentary behavior (SB) among Germans increased from 50% to 53.7% between the years 2002 and 2017 (López-Valenciano et al., 2020). The uptake of physical activity even in old age is beneficial to health (Hamer et al., 2014; Sperlich et al., 2020). Physical activity interventions targeting older adults have been shown to be effective (Kwan et al., 2020; Sansano-Nadal et al., 2019), but evidence regarding their effectiveness for behavior change maintenance is inconclusive (Stockwell et al., 2019; Zubala et al., 2017). This article's objective is to investigate *heterogenous change trajectories* in German older adults as a potential cause for inconclusive results regarding behavior change maintenance.

In health behavior change interventions, not every individual might follow the same change trajectory and the utility of particular behavior change techniques may vary across individuals. Theories such as the transtheoretical model (Prochaska et al., 1992; Prochaska & DiClemente, 1983) and the health action process approach (HAPA) (Schwarzer, 2008; Schwarzer et al., 2011) suggest that individuals with differing preconditions or characteristics move differently through stages of behavior change. These characteristics are known as *social-cognitive predictors*. Participants of physical activity intervention studies may consist of *subgroups*. For example, some may experience an increasing change trajectory and demonstrate high levels of maintenance self-efficacy (the perceived capacity of overcoming barriers to perform physical activity) or action planning (the ability to identify cues relating to when, where and how to be physically active). Others might keep their physical activity level constant or become less active and possibly demonstrate low levels of action self-efficacy (the perceived capacity of performing physical activity) (Zhang et al., 2019). Examining the existence of *latent* (i.e., unobserved) change trajectory subgroups could improve the understanding of heterogeneous behavior change occurring in interventions. This knowledge may assist future studies in more targeted recruitment efforts and in identifying required components of behavior change interventions required to improve effectiveness and maintenance, especially for subgroups belonging to low or decreasing physical activity trajectories (Pedersen et al., 2019).

The analysis technique *longitudinal mixture modeling* aims to identify latent homogenous subgroups with similar change or trajectory patterns (Berlin et al., 2014; van der Nest et al., 2020). Studies adopting this so-called person-centered approach show that individuals differ in their *long-term* physical activity change trajectories (Dishman et al., 2010; Lounassalo et al., 2019; Pettee Gabriel et al., 2019). That is, over the course of multiple years, distinct change trajectories can be observed. However, the evidence on differing *short-term* physical activity change trajectories in intervention studies spanning over a maximum of one year is scarce. A study on physical activity promotion in the office-setting over the course of one year identified three distinct change trajectories: a decrease from a high level, a stable moderate level, and an increase from a low level of physical activity (Pedersen et al., 2019). A recent study on young adults participating in a physical activity intervention trial reports four distinct trajectories over the course of one year, which they labeled normal/decrease, normal/increase, normal/rapid increase, and high/increase (Lampousi et al., 2021). In the early 2010's, researchers applied health behavior change theories to the prediction of latent physical activity trajectories and found associations with social-cognitive predictors (Dishman et al., 2010; Sweet et al., 2011). To the best of the authors' knowledge, an investigation of latent short-term trajectories and associations with social-cognitive predictors in physical activity interventions was not performed for older adults, yet.

The objective of this study was to investigate latent moderate-to-vigorous intensity physical activity (MVPA) trajectories and associated factors in older adults participating in a nine-month physical activity intervention trial. The secondary objective of this study was to identify and investigate latent change trajectories regarding SB. It was hypothesized that 1) there are *latent subgroups* which differ by their MVPA and SB *trajectory* over the course of the nine-month intervention period; and 2) latent *class membership* is associated with baseline social-cognitive predictors for physical activity behavior change.

Methods

Procedure and Participants

This study belongs to the Physical Activity and Health Equity: Primary Prevention for Healthy Ageing (AEQUIPA) research network (Forberger et al., 2017) and uses data obtained in the second study phase of the PROMOTE study (Pischke et al., 2020). The primary aim of the second study phase was to compare the effectiveness of two different physical activity intervention modalities (web- vs. print-based intervention) on changes in physical activity among older adults. Ethical approval for the study was obtained on July 3rd, 2018, from the Medical Association in Bremen. All study participants were fully informed about the study and provided informed consent. The data analyses reported in this paper are of exploratory nature.

A random sample of n = 3,492 adults aged 60 years and above residing in a large city in Northwestern Germany, was drawn from the residents' registration office and contacted via mail. Additionally, press releases and public talks were used to recruit study participants who could contact the study team and choose to participate after receiving further information on the study. Older adults were included if they provided informed consent and were either inactive or recently active, meaning that they had not been sufficiently physically active for more than one year. Individuals with time and health constraints, as well as those not owning a mobile phone or not being able to use it regularly, were excluded. Further details on eligibility criteria were published in the study protocol (Pischke et al., 2020). The final baseline study sample consisted of *n* = 242 individuals (see Additional file 1 (Appendix) for the flow chart). Eligible older adults were randomly assigned to a print-based intervention or a web-based intervention during a telephone interview with a study nurse. The intervention groups were assigned to alternating weeks. During the telephone interview, participants were randomized by having them choose a weekly appointment while being blinded to the intervention condition assigned to the chosen week.

The print-based intervention group (*n* = 113) received physical activity recommendations based on the World Health Organization guidelines (World Health Organization, 2010), a printed physical activity diary and a brochure with age-appropriate exercises. The web-based intervention group (*n* = 129) received the same program in the form of a website and an android smartphone-application. The interventions were designed to promote self-monitoring of physical activity, were based on health behavior change theory (Bandura, 1991; Schwarzer et al., 2011) and incorporated behavior change techniques (Michie et al., 2013). A subgroup (30% of the web-based intervention group, *n* = 38) additionally received an activity tracker (Fitbit Zip, Fitbit, San Francisco, USA), substituting the subjective self-monitoring intervention with an objective self-monitoring component. The interventions were mainly home-based but included face-to-face components. In the first intervention phase, each individual was offered to participate in ten weekly group sessions, covering 60 minutes of exercise training and 30 minutes of health education. During the second intervention phase lasting six months, four health education group sessions were offered. Older adults were not blinded to group affiliation once they were assigned to it, and neither were investigators.

Participants completed a self-administered questionnaire and wore an accelerometer for seven days during waking hours on their right hip at baseline (T0, January to April 2019), at the first follow-up (T1, April to July 2019) and at the second follow-up (T2, September 2019 to January 2020). A cognitive screening test was conducted during the first weekly group session. The dropout rate after T2 completion was 33.9% (see Additional file 1 (Appendix) for numbers per intervention group regarding loss to follow-up).

Measures

Physical Activity and Sedentary Behavior

Physical activity and sitting time were assessed using accelerometers (GT3X+, ActiGraph, Pensacola, USA). Valid days were identified using the Actilife 6.8.0 software and R 3.6.1. Valid days were defined as having at least eight hours of valid wear-time, with no definition of maximum wear-time. Participants needed to have at least three valid days, including one weekend day. Total minutes of light (0-2,690 counts per minute), moderate (2,691-6,166 counts per minute), and vigorous physical activity (6,167-9,642 counts per minute), as well as sitting time (0-99 counts per minute) were derived by using one-second epochs for the categorization of counts per minute according to cut-off values considering the vector magnitude (Sasaki et al., 2011). Minutes per week were derived by dividing the total minutes spent in light, moderate or vigorous physical activity, respectively, by the days the accelerometer was worn and then multiplying the value by seven. Additionally, MVPA was derived using 2,691-9,642 counts per minute and counting only the time spent in bouts of at least ten minutes according to the physical activity recommendations given in the study. The average minutes spent with SB per day were calculated by dividing the total minutes spent with SB in bouts of at least 30 minutes by the number of the days the accelerometer was worn.

Baseline Measures

Demographic information, including sex and date of birth, was assessed as reported in the study protocol (Pischke et al., 2020). The International Standard of Education (ISCED) (Statistisches Bundesamt, 2016) was used to code an educational status score, which was dichotomized into “low/moderate” and “high” educational status. Need-weighted income per capita was derived according to the German Microcensus (Boehle, 2015) and tertiled into “low”, “moderate” and “high”. Employment was dichotomized into “fully retired” and “other than fully retired”. Body mass index was calculated from self-reported weight and height and dichotomized into “underweight/normal weight” and “overweight/obese”. Cognitive screening was administered using the Mini Mental State Examination 2 - brief version (MMSE-2-BV) (Folstein et al., 2010a, 2010b).

Social-cognitive predictors for engaging in the recommended levels of physical activity were assessed using validated measures as reported in the study protocol (Pischke et al., 2020) and published results of the first study phase (Ratz et al., 2020). Older adults were asked to rate respective statements on Likert-scales from 1 (= totally disagree) to 7 (= totally agree). For example, intention was assessed with one item which consisted of the statement “I intend to engage in moderate endurance training for at least 150 minutes per week (not tiring, slightly sweating) and strength and balance training twice a week.” Furthermore, the following social-cognitive predictors were assessed: positive and negative outcome expectations (two items, respectively), self-efficacy (one item measuring action self-efficacy, two items measuring maintenance self-efficacy, and two items measuring recovery self-efficacy), action and coping planning (three items, respectively), and habit strength (two items). A detailed description of the assessed social-cognitive predictors has been provided in previous publications (Ratz et al., 2020). Mean scores were aggregated per social-cognitive predictor (Cronbach's alpha ranged from .72 to .96) except for negative outcome expectations (Cronbach's alpha = .65).

Outcome and Analysis Sample Definition

The primary outcome was minutes of MVPA in bouts of at least ten minutes per week, in line with the physical activity recommendations given to study participants. The secondary outcome was the average minutes spent sitting in at least 30-minute bouts per day. Subgroups were not defined a-priori as this study's objective was the identification of unobserved subgroups in terms of latent trajectories (not directly observed). However, based on a systematic review on physical activity trajectories (Lounassalo et al., 2019), the maximum possible number of trajectory classes was set to six, possibly including the following categories: increasing, stable high, stable sufficient, decreasing moderate, stable insufficient, and decreasing low physical activity. Older adults were included in the analysis sample if they were cognitively healthy (MMSE-2-BV ≥ 13) and had existing values for the primary outcome on at least one timepoint. The inclusion value for the MMSE-2-BV was ≥ 15 originally, but it was changed to ≥ 13 based on previous studies (Finger et al., 2014; Van de Winckel et al., 2020). The analyzed sample (*n* = 215, see Additional file 1 (Appendix)) did not differ from the recruited sample, which was tested considering a set of socio-demographic, psychological and health-related characteristics (effect sizes were all < .20).

Statistical Analyses

Latent Trajectory Analysis Strategy

Finite mixture models were calculated using an expectation-maximization algorithm for maximum likelihood estimation of model parameters in Mplus version 8.4 (Muthén & Muthén, 2017). The best-fitting latent trajectory model was determined following the steps proposed by van der Nest et al. (2020), and the recommendations provided by the Guidelines for Reporting on Latent Trajectory Studies (GRoLTS) Checklist (van de Schoot et al., 2017). The slopes for the three timepoints were set to be 0, 2.66 and 8.35 – according to the median months the measurements lay apart. Latent class growth analysis (LCGA) was conducted to identify latent MVPA and SB trajectories, respectively. LCGA for SB was adjusted for wear-time, as the amount of time the accelerometer was worn correlated with SB.

Investigated fit indices to determine LCGA model fit were the Bayesian Information Criterion (BIC), Akaike's Information Criterion (AIC), and sample size adjusted BIC (SABIC). An elbow plot of fit indices was created to visualize the point at which the decrease in fit indices became less in extent. The *p*-values of the Lo-Mendell-Rubin adjusted likelihood ratio test (LMR-LRT) and the bootstrapped likelihood ratio test (BLRT) were considered to determine whether the respective model provided a better fit than the model with one class less. To validate the selected model, the minimum class size was evaluated with the cut-off at 5% and an entropy approaching 1.000 indicating higher certainty. The selected model was critically reviewed for clinical and theoretical plausibility and meaningfulness. The models were rerun using different starting values to ensure that the estimation did not result in local maxima. The dataset including the categorical variable indicating the latent trajectory class was exported to SPSS 26 (IBM Corp. Released 2019. IBM SPSS Statistics for Windows, Version 26.0. Armonk, NY: IBM Corp) to investigate changes within latent trajectory classes and associations with baseline social-cognitive predictors.

Changes by Timepoint and Activity-Type and Associations with Social-Cognitive Predictors

To analyze whether a linear function could describe the data well, changes within the latent trajectory classes between the three timepoints were investigated using paired samples t-tests. Changes in MVPA, SB, light, moderate and vigorous physical activity were analyzed. Associations of latent trajectory class membership with social-cognitive predictors were investigated with independent samples t-tests. An investigation of social-cognitive indicators as predictors of latent trajectory class membership in logistic regression was deliberately omitted. Calculating odds ratios for social-cognitive indicators would provide information on the likelihood of belonging to a latent change trajectory given a one-unit increase in a social-cognitive indicator. Comparing the mean values between groups and testing for statistical significance between them, on the other hand, was deemed more relevant and more suitable with the aims of this manuscript.

Missing Data Handling and Interpretation of Effects

Finite mixture models were calculated using full maximum likelihood estimation, as missing value analysis indicated that the precondition of data missing at random was met. For analyses of changes within latent trajectory classes and associations with baseline variables, missing values were imputed using multiple imputation with predictive mean matching. For imputed data, the mean and standard error (*SE*) were calculated to report continuous indicators by latent trajectory classes for each assessment timepoint. Cohen's *d* was calculated as a measure of effect size based on the pooled mean differences and standard deviations and Cramer's *V* was averaged across all datasets. Analyses were carried out under the intention-to-treat assumption. We would like to stress that the analyses of this exploratory study did not serve to evaluate intervention effectiveness by comparing web- and print-based components of the physical activity intervention. These primary outcomes are reported elsewhere (Pischke et al., 2021). As primary outcome analyses showed that there was no substantial difference between the intervention groups in terms of effects on MVPA or SB (Pischke et al., 2021), the analyses reported here considered all intervention groups as a joint group under the assumption of no differential effect present between the intervention groups.

