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Individualization of mHealth Interventions for children and adolescents

Cumulative dissertation

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Hannes Baumann

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Examination board:

Chair of the examination board: Prof. Dr. Rüdiger Reer (University Hamburg)

First examiner: Prof. Dr. Bettina Wollesen (University Hamburg)

Second examiner: Prof. Dr. Alexander Woll (Karlsruhe Institute of Technology)

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PREFACE

This dissertation (PhD thesis) encompasses the following seven manuscripts, all of which have undergone peer review and have been published by the time of submission (four as first author):

Full Citation and DOI:	Open Access	Professional Audience	Citations	Impact-factor
1. Baumann, H., Fiedler, J., Wunsch, K., Woll, A., & Wollesen, B. (2022). Mhealth Interventions to Reduce Physical Inactivity and Sedentary Behavior in Children and Adolescents: Systematic Review and Meta-analysis of Randomized Controlled Trials. *JMIR MHealth and UHealth*, *10*(5), e35920. https://doi.org/10.2196/35920	yes	international	10	4.95
2. Meixner, C., Baumann, H., & Wollesen, B. (2020). Personality Traits, Gamification and Features to Develop an App to Reduce Physical Inactivity. *Information, 11(7),* 367.	yes	international	10	3.38
3. Bischoff, L. L., Baumann, H., Meixner, C., Nixon, P., & Wollesen, B. (2021). App-Tailoring Requirements to Increase Stress Management Competencies Within Families: Cross-sectional Survey Study. *Journal of Medical Internet Research*, *23*(7), e26376. https://doi.org/10.2196/26376	yes	international	5	7.08
4. Meixner, C., Baumann, H., & Wollesen, B. (2022). Gesundheitsbezogene Ziele der digitalen Prävention und Gesundheitsförderung in Familien. *Gesundheitswesen.* https://doi.org/10.1055/a-1860-0911	yes	german	0	0.99
5. Baumann, H.; Meixner, C.; & Wollesen, B. (2022): Voraussetzungen zur Vermittlung digitaler Gesundheitskompetenzen durch Sportlehrkräfte im Zuge der SARS-CoV-2-Pandemie: Eine explorative Mixed-Methods Studie im Schulkontext. In: *Zeitschrift für Studium und Lehre in der Sportwissenschaft - Themenheft Digitalisierung in der Sportlehrer*innenbildung* (5(1)), S. 5–18. DOI: 10.25847/zsls.2021.051.	yes	german	1	N.A.
6. Baumann, H., Heuel, L., Bischoff, L. L., Wollesen, B. (2023). mHealth interventions to reduce stress in healthcare workers (fitcor): study protocol for a randomized controlled trial. *Trials*, 24, 163 (2023). https://doi.org/10.1186/s13063-023-07182-7.	yes	international	1	2.75
7. Baumann, H., Heuel, L., Bischoff, L. L., Wollesen, B. (2023). Efficacy of Individualized Sensory-Based mHealth Interventions to Improve Distress Coping in Healthcare Professionals: A Multi-Arm Parallel-Group Randomized Controlled Trial. *Sensors*, 23(4):2322. https://doi.org/10.3390/s23042322	yes	international	0	3.85

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ABSTRACT/ SUMMARY

Introduction: Insufficient physical activity has been established as a significant risk factor for non-communicable diseases, increasing the risk of conditions such as cardiovascular disease, hypertension, diabetes, dementia, obesity, and breast and colon cancer. Meanwhile regular physical activity is associated with positive effects on stress management and related health risks. The benefits of physical activity are particularly impactful for children and adolescents, as behavioral changes during adolescence can extend into adulthood. However, the prevalence of insufficient physical activity and sedentary behavior among youth worldwide is steadily increasing, potentially due to the rise of digitalization and increased screen time. Surprisingly, longitudinal and representative data from the KIGGS study demonstrates no correlation between screen time and reduced physical activity in children. Addressing the digital realities of modern childhood and adolescents, digital health interventions (e.g., mHealth) may provide a life-relevant and motivating entry point for changing physical activity related behaviors. Numerous meta-analyses have demonstrated the effectiveness of smartphone interventions among youth, although effect sizes remain low. The lack of scientific foundations of content, non-specific approaches, inadequate age-appropriateness, low individualization, and poor usability are cited as possible reasons. Thus, innovative approaches are needed to increase the effectiveness and adherence of digital health interventions among children and adolescents, involving evidence-based techniques for behavior change (e.g., gamification, goal setting), age-appropriate developmental theories, motivational aspects, and multi-level individualization. As such, this dissertation focuses on the following research questions: (1) How does individualization and age as moderators impact the effectiveness of mHealth interventions for reducing sedentary behavior in children and adolescents? (2) What are the feasible mHealth-based physical activity and health objectives that can be achieved within the family context involving early adolescents? (3) How can digital health literacy be promoted in the school setting to encourage reflective and responsible use of mHealth applications among mid-adolescents? (4) How does individualization affect the effectiveness of physical activity-based mHealth interventions?

Methods: A cumulative dissertation consisting of seven pre-registered publications in national and international peer-reviewed journals was developed to address these research questions. To answer the first research question, a systematic review followed by a meta-analysis (1) was conducted to assess the effectiveness of digital health interventions for preventing insufficient physical activity and sedentary behavior in children and adolescents across different developmental stages, as well as to compare individualized interventions with non-individualized interventions. To answer the next two research questions, which were based on the results of the aforementioned literature review, two mixed-methods cross-sectional studies were conducted to examine the prerequisites for digital health promotion for children and adolescents in (2) family and (3) school settings. Qualitative sub-studies were analyzed using qualitative content analysis with MAXQDA, while quantitative sub-studies were analyzed using SPSS, rStudio, and JASP. The family-focused study (2) was an explanatory sequential mixed-methods study that aimed to identify family health goals through interviews with N=60 parents and focus groups with N=120 adolescents. The subsequent quantitative sub-study surveyed N=1008 families nationwide on their interest in the identified family health goals