Results

Latent Trajectory Analyses

Physical Activity

The estimated mean minutes of MVPA per week in the initial growth curve model assuming just one latent change trajectory were $M_{T0} = 83.45$, $M_{T1} = 81.90$ and $M_{T2} = 75.13$. This slight downward trend in MVPA in the whole study sample has been discussed elsewhere (Pischke et al., 2021).

A spaghetti plot displaying individual MVPA trajectories indicated some degree of variation in the trajectories, meaning the presence of underlying subgroups (data not shown). Therefore, the investigation of latent subgroups using LCGA was continued. The elbow plot (Additional file 2 (Appendix)) suggested that the decrease in fit indices became less steep after two classes. The BLRT *p*-value, however, remained significant. This phenomenon has been previously reported to occur in empirical studies (van de Schoot et al., 2017). However, the smallest class contained less than 5% in the three-class solution. Thus, no further classes were added to the model. Based on the elbow plot (Additional file 2 (Appendix)), an entropy of .949 (Table 4-1) and high classification probabilities (Table 4-2), the two-class model was chosen.

The sample was comprised of a “stable insufficient MVPA” class and a “stable high MVPA” class. The “stable insufficient MVPA” class consisted of $n = 197$ individuals with weekly mean (*SE*) MVPA = 59.23 (5.30) minutes at T0, 67.05 (6.34) minutes at T1 and 61.55 (7.64) minutes at T2. There was little, nonsignificant variation in MVPA between the timepoints and effect sizes were very small ($p_{T0\text{-}T1} = .239$, $d = .09$; $p_{T1\text{-}T2} = .517$, $d = .06$; $p_{T0\text{-}T2} = .789$, $d = .03$). Thus, the trajectory was labeled as stable over time at an insufficient level.

The “stable high MVPA” class consisted of $n = 18$ individuals with weekly mean (*SE*) MVPA = 348.55 (39.01) minutes at T0, 254.78 (50.36) minutes at T1 and 245.29 (49.13) minutes at T2. The mean difference between T0 and T2 seemed large with roughly 100 minutes, yet the difference did not reach statistical significance and effect sizes were small (p_{T0-T1} = .127, *d* = .38; p_{T0-T2} = .137, *d* = .39). There was also no difference between T1 and T2 (p_{T1-T2} = .876, *d* = .04). Thus, the trajectory was labeled as stable over time at a high level.

Sedentary Behavior

LCGA suggested that there were two latent subgroups regarding trajectories in SB. The entropy for the two-class solution was slightly below .800, but the elbow plot (Additional file 3 (Appendix)), likelihood ratio tests (Table 4-1) and classification probabilities (Table 4-2) provided sufficient evidence to select the two-class model.

The sample consisted of a “slightly decreasing high SB” class and a “slightly increasing moderate SB” class. There were *n* = 63 individuals in the “slightly decreasing high SB” class, with daily mean (*SE*) SB = 475.67 (9.68) minutes at T0, 444.28 (16.02) minutes at T1 and 437.09 (17.19) minutes at T2. Thus, at all timepoints the mean sedentary time was exceeding seven hours per day. Yet, there was a statistically significant mean decrease in SB between T0 and T2 by roughly 39 minutes with a small effect size (p_{T0-T2} = .022, *d* = .36). There was no significant difference between T0 and T1 (p_{T0-T1} = .073, *d* = .24) or between T1 and T2 (p_{T1-T2} = .720, *d* = .05).

The “slightly increasing moderate SB” class consisted of *n* = 152 individuals with daily mean (*SE*) SB = 263.38 (5.93) minutes at T0, 256.82 (9.82) minutes at T1 and 284.58 (8.56) minutes at T2. At each timepoint, the mean sedentary time equaled between four and five hours per day. SB did not differ significantly between T0 and T1 (p_{T0-T1} = .523, *d* = .08). It increased significantly by roughly 21 minutes between T0 and T2 (p_{T0-T2} = .019, *d* = .27). The difference between T1 and T2 was also significant (p_{T1-T2} = .008, *d* = .30). Yet, effect sizes were small.

Table 4-1

Fit statistics for the latent class growth analysis of change trajectories.

Class	Log likelihood	AIC	BIC	SABIC	Entropy	smallest class %	LMR-LRT	BLRT
Moderate-to-vigorous physical activity								
1	-2949	5908	5925	5909	1	-	-	-
2	**-2872**	**5760**	**5787**	**5762**	**0.949**	**8.37**	**.071**	**<.001**
3	-2846	5715	5752	5717	0.885	4.19	.741	<.001
Sedentary behavior								
1	-2963	5941	5965	5943	1	-	-	-
2	**-2907**	**5836**	**5873**	**5838**	**0.787**	**29.30**	**0.005**	**<.001**
3	-2877	5785	5836	5788	0.804	3.26	0.273	<.001

Note. Classes were consecutively added until the best fitting model was identified. The selected models are in boldface. AIC = Akaike's information criterion; BIC = Bayesian information criterion; SABIC = sample size adjusted BIC; LMR-LRT = *p*-value of Lo-Mendell-Rubin adjusted likelihood ratio test; BLRT = *p*-value of bootstrap likelihood ratio test.

Table 4-2

Numbers, proportions and posterior probabilities for the latent trajectory classes.

		Posterior Probabilities	
Latent Trajectory Class	Number (%)	Class 1	Class 2
Moderate-to-vigorous physical activity			
Stable high MVPA	18 (8.37)	0.924	0.076
Stable insufficient MVPA	197 (91.63)	0.007	0.993
Sedentary behavior			
Increasing moderate SB	152 (70.70)	0.965	0.035
Decreasing high SB	63 (29.30)	0.119	0.881

Note. MVPA = moderate-to-vigorous physical activity; SB = sedentary behavior.

Changes Within Latent Trajectories

In the "stable high MVPA" class, light physical activity seemed to increase at T1, but the difference in minutes was not significant by T2, with a moderate effect size ($p_{T0\text{-}T2}$=.590, *d*=.59). There were no significant changes in SB, moderate or vigorous physical activity. These findings support the assumption of stability across the study period (see Figure 4-1 A).

In the “stable insufficient MVPA” class, light physical activity increased significantly between T0 and T1 ($p_{T0\text{-}T1}$=.007, *d*=.22), but this effect did not last until T2 ($p_{T0\text{-}T2}$=.995, *d*=.001). The same pattern was observed for moderate physical activity. There were no significant changes in vigorous physical activity or SB. Thus, this trajectory was mainly characterized by stability over time (see Figure 4-1 B).

In the “slightly increasing moderate SB” class, there were no significant changes in MVPA, light, or vigorous physical activity, and very small effect sizes were noted. Moderate physical activity seemed to increase slightly at T1 but decreased significantly at T2 ($p_{T0\text{-}T1}$=.363, *d*=.08; $p_{T1\text{-}T2}$=.011, *d*=.30; $p_{T0\text{-}T2}$=.035, *d*=.23). This finding supported the assumption that this subgroup experienced a negative trajectory over time (see Figure 4-1 C).

For the “slightly decreasing high SB” class, findings supported the positive trajectory (see Figure 4-1 D). With a small effect size, MVPA increased significantly at T1, but the difference did not remain significant at T2 ($p_{T0\text{-}T1}$=.024, *d*=.32; $p_{T0\text{-}T2}$=.120, *d*=.26). However, significant increases between T0 and T2 were observed in moderate ($p_{T0\text{-}T2}$=.011, *d*=.43), and vigorous physical activity ($p_{T0\text{-}T2}$=.003, *d*=.49).

Associations Between Social-Cognitive Predictors and Latent Trajectories

Individuals in the “stable high MVPA” class reported significantly higher baseline levels of action planning compared to the “stable insufficient MVPA” class (*d* = .50). None of the other included baseline social-cognitive predictors were significantly associated with latent MVPA change trajectory class membership (see Table 4-3). Only action self-efficacy significantly predicted membership of the SB trajectories, with the “slightly decreasing high SB” class reporting higher baseline levels of action self-efficacy compared to the “slightly increasing moderate SB” class (*d* = .33, see Table 4-3).

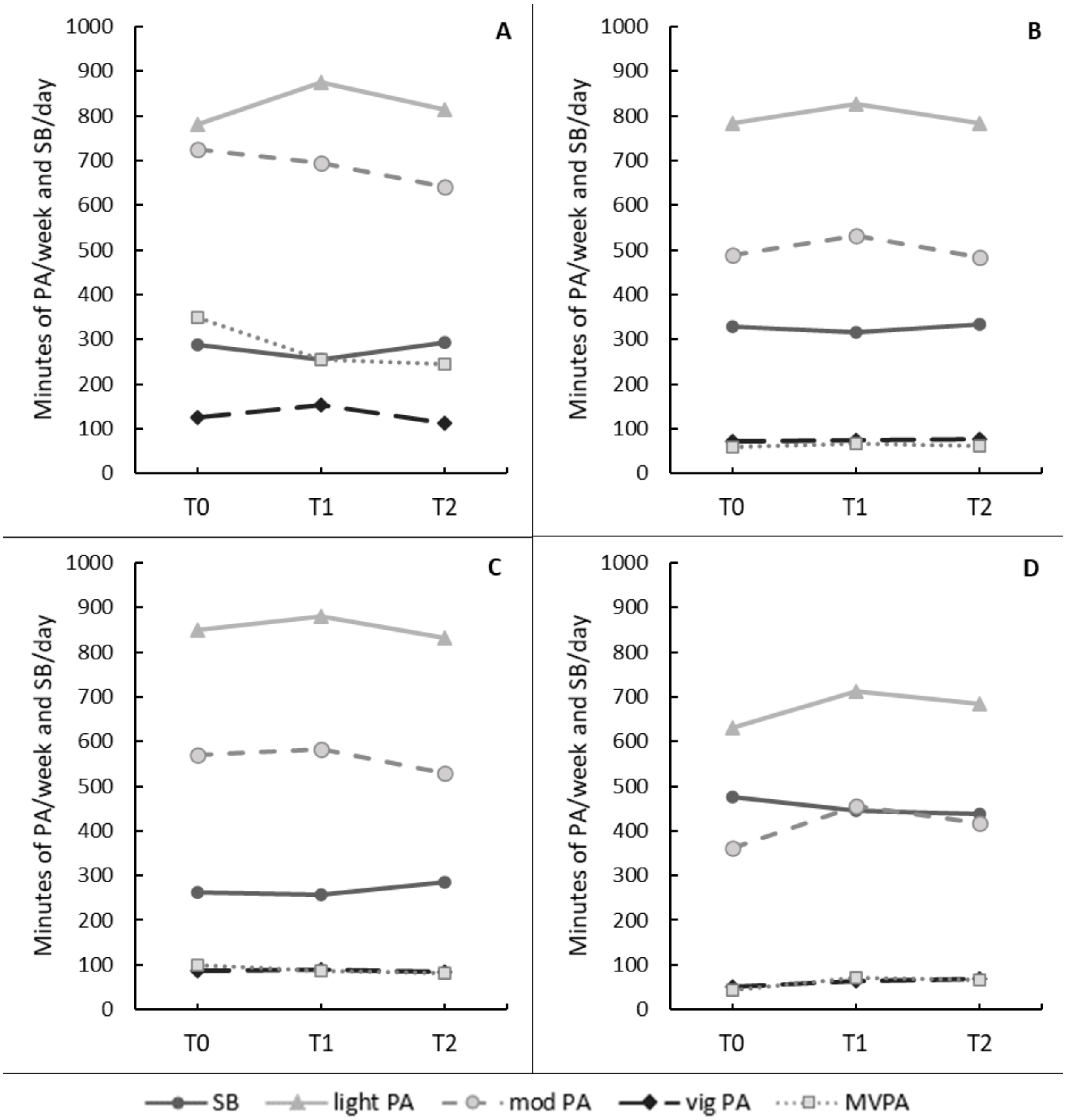

Figure 4-1. Changes in physical activity and sedentary behavior over the study period by latent trajectory class. Moderate-to-vigorous physical activity (MVPA) is lower than moderate and vigorous physical activity combined, because for MVPA calculation, only the time spent in bouts of at least ten minutes was counted. SB = sedentary behavior per day in 30-minute bouts; PA = physical activity; mod = moderate; vig = vigorous; MVPA = moderate-to-vigorous physical activity in ten-minute bouts. A. “stable high MVPA” class. B. “stable insufficient MVPA” class. C. “slightly increasing moderate SB” class. D. “slightly decreasing high SB” class.

Table 4-3

Associations of latent physical activity and sedentary behavior trajectory classes with baseline characteristics.

	Total	Moderate-to-vigorous physical activity			Sedentary Behavior		
	Total	Stable high	Stable insuff.		Increasing mod.	Decreasing high	
	n = 215	*n* = 18	*n* = 197	Effect size	*n* = 152	*n* = 63	Effect size
Social-cognitive predictors: *M* (*SE*)				**Cohen's *d***			**Cohen's *d***
POE	6.24 (0.08)	6.28 (0.24)	6.24 (0.09)	.03	6.20 (0.10)	6.35 (0.14)	.13
NOE - Takes too long	3.72 (0.18)	3.42 (0.55)	3.75 (0.19)	.16	3.67 (0.20)	3.84 (0.30)	.08
NOE - Too costly	2.38 (0.15)	1.92 (0.41)	2.42 (0.17)	.26	2.42 (0.19)	2.28 (0.27)	.08
Intention	5.25 (0.12)	5.29 (0.42)	5.25 (0.12)	.03	5.28 (0.14)	5.19 (0.21)	.05
Action S-E	4.88 (0.12)	5.11 (0.29)	4.86 (0.12)	.15	**4.72 (0.14)**	**5.27 (0.22)**	**.33**
Maintenance S-E	4.55 (0.10)	4.83 (0.31)	4.52 (0.11)	.20	4.48 (0.13)	4.71 (0.18)	.15
Recovery S-E	4.77 (0.11)	4.47 (0.33)	4.80 (0.12)	.21	4.65 (0.13)	5.08 (0.20)	.27
Action planning	4.49 (0.15)	**5.46 (0.43)**	**4.40 (0.16)**	**.50**	4.50 (0.17)	4.46 (0.19)	.02
Coping planning	3.81 (0.13)	4.03 (0.44)	3.79 (0.14)	.12	3.82 (0.16)	3.78 (0.25)	.02
Habit strength	3.03 (0.14)	3.92 (0.51)	2.94 (0.15)	.47	3.08 (0.17)	2.90 (0.26)	.08
Continuous Covariates: *M* (*SE*)							
Age	68.44 (0.36)	67.50 (1.08)	68.53 (0.38)	.19	68.14 (0.41)	69.17 (0.72)	.20
Wear-time (min/day)	832.23 (5.60)	816.26 (13.70)	833.69 (5.98)	.21	**814.89 (6.54)**	**874.06 (8.86)**	**.76**
Categorical covariates: *n* (%)				**Cramer's *V***			**Cramer's *V***
Sex, female	143 (66.5)	10 (55.6)	133 (67.5)	.07	**109 (71.7)**	**34 (54.0)**	**.17**
ISCED, high	118 (54.9)	12 (66.7)	106 (53.8)	.07	86 (56.6)	32 (50.8)	.05
Fully retired	124 (57.7)	9 (50.0)	115 (58.4)	.05	82 (53.9)	42 (66.7)	.12
Income				.09			.14
moderate	80 (37.2)	8 (44.4)	74 (37.6)		52 (34.2)	29 (46.0)	
high	72 (33.5)	7 (38.9)	63 (32.0)		56 (36.8)	15 (23.8)	
Overweight/obese	123 (57.2)	9 (50.0)	113 (57.4)	.04	**77 (50.7)**	**45 (71.4)**	**.19**
Group, web-based	121 (56.3)	12 (66.7)	109 (55.3)	.06	86 (56.6)	35 (55.6)	.01

Note. Associations were tested on a univariate level using Chi²- or T-tests. Statistically significant differences (p-value <.05) are in bold.
insuff. = insufficient; ISCED = International Standard of Education; *M* (*SE*) = mean (standard error); mod = moderate; NOE = negative outcome expectations; POE = positive outcome expectations; S-E = self-efficacy.
Reference categories: male sex; low/moderate ISCED; other than fully retired; low income; underweight/normal weight; print-based intervention group.

Discussion

The analyses reported in this study were conducted assuming that change in MVPA and SB occurs heterogeneously in a nine-month intervention study for the promotion of physical activity targeted at older adults. In line with this hypothesis, latent subgroups could be identified for each behavior: a “stable high MVPA” and a “stable insufficient MVPA” trajectory, as well as a “slightly decreasing high SB” and a “slightly increasing moderate SB” trajectory. Effect sizes were mostly small but might be clinically relevant. Contrary to the second hypothesis, social-cognitive variables at baseline were not significantly associated with the latent trajectories, except for action planning and action self-efficacy.

Individuals who were consistently sufficiently physically active during the study period had higher levels of action planning at baseline. Individuals who changed their behavior towards decreasing SB and increasing MVPA during the study period had higher levels of action self-efficacy at baseline. This finding matches theory (Schwarzer, 2008; Schwarzer et al., 2011; Zhang et al., 2019). Generally, physical activity interventions have been reported to be effective in older adults (Grande et al., 2020; Kwan et al., 2020; Sansano-Nadal et al., 2019; Zubala et al., 2017). This study’s assumption was that such a positive trajectory might be masked for the whole study sample in primary outcome analyses (Pischke et al., 2021), but that it might occur in distinct latent subgroups. This phenomenon could be shown for individuals identified as belonging to the “slightly decreasing high SB” class, as they could significantly decrease sitting by approximately 40 minutes and increase moderate and vigorous physical activity by approximately 60 and 20 minutes, respectively. The latent MVPA trajectories, however, were both stable, as there was no significant change by the end of the study period, even though short-term increases may have been present at T1.

A potential explanation for the decline in physical activity after T1 could be the concurrent end of weekly group meetings which were only part of the first intervention phase. A longitudinal study has shown that exercise group membership predicted long-term physical activity engagement in older adults (Stevens & Cruwys, 2020). In a group-based randomized trial targeting older adults, exercise adherence was found to be associated with perceived group cohesion (Beauchamp et al., 2021). Several other findings reported here are corroborated by former studies. For example, a high prevalence of sitting for more than four hours per day is in line with previous research on SB in older adults (Harvey et al., 2013). According to a systematic review on physical activity trajectories during the life course, the inactivity trajectories seem to be more stable than the activity trajectories (Lounassalo et al., 2019) which highlights the difficulty of promoting a behavior change in old age. This finding might also explain why an "increasing MVPA" trajectory could not be identified in this sample of rather inactive older adults. In fact, there was a low proportion of very active older adults already at baseline. As the inclusion criteria allowed older adults to be either initially inactive or recently active, it is possible that the highly active individuals had started to be sufficiently physically active within the past year and were successful in turning their activity into a habit during the study period.

Study Strengths and Limitations

The existence of three assessment points enabled the calculation of statistically advanced longitudinal mixture models, granting novel insights into latent trajectories in a physical activity intervention study targeted at older adults. The physical activity data were objectively assessed, which is an advantage over many studies assessing self-reported data.

However, the results of this study need to be interpreted carefully, acknowledging various methodological weaknesses. Only linear trends could be investigated as there were only three timepoints to be considered. Alternative functions, such as quadratic or cubic functions, might have fit the data better, but testing this was not possible as this requires more than three timepoints. Another major limitation of this study is its sample size and a missing power calculation, as the analyses presented here are only exploratory in nature. This has been described as a common concern in LCGA performed on intervention data (Lampousi et al., 2021). Even though the selected finite mixture models converged successfully and provided theoretically and statistically plausible as well as meaningful results, the subgroup analyses suffered from low cell counts. It could therefore be argued that assessing the clinical utility of the observed model structure requires a larger sample size, even though it met the criterium of a minimum sample size of 200 participants (Kim, 2012). Also, this study used a classify-analyze approach, which is criticized for not addressing the classification uncertainty when analyzing predictors of latent class membership (Bray et al., 2015). However, this criticism was based on cross-sectional and not developmental latent class analysis. Adding the social-cognitive predictors to the LCGA model, which is the suggested solution for cross-sectional latent class analyses, was not feasible as any missing baseline values in social-cognitive predictors would have significantly reduced the analysis sample size.

It also needs to be noted that assessments took place in different seasons: T0 and T2 in fall/winter months and T1 in spring/summer months. The physical activity level of German community-dwelling older adults has been shown to be influenced by weather conditions on a cross-sectional level (Albrecht et al., 2020; Klenk et al., 2012). However, this association may have less relevance in longitudinal within-person changes. In latent class growth models testing within-person changes in steps in a sample of women, for example, seasonal changes did not seem to account for a practically significant difference (Kim et al., 2016). A recent study of German young and middle-aged adults has shown high variability in wearable usage between individuals, but non-significant main effects for weather conditions, suggesting that these external factors may be less relevant than individual factors in continuous use (Hendker et al., 2020). Yet, it cannot be ruled out that increases in physical activity level at T1 were related to the assessment having taken place in spring or summer. Furthermore, social-cognitive predictors of behavior change were only assessed for physical activity as this was the intervention trial's target behavior, but not for sitting. Associations between SB trajectory class and social-cognitive predictors might, therefore, have been weak. These analyses could also be limited because they did not include the latest definition of MVPA according to the World Health Organization. They recently adapted their physical activity recommendations with the most significant modification being the removal of the ten-minute bout benchmark for MVPA (Segar et al., 2020; World Health Organization, 2020). This study, however, considered MVPA in bouts of at least ten minutes as the primary outcome variable, as this was the recommendation given to study participants. Lastly, the external validity of this study is limited in terms of the results stemming from a selected sample of older adults matching the rather strict inclusion criteria, that is, access to mobile technology, and absence of cognitive or health impairments.

Conclusions

Identifying short-term physical activity trajectories in intervention studies can provide valuable insights on the change patterns in heterogenous study samples. Knowledge regarding baseline social-cognitive indicators associated with latent MVPA and SB trajectories (such as action self-efficacy and action planning) could be used in future research to better address the needs of particular latent trajectory classes. Theories on health behavior change may be utilized to identify distinct needs. However, research in this field is scarce and the advanced analyses require longitudinal studies with high methodological quality, including sufficiently long follow-up periods, repeated measurements, and a sufficient sample size.

This study contributes to the research field of longitudinal health behavior change by suggesting a more tailored approach. Promoting an increasing change trajectory in initially inactive older adults requires large efforts and calls for targeted intervention strategies.

Findings propose that certain characteristics may serve as predictors of latent change trajectories and that researching this further can unveil distinct needs of inactive individuals who are likely to belong to stable or decreasing change trajectories.

Declarations

Ethics Approval and Consent to Participate

Ethical approval for this study was obtained on July 3rd, 2018 from the Medical Association in Bremen (RA/RE-635). All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. All study participants were fully informed about the study and provided informed consent.

Consent for Publication

Not applicable.

Availability of Data and Materials

The dataset analyzed during the current study is not publicly available as it contains indirect identifiers and consent for its publication could not be obtained, as this would violate confidentiality. The analyzed dataset is available from the corresponding author on reasonable request.

Competing Interests

The authors declare that they have no competing interests.

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Authors' Contributions

SL, CRP and CVR acquired funding, conceived the study, and commented on previous versions of the manuscript. The first draft of the manuscript was written by TR. TR analyzed and interpreted the data. All authors designed the work and supervised data acquisition. All authors read and approved the final manuscript.

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Chapter 5. Discussion

5.1. Summary of Results

This section serves to synthesize the findings obtained within the three studies building this thesis. This is achieved, firstly, by summarizing the studies' methodology, and secondly, by relating their essential results to the initially proposed research gaps regarding heterogeneity in digital, theory-based physical activity interventions (see chapter 1.3.). This will allow for discussing the results jointly in the context of the applied methodological and theoretical framework (see chapter 1.4.), and finally answering the proposed research questions (see chapter 1.5.).

Summary of the Studies' Methodology

Study 1 (chapter 2) aimed to analyze whether two tailored web-based physical activity interventions targeting community-dwelling older adults could successfully foster changes in social-cognitive predictors of physical activity and whether these increases in turn led to movement between the stages of physical activity behavior change. Data of the PROMOTE I study were analyzed, which was a randomized controlled intervention trial comparing two web-based physical activity interventions (subjective self-monitoring versus both subjective and objective self-monitoring) to a delayed intervention control group. The study took place between 2015 and 2018 in five urban or suburban communities with low community readiness for physical activity programs. It was targeted at community-dwelling older adults aged between 65 and 75 years and included n = 589 study participants in total. Changes in social-cognitive predictors were firstly analyzed using repeated measures mixed-effects ANOVA. Potential social-cognitive predictor mediations between intervention group and stage of change movement regarding endurance and muscle strengthening training were then investigated using the PROCESS macro for ordinal least squares regression with dependent mediators.

Study 2 (chapter 3) aimed to investigate selective study dropout from digital physical activity interventions targeted at older adults by analyzing whether the initial health-related lifestyle could predict early study discontinuation. In this study, data from the PROMOTE I study were analyzed using latent profile analysis to identify latent patterns in lifestyle-related indicators at baseline. The analyses were conducted under the assumption that the study population consisted of underlying unobserved subgroups, the membership of which could be identified based on patterns in observed continuously scaled indicators of health-related behaviors. Six baseline measures for health-related lifestyle were considered, including physical activity, sedentary behavior, fruit and vegetable intake, alcohol consumption, nocturnal sleep duration, and social activity. After the potential latent lifestyle profiles were identified, Poisson regression models with robust standard errors were run to retrieve adjusted risk ratios for study dropout. Additionally, it was investigated whether the self-rated health status and satisfaction with life at baseline were independently associated with dropout risk.

Study 3 (chapter 4) aimed to investigate the existence of latent change trajectories regarding weekly physical activity and daily sedentary behavior in a randomized intervention trial targeted at older adults. This study analyzed data obtained in the PROMOTE II study, a cross-over intervention trial that compared adapted versions of the digital PROMOTE I interventions to a newly developed print-based version. In total, $n = 242$ older adults aged at least 60 years who had not been regularly sufficiently active during the past year were recruited. The nine-month intervention phase of the study took place during 2019. The existence of latent trajectories for physical activity and sedentary behavior, respectively, was investigated in $n = 215$ eligible individuals using latent class growth analysis FIML estimation. The changes within the latent trajectory classes were analyzed using paired-samples t-tests. Furthermore, the baseline social-cognitive predictor profile was compared between the distinct latent trajectory classes using independent-samples t-tests.

Summary of Main Findings

Please see Table 5-1 for an overview of the proposed research questions, the corresponding hypotheses, and the study results for study 1 (chapter 2), study 2 (chapter 3), and study 3 (chapter 4). In addition, Figure 5-1 depicts a summary of findings and conclusions, which was integrated into the researched areas of heterogeneity in the health behavior change process, as explained in chapter 1.5. and depicted in Figure 1-1. In this section, the results will be summarized by referring to the areas of heterogeneity proposed in the figure.

Table 5-1

Synthesis of research questions, hypotheses and results.

Study	Research Questions	Hypotheses	Results
Study 1	To what extent is there a mediating effect of social-cognitive changes on physical activity stages of change resulting from web-based interventions in community-dwelling older adults?	(1) there is a significantly elevated direct effect of the two intervention groups on physical activity stage of change in comparison to the delayed intervention control group (2) this effect is more pronounced in the intervention group additionally monitoring their physical activity objectively in comparison to the intervention group only monitoring their physical activity subjectively (3) the intervention effect can be explained by a positive change in social-cognitive predictors for physical activity	(1) As hypothesized, IG1 had direct effects on stage of change movement in endurance training (relative direct effect: b_{IG1} = 0.44 [*se* = 0.15, [0.15, 0.73]]), and both interventions had direct effects on stage movement regarding strength training (relative direct effect: b_{IG1} = 1.02 [*se* = 0.16, [0.71, 1.33]]; b_{IG2} = 1.24 [*se* = 0.16, [0.92, 1.56]]). (2) Hypothesis rejected: IG2 was not found to outperform IG1 because coefficient confidence intervals of the two intervention groups overlapped. (3) As hypothesized, IG1 showed a direct intervention effect on task/action self-efficacy and a decrease in negative outcome expectancies while IG2 showed a direct positive intervention effect on intention. Social-cognitive predictors did not fully explain intervention effects. Only the observed effect on endurance stage of change in IG2 was fully mediated by a change in intention.
Study 2	To what extent does the initial health-	(1) older adults can be categorized into latent	(1) As hypothesized, latent lifestyle profiles were identified. The four-profile solution

	related lifestyle profile predict study dropout from a web-based physical activity intervention trial targeting older adults?	subgroups based on similar patterns in lifestyle-related behaviors (2) a combination of risk behaviors is associated with an increased risk of study dropout (3) good self-rated health and satisfaction with life are associated with a decreased risk of study dropout	consisted of “slightly unhealthy” (*n* = 449, 76.2%), “highly physically active” (*n* = 36, 6.1%), “socially inactive” (*n* = 23, 3.9%), and “health-promoting” (*n* = 81, 13.8%) lifestyle. (2) Hypothesis rejected: Older adults in the profile “slightly unhealthy lifestyle” had a by 27% reduced risk to drop out (aRR = 0.73). Instead, “socially inactive” older adults were at a 1.91-fold increased risk compared to the mean of all profiles (aRR = 1.91). (3) As hypothesized, less good/poor subjective health significantly predicted a higher study dropout risk (aRR = 1.48). However, satisfaction with life did not.
Study 3	To what extent do older adults participating in a physical activity intervention trial experience different short-term activity-related change trajectories and are these associated with baseline social-cognitive predictors of physical activity behavior change?	(1) there are latent subgroups which differ by their moderate-to-vigorous intensity physical activity and sedentary behavior change trajectory over the course of the nine-month intervention period (2) latent trajectory membership is associated with baseline social-cognitive predictors for physical activity behavior change	(1) As hypothesized, two latent subgroups could be identified for each behavior: a “stable high MVPA” (*n* = 197, 91.6%) and a “stable insufficient MVPA” (*n* = 18, 8.4%) trajectory, as well as a “slightly decreasing high SB” (*n* = 63, 29.3%) and a “slightly increasing moderate SB” (*n* = 152, 70.7%) trajectory. (2) As hypothesized, individuals in the “stable high MVPA” class reported significantly higher baseline levels of action planning compared to the “stable insufficient MVPA” class (*d* = .50). The “slightly decreasing high SB” class reported higher baseline levels of action/task self-efficacy compared to the “slightly increasing moderate SB” class (*d* = .33). However, no other associations with social-cognitive predictors were observed.

Note. aRR = adjusted Risk Ratio; IG1 = intervention group 1 (subjective self-monitoring physical activity intervention); IG2 = intervention group 2 (subjective and objective self-monitoring physical activity intervention); MVPA = moderate-to-vigorous intensity physical activity; SB = sedentary behavior.

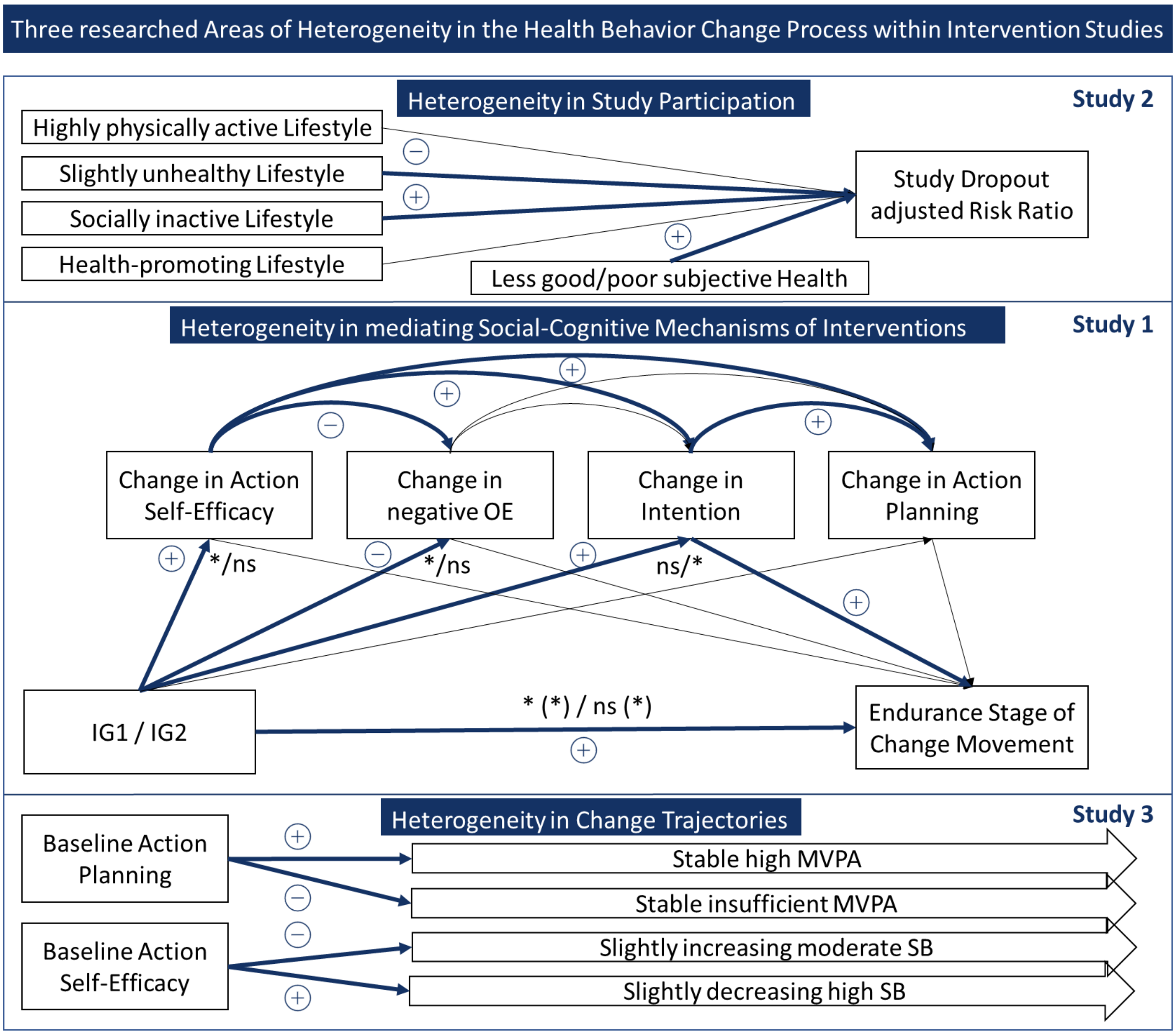

Figure 5-1. Summary of findings and conclusions. See chapter 2 for more detail on study 1, chapter 3 for more detail on study 2, and chapter 4 for more detail on study 3. Statistically significant associations are indicated as blue arrows in bolt. Plus- and minus-icons indicate the direction of the association. For social-cognitive mechanisms of change (study 1), the value in front of the slash stands for intervention group 1, the value after the slash stands for intervention group 2. IG1 = intervention group 1 (subjective self-monitoring); IG2 = intervention group 2 (subjective and objective self-monitoring); MVPA = moderate-to-vigorous intensity physical activity; OE = outcome expectancies; SB = sedentary behavior. * statistically significant; ns statistically non-significant.

Heterogeneity in Social-Cognitive Mechanisms within Interventions

The first barrier to physical activity behavior change, that has been identified as a relevant research gap for this thesis (chapter 1.3.), is the complexity of the behavior change process. Study 1 (chapter 2) and study 3 (chapter 4) both included hypotheses of social-cognitive predictors of health behavior change playing a role in how individuals change over time while participating in a physical activity intervention trial. Thus, both studies aimed to better understand how the knowledge of social-cognitive predictors and their role in the change process can be utilized for future intervention development and tailoring to individual needs.

In line with the first hypothesis of study 1, the intervention group with subjective self-monitoring experienced a significant effect on the stage of change regarding endurance training, compared to the waitlisted control group as reference. Even though inclusion of potential social-cognitive mediators explained a significant share of the total effect (in line with hypothesis 3), the direct effect stayed significant, revealing an independent intervention effect. The significant total effect experienced in the intervention group with subjective and objective self-monitoring, however, was not replicated for the independent effect. This means that the observed intervention effect on endurance training stage of change could be fully attributed to the intervention-related changes in social-cognitive predictors. In contrast to endurance training, both intervention groups experienced significant total and direct effects on stage of change movement regarding muscle strengthening training. The finding that the effects observed in the two intervention groups were not significantly different from each other with regards to stage of change movement was not in line with the second hypothesis. However, study 1 showed that the stage-tailored, theory-based interventions had differing effects on the stages of change regarding the two targeted physical activity behaviors. Analyses revealed that the different modes of delivery brought about different changes in social-cognitive predictors, which was also reflected by heterogenous dependent mediator relationships. While older adults in the subjective self-monitoring only intervention group experienced significant increases in action/task self-efficacy and significant decreases in negative outcome expectancies, older adults in the intervention group with objective and subjective self-monitoring experienced significant increases in intention.

In fact, several dependent mediator relationships were detected in study 1, with a change in action/task self-efficacy being related with changes in intention, negative outcome expectancies and action planning. Additionally, a change in intention was associated with a change in action planning. Via these mechanisms, the effect experienced in the intervention group with objective and subjective monitoring on stage of change for endurance training was completely mediated by changes in intention. Significant chain mediations including action/ task self-efficacy, intention and action planning were found, with the stage of change for strength training being significantly associated with changes in action planning for both intervention groups. Thus, both interventions were successful in bringing about movement in stages of physical activity behavior change but there was heterogeneity in, firstly, intervention mechanisms via different social-cognitive predictors and, secondly, effectiveness based on baseline stages of change. It became clear that the two web-based interventions addressed baseline stages of change differently and brought about change via differing social-cognitive mechanisms.

However, while study 1 (chapter 2) included a psychological measure as the outcome being predicted by social-cognitive factors, study 3 (chapter 4) aimed to research whether baseline social-cognitive factors were associated with latent trajectory class membership. Contrary to the second hypothesis in study 3, latent trajectory class membership seemed to be mainly independent from baseline social-cognitive predictors of physical activity behavior change. Physical activity and sedentary behavior latent trajectory classes merely differed by one social-cognitive predictor, respectively. The stable high physical activity trajectory class showed higher action planning levels compared to the stable insufficient physical activity trajectory class. In contrast, the decreasing high sedentary behavior trajectory class showed higher action self-efficacy levels compared to the increasing moderate sedentary behavior trajectory class. Thus, physical activity behavior change could still be related to psychological predictors, yet associations were rather scarce in comparison to study 1, which was completely embedded in the HAPA framework.

Heterogeneity in Baseline Profile and Change Trajectory Class Memberships

Study 1 concentrated on heterogeneity in intervention mechanisms within pre-defined groups (i.e., stages of change and intervention groups) and thus mainly tackled the first barrier identified in chapter 1.3. of this thesis: the complexity of the behavior change process. Study 2 (chapter 3) and study 3 (chapter 4), in turn, both focused on identifying and investigating unobserved subgroups within the study sample populations. By these means, they contributed to researching barrier 3 (distinct subgroups are widely unknown), while simultaneously aiming to also enhance the understanding of the behavior change process in physical activity interventions for older adults.

The latent profile analysis in study 2 revealed that there were four distinct lifestyle profiles underlying the whole study population. In particular, the following four latent lifestyle profiles were identified: slightly unhealthy lifestyle, highly physically active lifestyle, socially inactive lifestyle, and health-promoting lifestyle. The majority of older adults (about three out of four individuals) were categorized into the slightly unhealthy lifestyle profile based on posterior probabilities, whereas the other three lifestyle profiles presented a lower cell count. The main interpretation of this finding was that the PROMOTE I study had recruited a very homogenous group of older adults in terms of initial lifestyle profile. A lower proportion of participants, however, clearly differed from the population mean and could be attributed to latent subgroups which significantly differed from each other by lifestyle patterns.

The results obtained in study 3, using latent class growth analysis, were in line with the first hypothesis and suggested the existence of two distinct latent change trajectory classes regarding both physical activity and sedentary behavior, respectively. With regard to weekly moderate-to-vigorous intensity physical activity, both identified latent trajectories were labeled as stable, meaning that there were no significant changes in moderate-to-vigorous intensity physical activity over the course of the nine-month study period. Instead, the majority of older adults was found to belong to a trajectory class that was insufficiently active at both baseline and follow-up. Only a small proportion of older adults were already sufficiently active at baseline and kept that level stable over time. In contrast, latent class growth analysis identified two latent sedentary behavior trajectory classes that were characterized by significant changes over time. While older adults who were moderately sedentary at baseline experienced a slight increase in sitting time, those individuals who were found to belong the highly sedentary class were the only ones experiencing positive changes over time in terms of decreasing sitting time and increasing physical activity levels.

Heterogeneity in Continued Study Participation

The second barrier, that was identified as a research gap in chapter 1.3. of this thesis, addresses low intervention adherence and high study dropout. Combined with barrier 3, the need to learn more about the needs of distinct subgroups, investigating these two corresponded to exploring the heterogeneity in continued study participation.

As hypothesized in study 2 (chapter 3), the membership regarding latent lifestyle profiles was significantly associated with the adjusted risk ratio of dropping out of the study prior to the twelve-week follow-up assessment. Older adults belonging to the socially inactive lifestyle profile had a 1.91-fold increased risk to drop out of the study compared to the mean of all profiles. Older adults rating their health as less good or poor had a 1.48-fold increased risk of dropping out. Protective factors, in contrast, were belonging to the slightly unhealthy lifestyle profile (dropout risk reduced by 27%) and rating the general health as very good or excellent (dropout risk reduced by 33%). It was not initially hypothesized that individuals with an unhealthy lifestyle would be at a decreased risk of study dropout. Rather, the expectation was that the association would go into the same direction as was seen with poor self-rated health being associated with higher dropout-risk. However, the fact that social participation seems to play a role in dropout risk may also allow for the assumption that individuals belonging to the largest lifestyle profile did not drop out of the study because they felt in the right place, being among equals.

5.2. Comparison with Prior Research

This thesis presents a range of findings, some of which are corroborated by previous studies and some of which are not in line with a-priori hypotheses. In this section, the results presented in this thesis will be discussed in the context of prior research, considering parallels, discrepancies, and potential explanations of unexpected findings. These discussions are organized by the main themes running along in this thesis, that is: 1) success and failure of digital interventions for older adults, 2) the discrepancy between theory and practice, 3) latent subgroups within physical activity interventions, 4) social-cognitive factors as predictors of group membership, and 5) health-related determinants of study/ physical activity participation.

Success and Failure of Digital Interventions for Older Adults

Both PROMOTE studies did not lead to significant increases in moderate-to-vigorous intensity physical activity, nor could they significantly reduce sedentary behavior in primary analyses (Muellmann et al., 2019; Pischke et al., 2021). Study 3 of this thesis confirmed primary results regarding moderate-to-vigorous intensity physical activity by identifying two stable latent physical activity trajectories over the nine-month study period of PROMOTE II. When considering promising intervention features, this may be surprising as the interventions strongly encouraged self-monitoring, which has been identified as one of the central BCT’s being associated with increases in motivational physical activity constructs (Knittle et al., 2018). Interventions including monitoring and feedback have also been found to yield positive effects on exercise adherence in older adults, even though the systematic review synthesizing the results acknowledged the studies' high risk of bias (Room et al., 2017). In addition to web-based and print-based material, the PROMOTE studies included face-to-face features, which also have been shown to produce larger effect sizes regarding motivational constructs, compared to interventions without face-to-face components as reported by a meta-analysis (Knittle et al., 2018). Yet, it needs to be noted that this meta-analysis included participants of any age group. A qualitative study investigating the barriers and facilitators of an internet-based physical activity intervention incorporating pedometers supports the utility of activity trackers for raising the awareness of time spent sitting and for encouraging goal setting regarding daily steps (McCormack et al., 2019). Yet again, this study included a sample of over 80% being female with a wide age range of 24 to 68 years. An umbrella review including 11 reviews of 182 eHealth and mHealth physical activity and sedentary behavior interventions reports that 59% of them were effective and listed having a theoretical foundation among the determinants of effective interventions (Fiedler et al., 2020). The authors even cited one systematic review which suggested the particular effectiveness of basing interventions on social cognitive theory, but this review focused on physical activity eHealth interventions targeting school, college or university students (McIntosh et al., 2017). A meta-analysis which included five wearable activity-tracker interventions for inactive or sedentary community-dwelling older adults found that the interventions significantly increased step count and moderate-to-vigorous intensity physical activity compared to passive control groups (Liu et al., 2020). However, none of the included studies was conducted in Europe, but stemmed from Canada or the US. Based on another meta-analysis of six intervention trials, mobile health applications do not seem to significantly increase physical activity or decrease sedentary behavior in older adults, (Yerrakalva et al., 2019). A meta-analysis of 18 eHealth physical activity interventions in healthy adults over the age of

55 years – including studies from the Netherlands and Belgium – found eHealth interventions to outperform non-intervention as well as non-eHealth intervention control groups regarding steps per day. The authors further reported that eHealth intervention effectiveness was independent from age regarding their positive effects on steps per day as well as daily and weekly minutes of moderate-to-vigorous intensity physical activity (Núñez de Arenas-Arroyo et al., 2021).

Even though the lack of primary outcome effectiveness for the PROMOTE studies does not match theory- and evidence-based expectations, looking closer at the literature shows that there is not much research on the thesis-specific target group: German, community-dwelling older adults participating in a digital theory-based physical activity intervention. Why the interventions did not lead to the expected results is thus to be researched and understood in the future, using both PROMOTE data (as demonstrated in this thesis) but also independent studies attempting similar research objectives.

The Discrepancy Between Theory and Practice

Despite the realization that the two theory-based physical activity intervention trials analyzed in this thesis were not found to be successful in primary analyses, there are several methodological considerations to be derived from this thesis. For example, it highlights the dilemma which theory-based health behavior change research is generally facing: Existing health behavior change theories only explain their target behaviors to a certain extent and there is no guarantee that interventions based on an established and validated theory lead to the desired effects. Study 1 (chapter 2) contributed to understanding differential psychological mechanisms in digital physical activity interventions, providing evidence that the stage-tailored interventions were effective in promoting stage movement in older adults. This is in line with a systematic review and meta-analysis which reports that a higher number of BCT’s was associated with stage of change movement in the included physical activity interventions (Knittle et al., 2018). Both studies 1 (chapter 2) and 3 (chapter 4) showed that – depending on individual preconditions –

different social-cognitive predictors are relevant for change processes in physical activity behavior. A recent study reports similar observations, with habit strength and self-efficacy moderating the importance of intention and planning in physical activity behavior. The researchers proposed that intentions become especially useful when physical activity is not a habit, and that individuals need to have high levels of self-efficacy in order to be able to translate plans into action (Di Maio et al., 2021).

However, what value do the validated and commonly recognized theories have if they do not sufficiently contribute to reaching the primary intervention outcome? The recruitment of mainly already active older adults, selective study dropout in the less healthy and educated individuals, and low technological experience and affinity are valid reasons for the PROMOTE interventions failing to reach their primary goal. However, the discrepancy between significant increases in social-cognitive predictors of physical activity behavior change and the absence of accompanying increases in the target behavior is an indicator of the need to further research and understand how successful health behavior change forms. Di Maio et al. (2021) raised the concern that not only the between-person differences should be investigated when analyzing social-cognitive mechanisms (that is, comparing average levels between individuals), but that examining within-person fluctuations may reveal yet unknown processes of physical activity behavior. With this, they agreed with an earlier study which showed that the assumptions on an interindividual level proposed in the HAPA do not translate as well to the intraindividual level (Bierbauer et al., 2017). This shows yet another area of person-centered associations at risk to be overlooked, with common practice often focusing on variable-centered associations. This leads to the next main theme of this thesis.

Latent Subgroups Within Physical Activity Interventions

Applying principles proposed in the CCAM (Lippke, 2014), this thesis extended the investigation of health behaviors occurring in clusters based on binary indicators (such as yes/no, high/low, or insufficient/sufficient) to exploring latent lifestyle profiles based on similar patterns in continuous lifestyle indicators. That individuals who engage in a less healthy lifestyle also rate their general health as worse compared to individuals who do not engage in a combination of health-risk behaviors has been demonstrated in previous studies, such as in Finnish adults (Dieteren et al., 2020) as well as older adults from both Western as well as Eastern countries (Liao et al., 2019). According to a latent transition analysis of health behavior profiles from the UK, the majority of adults remained in their lifestyle profile during mid-adulthood (Mawditt et al., 2019). A 22-year Canadian cohort study of roughly 2000 adults aged between 18 and 60 years identified individuals belonging to the stable inactive latent class to make up 53%, with older age being one of the sociodemographic factors being associated with a lower likelihood of following an active leisure-time physical activity trajectory (Barnett et al., 2008). A sample of women participating in an 18-month long study on step-count data in the US were found to consist of three physical activity trajectories, again with the low-active trajectory contributing the largest proportion (46.8%) and age over 60 years predicting membership of the low-activity trajectory (Y. Kim et al., 2016). The fact that transitions to healthy lifestyle profiles or a physically active lifestyle are less likely than sustaining an unhealthy lifestyle when following up cohorts during their lifetime shows how important effective interventions are for nudging adults and older adults towards health behavior change.

A Finnish longitudinal study recently combined the concept of health behavior clusters and latent physical activity trajectories while investigating trajectories in leisure-time physical activity from adolescence to adulthood (Lounassalo et al., 2021). They found that both stable high leisure-time physical activity and over time increasing leisure-time physical activity were associated with a healthy diet, less smoking, and higher quality of sleep. Applying such analyses focusing on the transition from adulthood to old adulthood – should they come to the same conclusion – would contribute to the evidence base suggesting benefits of becoming physically active even in old age (Laddu et al., 2018; Moholdt et al., 2021; Stephan et al., 2020). With this, researchers could provide a stronger argument for why the existence of clusters and carry-over effects of multiple health behaviors should be considered in physical activity intervention planning.

Analyzing the existence of distinct physical activity and sedentary behavior trajectories in both the short-term (such as up to one year) as well as the long-term (such as spanning over decades and life phases) is not a new area of research. Latent class growth analysis, which has been the analysis method in study 3 (chapter 4), is an increasingly common method in epidemiology for analyzing physical activity change trajectories. For example, it has previously been performed on heart disease patients over the course of twelve months (Blanchard et al., 2014) as well as women living in the US across 18 months (Y. Kim et al., 2016). What this thesis contributes to the evidence base of latent person-centered research is the analysis of lifestyle profiles and short-term physical activity and sedentary behavior trajectories during a relatively short intervention trial period, which have not been conducted for an older adult population before. Being aware of the existence of heterogenous groups of older adults with regards to stages of change, lifestyle profiles, and physical activity change trajectories, the next question raised by this thesis concerned how these heterogenous subgroups differed from each other in terms of their social-cognitive profiles.

Social-cognitive Factors as Predictors of Group Membership

Despite current health behavior change theories only producing small effect sizes on mediations in physical activity interventions, their value as a theoretical basis for intervention development is still recognized (Rhodes, Boudreau, et al., 2021). Promoting sustained adherence to recommended behaviors is one of the major objectives in the science of health behavior change, and recent developments in digital health call for behavioral theory integration. One example for digital applications and tools that are used in individuals' day-to-day lives are self-management or treatment applications for chronic diseases (Klonoff, 2019). Understanding how social-cognitive constructs relate to the reception of digital tools as well as latent change trajectories can thus contribute to the theory-based development of digital technologies. Latent lifestyle profiles significantly differed by the baseline stage of change, with a large effect size, in study 2 (chapter 3). However, this thesis' results question the extent to which social-cognitive factors can predict latent behavior classes as opposed to psychologically determined latent classes. Researchers who conducted a latent profile analysis of attitudes towards healthy eating and physical activity, for example, found that participants in the latent profile with negative exercise attitudes were also characterized by low levels of social support, positive outcome expectancies, and self-efficacy (Vaughan et al., 2018). In study 3 (chapter 4), within which latent physical activity change trajectory classes were analyzed, only a few associations were found between latent trajectory classes and social-cognitive predictors.

Even though the social-cognitive predictors investigated in this thesis were assessed for physical activity, they were also associated with sedentary behavior trajectories. This is not self-evident, as physical activity and time spent sitting are not mutually exclusive behaviors but individuals with a sedentary office job can still meet weekly physical activity recommendations. However, a meta-analysis has only recently reported that the strength of the association between physical activity related self-efficacy and sedentary behavior is similar to the strength of the association between sedentary behavior specific self-efficacy and sedentary behavior itself (Szczuka et al., 2021). According to the authors, this might be explained by individuals perceiving the two behaviors as one construct, or that the behaviors can be considered proxies of each other, meaning that the absence of one could mean the presence of the other. Additionally, cross-behavior cognitions could be present (Szczuka et al., 2021). In multiple health behavior change theory it is assumed that cross-behavioral associations do not only occur in the behaviors but also in specific social-cognitive constructs such as self-efficacy, intention, or planning (Geller et al., 2017; Lippke et al., 2021). Thus, as physical activity and sedentary behavior are related lifestyle indicators, this association may apply to their social-cognitive predictors as well.

Health-related Determinants of Study/ Physical Activity Participation

Despite utilizing the CCAM, a social cognitive theory on multiple health behavior change, this thesis does not include an investigation of whether the PROMOTE studies led to multiple health behavior changes. Rather, the CCAM was used as the theoretical framework for investigating how several lifestyle indicators were related in a sample of German older adults and how the latent lifestyle profile impacted study participation. As Geller et al. (2017) concluded, there is evidence for successful multiple health behavior change interventions, yet their potential to prevent disease still requires consistent methodology and a deeper understanding of mechanisms. For example, a study involving a Latino population with diabetes mellitus type 2 reports that 35% of participants seemed to show a similar readiness to change based on the transtheoretical model for multiple health behaviors (Salinas Martínez et al., 2021). More specifically, 35% were in the precontemplation or contemplation stage for at least two of the unhealthy behaviors which diabetes patients are advised to abstain from.

There is previous research that aimed to identify predictors of latent group membership regarding healthy lifestyle adherence. For example, one study analyzed adherence to weight management behaviors using latent class analysis and they included health-related quality of life, social support, perceived stress and self-rated health as predictors (Fitzpatrick et al., 2018).

However, among these, they only found social support to predict latent class membership, in terms of higher levels of social support being associated with a higher likelihood of belonging to the physical activity maintainers class. Dieteren et al. (2020) analyzed combinations of unhealthy SNAP behaviors in Dutch adults and found that individuals engaging in multiple unhealthy behaviors were more likely to focus on short-term consequences for their health rather than having a high risk perception for long-term consequences. One explanation for why the PROMOTE I study did not seem to have included a latent unhealthy lifestyle profile may thus be that older adults belonging to this group did not perceive the long-term benefit as a relevant reason for participation and thus were not recruited.

As hypothesized, self-rated health had an independent effect on study dropout risk. Yet, there is rather scarce evidence on the connection between older adults' self-rated health and their physical activity participation or intervention effectiveness. Instead, research so far has mainly focused on the effects of physical/study participation on health and wellbeing (e.g., see Bae et al., 2017; Buecker et al., 2020; Kekäläinen et al., 2020) or on cross-sectional associations (e.g., see Klussman et al., 2021). This demonstrates that the question of whether the association might also work vice versa requires further research. Coming vaguely close to the research topic is the study by Rector et al. (2019), who conducted a latent class analysis and found higher levels of wellbeing to increase the chance of belonging to a sustained physical activity class in middle-aged adults living in the US. Additionally, according to a meta-analysis investigating dropout-rates from yoga-interventions, having medical conditions seemed to be associated with higher dropout-rates (Cramer et al., 2016).

However, this thesis' findings match the countless reports on social aspects of physical activity being an important reason for engaging in a physically active lifestyle in older age – for example, as a result of age-related shifts in what determines motivation for exercise (Steltenpohl et al., 2019). The observation that older adults in the socially inactive lifestyle profile were at a higher risk of dropping out of the study (study 2, chapter 3) should be interpreted with caution as this lifestyle profile consisted of a rather low number of older adults. However, the finding fits well into various reports of social aspects playing a relevant role in physical activity participation as well as experienced benefit from interventions. For example, Franke et al. (2021) observed that physical activity only decreased between mid-intervention (3 months) and post-intervention (6 months) in older adults self-identifying as lonely. Yet, they further emphasized that loneliness decreased during the physical activity intervention, highlighting how incorporating social aspects into interventions can be beneficial for older adults' physical activity as well as perceived levels of loneliness. Being already physically active and having wider social networks was associated with physical activity maintenance after a 24-week physical activity intervention's completion in English older adults (Kendrick et al., 2018). These reports match the findings obtained in study 2 and suggest that placing the strongest focus on the health benefits of physical activity may not be the most promising approach when the target group consists of older adults (Morgan et al., 2019). Yet, it needs to be noted that health status still plays a role in the relationship between social aspects and physical activity participation, as there is research showing that social networks, health status and physical activity are linked (Ang, 2018; Stevens et al., 2021).

5.3. Limitations and Strengths

Up to this point, the contributions and results of this thesis have been presented in detail, discussing how the findings corroborate, contradict, or complement the current evidence base. These considerations should be interpreted being aware of the diverse strengths as well as limitations accompanying this thesis. Thus, the following section firstly presents what features make this thesis a strong contribution to the current evidence base, and secondly points towards methodological weaknesses and unaddressed questions that readers should be aware of.

Strengths

The major strength of this thesis is that it draws from different disciplines, including health psychology, epidemiology, and public health. The strong methodological focus and its embedment in a theoretical framework enabled advanced, complex, and versatile longitudinal analyses. Different viewpoints were interconnected to advance the usage of health psychology in applied intervention research. By these means, this thesis contributes to theory-based health behavior change research by addressing heterogenous physical activity behavior change in diverse areas of clinical digital intervention trials, ranging from psychological mechanisms of change, over lifestyle-related study participation, to actual physical activity change trajectories. Drawing from these different disciplines, this thesis lays out intervention evaluation methods that take both psychological and epidemiologic considerations into account and can then be applied to recommendations on which aspects should be considered for future intervention development.

Also, this thesis bears the advantage of having access to high quality data from a clinical science point of view, as randomized controlled intervention trials can enable researchers to explore causal relationships by being comparatively free from bias. Thus, the data source spanning over two intervention trials with over 800 participants was suitable for conducting complex longitudinal analyses with the opportunity to include a large and diverse amount of behavioral, psychological, and health-related, as well as demographic and anthropometric indicators. The opportunity to analyze the effects and underlying mechanisms of different physical activity interventions enabled a broad view on physical activity promotion in older adults, focusing on digital interventions but additionally incorporating print-based and face-to-face and group-based components. Also, this thesis contributed research on German older adults, and thus adds to the current evidence base which to a large extent consists of studies conducted in Northern America and the UK.

A further strength of this thesis is the consideration of diverse indicators of physical activity. While study 1 (chapter 2) concentrated on the stage of physical activity behavior change and study 2 (chapter 3) included subjectively reported physical activity levels, study 3 (chapter 4) reported objectively assessed physical activity. The investigation of such a wide range of physical activity indicators allows for painting a bigger picture of this complex health behavior. The differences between those indicators are evident as, for example, a meta-analysis of physical activity interventions for healthy inactive adults reports significant effects on self-reported physical activity but nonsignificant effects on objectively assessed physical activity (Howlett et al., 2019). There are even more ways of assessing and evaluating changes in physical activity. For example, a minimum clinically important difference in daily average acceleration has been recently proposed for inactive older adults (Rowlands et al., 2021). It is difficult to say at which point changes in predictors of physical activity are meaningful, but this realization highlights the importance of researching the relevance of psychological indicators as predictors of behavior change processes. This insight may not be the primary goal in physical activity promotion, given the "everything counts" message posed by the current WHO recommendations (Segar et al., 2020). Nevertheless, considering diverse physical activity indicators can contribute to understanding intervention mechanisms and intercorrelations, and by investigating different physical activity behavior change processes among older adults, this thesis contributes to closing research gaps regarding heterogenous change mechanisms.

Limitations

Referring directly to the last-mentioned strength, the methodological variation concerning physical activity measures could also be seen as a weakness because it limits the extent to which the three studies can be compared and put into context with each other. Besides that, several other methodological considerations need to be mentioned when evaluating the findings of this thesis. Apart from the thesis acknowledging that understanding the requirements coming along with older age is extremely important in the face of the demographic change, the studies building this thesis only marginally addressed the large impact that demographic differences have on physical activity behavior, intervention effectiveness, and even intervention reach. Studies show that demographics are important factors to be considered for physical activity intervention tailoring (Holliday et al., 2017). One main reason for why this was not intensely addressed in this thesis was that the PROMOTE studies included samples of community-dwelling older adults living in the area of Northwestern Germany around Bremen, thus narrowing down the sample heterogeneity in terms of demographic differences. Generally, the two PROMOTE studies suffered from low recruitment rates, especially when it came to enrolling initially inactive older adults. The PROMOTE I study included a high proportion of individuals in the actor stage at baseline. Accordingly, one of the adaptations realized for PROMOTE II was to exclude individuals from participation if they already had been regularly sufficiently physically active for at least one year. Given the rather healthy and active samples with access to and ability to use digital technology in the included studies, the issue of limited external validity has thus to be kept in mind.

One methodological limitation that was faced in all three included studies is that none of them were conducted for the purpose of confirmatory analyses. The exploratory nature of the secondary analysis studies came along with the lack of an appropriate power calculation for the analyzed outcomes. Thus, the generalizability of obtained results needs to be considered carefully when interpreting them. The fact that the PROMOTE studies were not primarily designed for the purpose of the analyses conducted in this thesis meant that analysis possibilities quickly faced their limitations when it came to data quality, sample size, robustness to bias, and clinical relevance of effect sizes. Also, the exploration of non-linear growth trajectory analyses would have been enabled, had the PROMOTE studies included more than three assessment timepoints. The PROMOTE I study did not include a second follow-up at all, as the single follow-up assessment took place at twelve weeks, directly after intervention end. The PROMOTE II study included a six-month maintenance intervention and a follow-up after nine months, but still, follow-up periods were too short in order to assess long-term effects.

Furthermore, it needs to be acknowledged that the interventions included in this thesis do not depict the current state of the art. As digital health evolves and grows rapidly, the web-based self-monitoring physical activity diaries used in the included PROMOTE studies, along with other digital technologies and modes of delivery analyzed not even a decade ago (e.g., Laranjo et al., 2015) can be described as outdated. Thoughts on affinity to technology and participation in digital intervention therefore need to be newly evaluated within the context of established digital innovations.

5.4. Implications for Research and Practice

Implications for Research

The reported results call for incorporating insights on barriers and motivators of physical activity participation into intervention development and participant support throughout intervention studies (Spiteri et al., 2019). The relevance of effective and tailored interventions, recommendations and resources for vulnerable or hard to reach groups, or individuals in times of crisis, such as the COVID-19 pandemic (Kluck et al., 2021), is acute. Social networking and the utilization of modern platforms for virtual social connection are gaining increasing importance, also for physical activity during the COVID-19 pandemic. While needs, experiences and perceptions associated with digital technologies and modes of delivery may have changed, this thesis' results have kept their relevance as they give insights on important aspects to consider when designing and evaluating physical activity programs for older adults. How to adopt and especially maintain a physically active lifestyle even in the face of change and challenges has become an even more common question in early 2020, urging future research to build on studies such as those included in this thesis.

Identifying and preventing factors that lead to selection or attrition bias is essential in epidemiologic practice, which is why more research is needed on determinants of selective study dropout as well as strategies to recognize and support dropout-vulnerable subgroups. Such subgroups could be technologically non-affine or socially inactive older adults in the context of digital physical activity studies, as seen in study 1 (chapter 2) and study 2 (chapter 3). Additionally, subgroups who are vulnerable to remain in stable insufficient health behavior trajectories could be those who display low levels of social-cognitive predictors at baseline, which need to be adequately addressed in order to foster a change in behavior (see study 3, chapter 4).

Systematic reviews and meta-analyses on the effectiveness of digital physical activity interventions have addressed the lack of evidence when it comes to long-term intervention effects and behavior change maintenance (Afshin et al., 2016; Yerrakalva et al., 2019). This limitation has also been reported by systematic reviews on structured interventions which included exercise sessions for healthy, insufficiently active adults (e.g., see Willinger et al., 2021). A meta-analysis of randomized controlled trials on mHealth physical activity interventions found them to foster sustained physical activity increases, especially in at-risk and sick populations, but that effect sizes decreased over time (Mönninghoff et al., 2021). Even though they require intensive financial, personal and time resources and face the risk of high attrition rates over time, longitudinal trials involving theory-based physical activity interventions and including sufficient follow-up periods are necessary in the future. Availability and support provided by study staff, for example, can be a valuable tool to ensure high adherence and retention in physical activity monitoring studies (Xu et al., 2018), and supporting older adults to increase self-efficacy is essential for the use of eHealth (Wilson et al., 2021). However, such large efforts can be difficult to keep up over longer time periods and one of new technologies' advantages should be the users' physical and timely independence from study facilitators. Digital intervention components should thus be straight forward and well thought through, ideally coding included features as BCT's within the framework of an established taxonomy (e.g., see Michie et al., 2013) and mapping them to their MoA (e.g., see Carey et al., 2018) in order to foster sustainable physical activity behavior change. This objective requires a thorough understanding of social-cognitive mechanisms pertaining to specific intervention components and modes of delivery. Depending on the stage of change at baseline, intervention success of different technological components can vary, as indicated by stage of change movement or positive changes in social-cognitive predictors (see study 1, chapter 2). Future research should thus place a stronger focus on how well social cognitive theory can explain behavior-related changes and latent change processes during interventions.

Furthermore, how associations between health-related indicators can be utilized to foster healthy lifestyle adoption and maintenance in physical activity interventions should be further investigated. Next to confirming the hypothesis that poor self-rated health is a barrier of physical activity intervention participation, this thesis sheds light on the importance of social participation (study 2, chapter 3). Social factors seem to play an essential role in the current generation of older adults and this thesis raises the question as to whether this may be largely linked to a sense of connectedness. That is, it might be possible that simply belonging to the biggest latent lifestyle profile could provide a sense of belonging which might in turn be associated with participating in an intervention study. It is thus one implication for future research to explore retention and attrition in individuals who feel that they belong in the study sample compared to those who do not. Another implication that can be derived from study 2 is that it suggests that certain health behaviors may interrelate and that their combination might influence how older adults experience physical activity interventions. For example, individuals in the socially inactive lifestyle were also characterized by a less healthy lifestyle in general, the combination of which may have been the reason for the increased dropout risk.

Both study 2 and study 3 (chapters 3 and 4) concluded that there are heterogenous groups within study populations and that positive outcomes or effects could be observed in those groups who were the ones in need of the interventions, that is, the ones with unhealthy habits and highly sedentary behaviors. These associations could only be detected after having identified unobserved subgroups. Thus, one essential implication for research that this thesis contributes is that latent subgroup analyses may reveal masked intervention effects or underlying mechanisms. Yet, it is necessary to warn about loss of power when conducting subgroups analyses, especially when they are of exploratory nature. Even though investigations of differential intervention effects in latent subgroups have rarely been conducted in the context of theory-based physical activity interventions, there is health behavior research corroborating the issue of low power. For example, a study of alcohol use trajectories in a stage-tailored intervention study concluded that the complexity of their analyses would have required a larger sample size for more robust estimates, which may have been the reason for non-significant differences between identified latent trajectory classes (Baumann et al., 2015). Furthermore, researchers applying cross-sectional o longitudinal latent class analyses need to be aware of their complexity, because choosing the optimal class-solution requires researchers to carefully interpret fit-indices and weigh statistical significance against plausibility and clinical relevance, which may not always go hand in hand (Twisk & Hoekstra, 2012).

This thesis shows that moderate-to-vigorous intensity physical activity is not the single relevant indicator of intervention effectiveness or indicator of individual change, as improvements in social-cognitive mechanisms and sedentary behavior were observed. Also, results obtained in study 1 (chapter 2) showed that intervention effects on stage of change movement differed between aerobic endurance and muscle strengthening training activities. The target behavior or outcome should thus be carefully considered in concordance with the target population and relevant determinants of physical activity. For example, authors of a recent editorial claim that the public health focus on leisure time physical activity is contributing to socioeconomic inequalities rather than narrowing the gap (Straker et al., 2021).

Furthermore, it needs to be noted that this thesis was conducted in the health promotion and prevention context, focusing on healthy ageing of older adults, that is, the main focus lied on sustaining the health of older adults. Naturally, future research should place an equally large focus on older adults with multimorbidity, as studies have shown that multimorbid older adults are highly likely to belong to low or declining healthy ageing trajectories (Nguyen et al., 2021). The treatment of non-communicable diseases such as diabetes, however, has been the research area dominating mHealth research during the last decade (Ali et al., 2016). Even though the use of mHealth for health promotion and prevention has rocketed as well since the early 2010's, this purpose remained being less researched compared to mHealth interventions for monitoring or diagnosis of disease, or as a supporting tool in healthcare – according to an analysis from 2016 (Ali et al., 2016). Thus, scientifically evaluating digital strategies and theory-based programs for prevention and health promotion is in fact a research area to focus on in the future. Another implication which is located in the public health area is that implementation research needs to be one of the future priorities (Luszczynska, 2020), as interventions can only be of limited usefulness if they are effective in an experimental setting but are not rolled out for use outside the research environment.

Implications for Practice

Even though it was already mentioned as a limitation that the analyzed digital interventions do not represent the current state of the art, there are several implications this thesis poses for practice. To tackle the internationally recognized issue of physical inactivity and reduce its global prevalence by 15%, the WHO issued the new global action plan on physical activity 2018–2030, in short: the GAPPA (World Health Organization, 2018). With their vision being “more active people for a healthier world” and aiming to contribute to reaching the global sustainable development goals, GAPPA includes four strategic objectives with several proposed policy actions. This thesis most closely contributes to objective 3: “create active people”. The policy action 3.4 within this objective comprises appropriately tailored programs aimed at increasing physical activity and reducing sedentary behavior in older adults to support healthy ageing (World Health Organization, 2018). It needs to be acknowledged that international policy places a strong focus on relational prevention as opposed to behavioral prevention, which is a very important objective to pursue (e.g., see Garnica Rosas et al., 2021). Nevertheless, this thesis poses relevant implications for the interconnection between digital health, prevention, health psychology and behavioral medicine.

The need to increase the proportion of sufficiently physically active older adults in Germany is high. A population-based cohort study of German older adults, for example, found that baseline physical activity level, higher socioeconomic status, younger age, and social support predicted physical activity twelve years later (Manz et al., 2018). This thesis adds to the evidence base on physical activity promotion in German older adults by advising that health-related, behavioral, and psychological factors at baseline should be considered in physical activity program planning. The results of this thesis imply that subjective and objective self-monitoring components can both lead to significant stage of change movement but via different social-cognitive mechanisms (see study 1, chapter 2). Specifically, older adults who do not intend to change their physical activity behavior may benefit more from additionally receiving a fitness tracker which increases their intention. Older adults who already have developed the intention to change may benefit more from being prompted to monitor their physical activity behavior subjectively, as this can increase their self-efficacy.

In new digital interventions, for example via smartphone applications (Moller et al., 2017), strong self-management and self-regulation as well as high intervention adherence can inherit an ever-growing importance as many interventions are tending towards less personal and more virtual contact. eHealth and electronic patient data are on the rise, with an important milestone being the recently established digital programs following the German Digital Health Care Act in late 2019, such as digital health applications being medical devices for the treatment and secondary prevention of existing disease (so-called “apps on prescription”), digital health applications to be used in nursing, and digital primary prevention programs as certified health promotion courses. Even as of today, the supply of freely accessible mobile applications for physical activity in older adults is vast, but a current analysis classified only 5% as evidence-based (Portenhauser et al., 2021), showing that there is a clear need of scientifically sound digital solutions that need to be surpass their less qualitative alternatives.

The future of digital interventions and behavioral medicine (including physical activity promotion in older adults) will be marked by academic-industry partnerships (e.g., see Arigo et al., 2019), bringing the best of both worlds together. While industry can contribute state of the art technology, research can ensure that approaches are theory- and evidence-based as well as sufficiently scientifically evaluated. This thesis is an example of epidemiology and psychology being connected, whereas its implications for practice call for the collaboration between business development, technology and data science specialists, medical experts, clinical researchers, and health psychologists.

5.5. Conclusion

This thesis was able to demonstrate the importance of understanding heterogenous behavior change in older adults participating in digital physical activity interventions. It could show that the existence of latent change trajectories can mask significant changes in whole sample analyses, whereas the membership of latent lifestyle profiles is associated with study dropout risk. Further, this thesis contributes results on potentially differing change mechanisms dependent on digital components of physical activity interventions and behavior change related mindsets at baseline.

Digital and theory-based components of physical activity interventions, such as subjective and objective self-monitoring, can lead to significant stage of change movement in older adults, partly by increasing the relevant social-cognitive predictors. Groups of older adults that are especially likely to experience positive changes, to be unaffected by the interventions, or to discontinue the study early can be identified by applying principles from stage-based social cognitive theory as well as person-centered analysis methods. Latent lifestyle profiles are likely to exist among older adults participating in physical activity interventions and their membership may be associated with study dropout risk, as was the case for socially inactive individuals in the PROMOTE I study analyzed within this thesis. On the other hand, certain individuals may belong to latent classes that are characterized by positive change trajectories without researchers identifying them as such, as was observed for highly sedentary older adults in the PROMOTE II study analyzed within this thesis.

Combining a theoretical framework of health behavior change with methodological considerations on missing information and latent subgroups in intervention studies, this thesis demonstrated several areas of heterogeneity in the physical activity behavior change process of older adults participating in digital interventions. Relevant implications for both research and practice are that initial knowledge of older adults' social-cognitive mindsets, lifestyle, self-rated health as well as social and physical activity levels can be valuable sources of information for identifying barriers, limitations, facilitators, and predictors of successful health behavior change. The knowledge of these associations can enable the identification of underlying subgroups, tailoring intervention components and behavior change strategies to their needs during intervention development, as well as the prevention of selective study dropout. Heterogeneity in physical activity behavior change spans over several levels along the health behavior change process, including study participation, social-cognitive mechanisms of change, and latent change trajectories. These levels should be considered in both the design and evaluation phase of digital physical activity interventions targeted at older adults.

This thesis calls for more extensive research on the proposed levels of heterogeneity, integrating psychological and epidemiologic principles in the design and evaluation of theory-based, sufficiently powered, longitudinal, implementation-oriented, state of the art digital physical activity interventions targeted at older adults.

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Appendix

Supplementary Material 1 – Study 1

Overview of features and behavior change techniques used in the exercise interventions.

Feature	Implementation	Behavior Change Technique[a]	Website	Printed Material	Weekly Meetings
Behavioral Monitoring	Participants in IG1 completed the online diary weekly. Participants in IG2 additionally carried an activity tracker and the daily steps were displayed on the website	– Feedback on behavior [2.2]	X		
		– Self-monitoring of behavior [2.4]	X		
Behavioral Refinement	Behavior (frequency and intensity) was displayed weekly in graphical form	Discrepancy between current behavior and goal standard [1.6]	X		
Behavioral Norms	Participants in the same intervention group could share their activities with and follow others by sending a friend request	Social comparison [6.2]	X		
Social Networking	Participants were able to communicate with each other via a forum on the website and during weekly meetings		X		X
Modeling	Participants performed exercises together in weekly group meetings and received corrective feedback by trained students	– Modeling/ Demonstration of the behavior [6.1]			X
		– Instruction on how to perform a behavior [4.1]			X
Prompts	– All participants received the same PA recommendations.	Goal setting [1.1]	X	X	X
	– Participants were informed weekly about possibilities for PA in their area as well as recommendations on how to integrate PA into their daily life (such as taking the stairs instead of the elevator)	– Behavior substitution [8.2]			X
		– Generalization of a target behavior [8.6]			X
		– Restructuring the physical environment [12.1]			X
Rewards	Participants received rewards in form of trophies when they achieved the weekly PA recommendations	Social reward [10.4]	X		

Note. PA = physical activity; IG1 = intervention group 1; IG2 = intervention group 2.
[a]Behavior change techniques are coded based on Michie, S., Richardson, M., Johnston, M., Abraham, C., Francis, J., Hardeman, W., . . . Wood, C. E. (2013). The behavior change technique taxonomy (v1) of 93 hierarchically clustered techniques: building an international consensus for the reporting of behavior change interventions. *Annals of Behavioral Medicine, 46*(1), 81-95. doi:10.1007/s12160-013-9486-6.

Supplementary Material 1 – Study 1(continued)

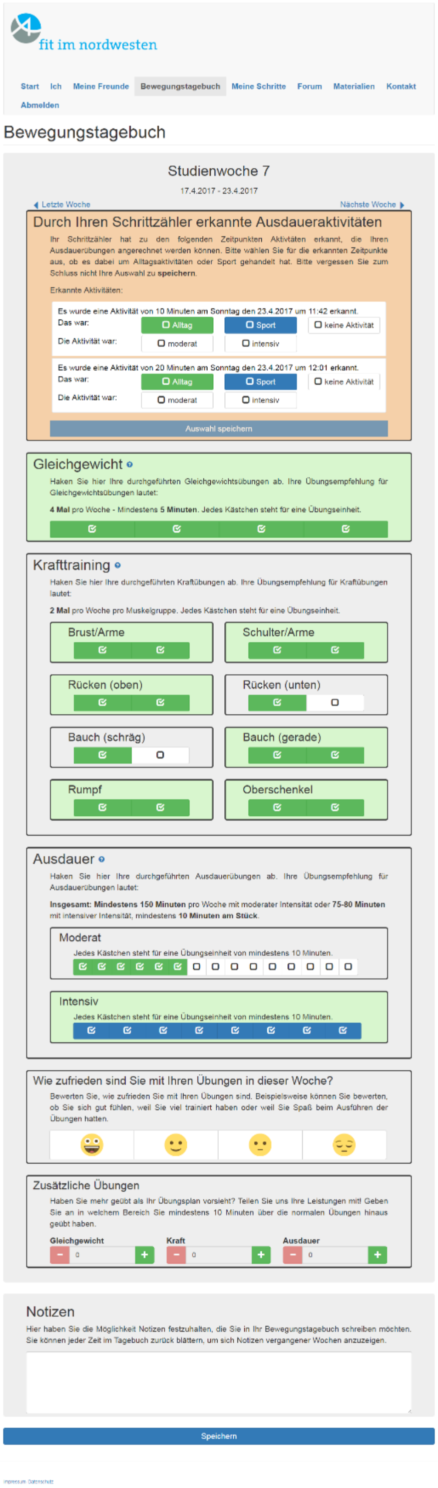
Overview of features and behavior change techniques used in the exercise interventions.

Features	Implementation	Behavior Change Techniques[a]	Website	Printed Material	Weekly Meetings
Resources	– Participants were informed about consequences of physical inactivity as well as advantages of being active	Information about health consequences [5.1]		X	X
	– Participants learned how to use if-then-plans and how to identify and overcome barriers in weekly group meetings	– Action planning [1.4]			X
		– Coping planning [1.2]			X
		– Pros and cons [9.2]			X
	– Participants were informed about the importance of social support and advised on including others for better performance of the behavior	Social support (general [3.1], practical [3.2] and emotional [3.3])			X
Tailoring	– At baseline, participants received feedback based on their motivational stage (nonintention, intention or action) to engage in the recommended endurance and strength training behavior, respectively. Targeted social-cognitive predictors were: ○ nonintention stage: positive outcome expectancies ○ intention stage: action planning ○ action stage: coping planning			X	
	– The printed exercise guide was tailored to fitness level assessed with the short physical performance battery. They were divided in difficulty levels from 1 to 3. Tailoring of endurance and strength training exercises was based on the chair-rising test. Tailoring of balance exercises was based on the balance test			X	
	– The printed exercise guide contained pictures of men or women of the target age group demonstrating the exercises, tailored to the respective gender			X	

Note. PA = physical activity; IG1 = intervention group 1; IG2 = intervention group 2.
[a]Behavior change techniques are coded based on Michie et al. (2013). The behavior change technique taxonomy (v1) of 93 hierarchically clustered techniques: building an international consensus for the reporting of behavior change interventions. *Annals of Behavioral Medicine, 46*(1), 81-95.

Supplementary Material 2 – Study 1

Screenshot of the online physical activity diary on the study website in German.



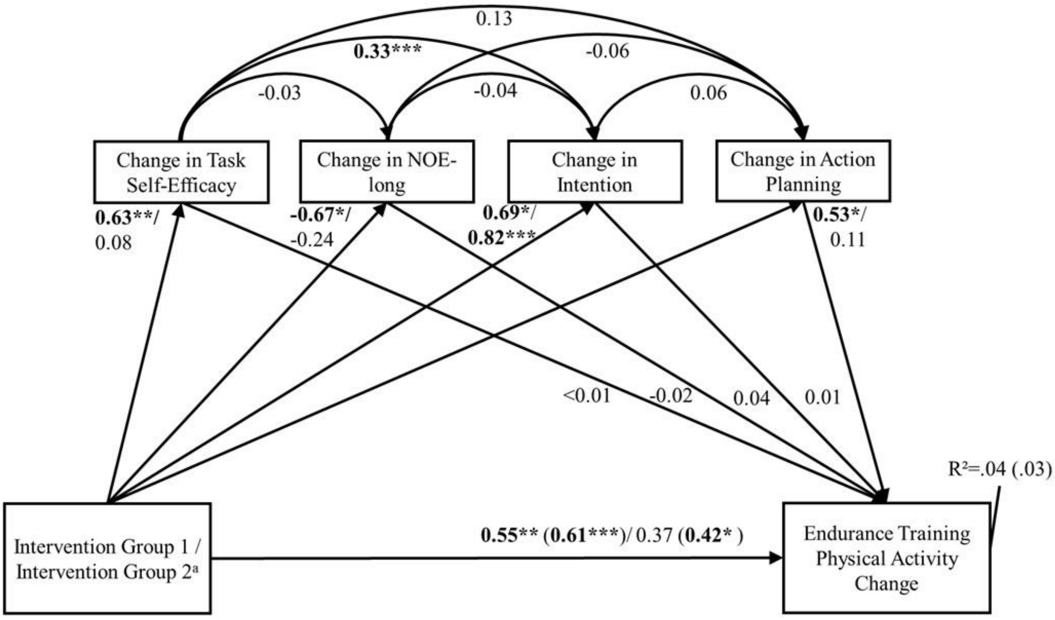
Supplementary Material 3 – Study 1

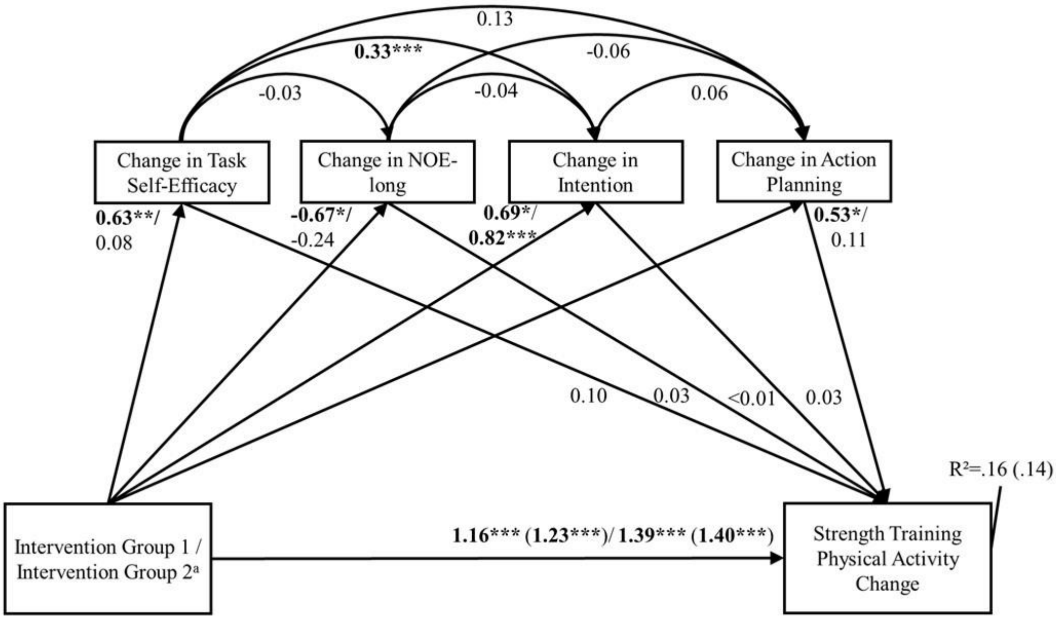
Screenshot of display of daily steps on the study website in German.

Supplementary Material 4 – Study 1

Items of social-cognitive predictors at baseline and follow-up assessment.

Social-cognitive Predictor	Item
Intention	I intend to engage in strenuous endurance training for at least 75 minutes per week (heart beating faster, sweating) and strength- and balance training twice a week
	I intend to engage in moderate endurance training for at least 150 minutes per week (not tiring, slightly sweating) and strength and balance training twice a week
Outcome Expectancies	The recommended endurance, strength and balance training…
Positive outcome expectancies	…is good for my health
	… makes me feel better afterwards
Negative outcome expectancies	…takes too long
	… is too costly
Self-efficacy	
Task self-efficacy	I can engage in the recommended endurance, strength and balance training even if it gets difficult
Maintenance self-efficacy	I can regularly engage in the recommended training…
	…even if it takes long until it is a habit
	…even if I am worried or face problems
Recovery self-efficacy	I can engage in the recommended training regularly again…
	… even if I postponed my plans several times
	…even if I suspended several times
Planning	For the next month I have already planned…
Action planning	…where I will be physically active
	…how I will be physically active
	…when and how often I will be physically active
Coping planning	…when I have to take care not to suspend
	…what I can do in difficult situations to stick to my intentions
	…how I can remain physically active even if there are barriers
Habit strength	Engaging in the recommended endurance, strength and balance training is something…
	…that has become my habit
	…that I do without thinking about it





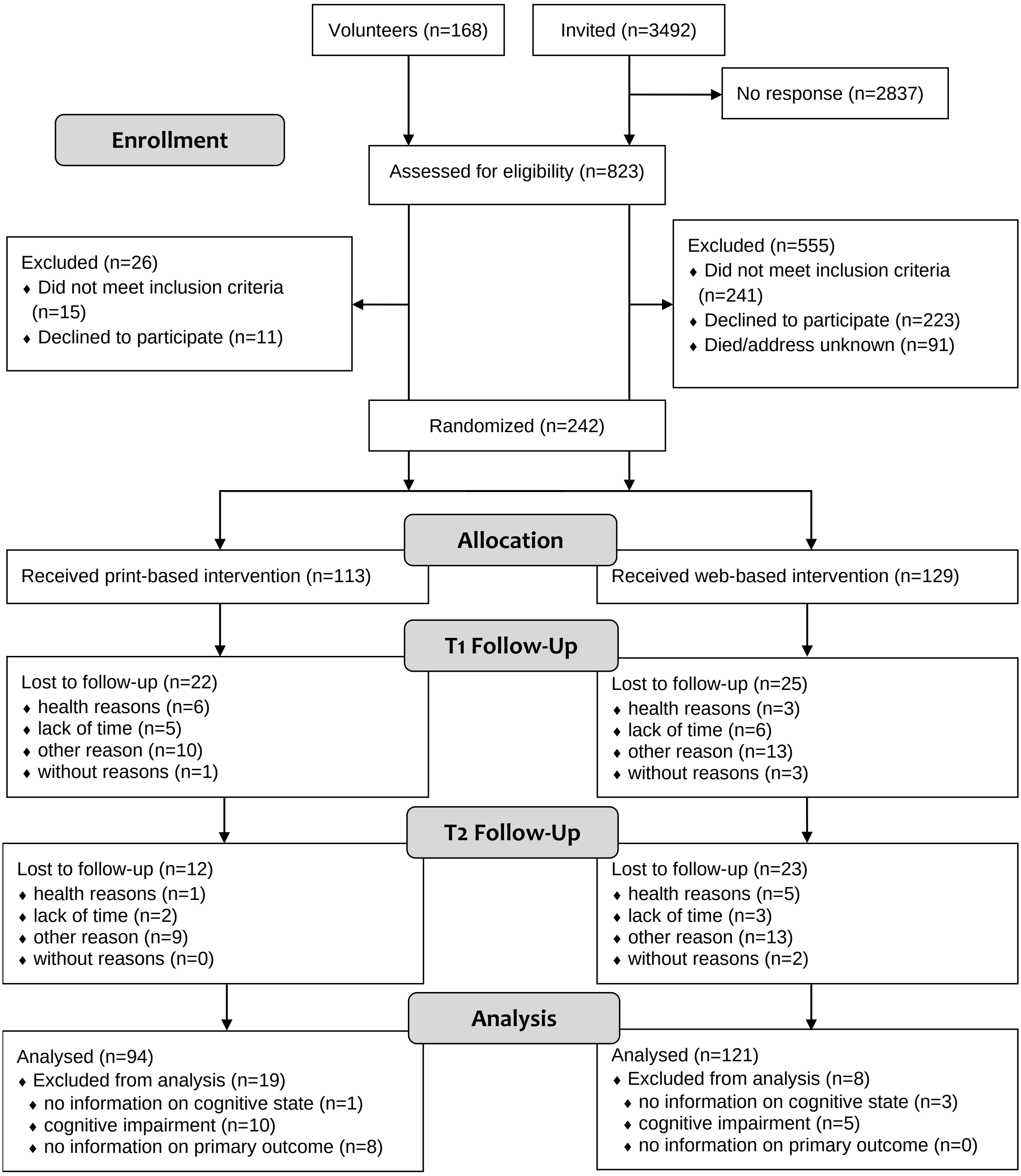
Supplementary Material 5 - Study 1. Dependent mediator model for intervention effects on endurance/ strength training physical activity (PA) change. Social-cognitive predictors were defined as dependent mediators. Unstandardized regression coefficients indicate the intervention effects (first coefficient for intervention group 1 and second coefficient for intervention group 2) and the social-cognitive predictor effects on endurance/ strength training PA change. Total effects are given in parentheses. Mediating effects can be determined by multiplying the intervention effects on social-cognitive predictors with the social-cognitive predictor effects on PA change. Not adjusted for baseline values. Delayed intervention control group was set as reference. Significant regression coefficients are in boldface. NOE-long = negative outcome expectancy – takes too long.

[a]Delayed intervention control group was set as reference.

* p < .05. ** p < .01. *** p < .001.

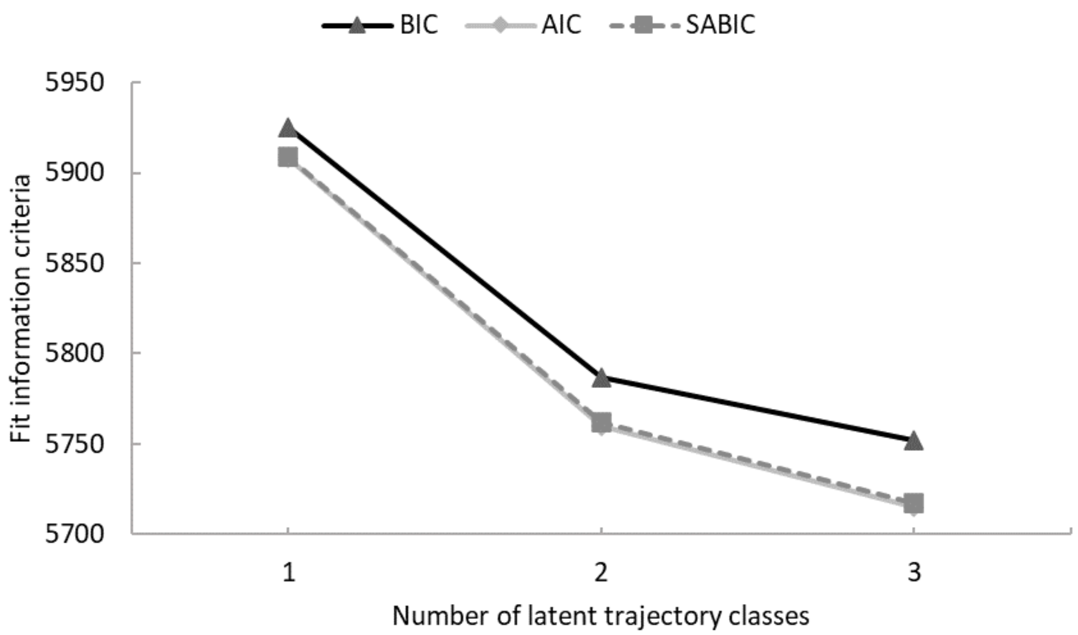
Additional file 1 – Study 3

Flow chart.



Additional file 2 – Study 3

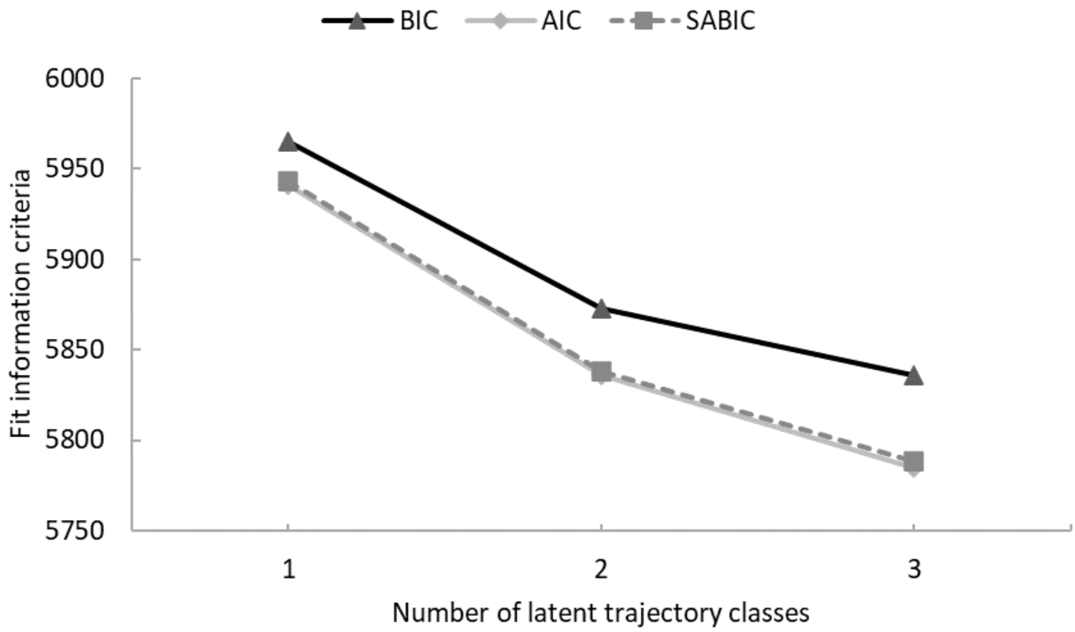
Elbow plot of fit statistics based on latent class growth analysis of physical activity change trajectories.



Note. The point at which the information criterion value becomes stable, even if more classes are added, is used as indication of the solution best fitting the data. AIC = Akaike's information criterion; BIC = Bayesian information criterion; SABIC = sample size adjusted BIC**.**

Additional file 3 – Study 3

Elbow plot of fit statistics based on latent class growth analysis of sedentary behavior change trajectories.



Note. The point at which the information criterion value becomes stable, even if more classes are added, is used as indication of the solution best fitting the data. AIC = Akaike's information criterion; BIC = Bayesian information criterion; SABIC = sample size adjusted BIC.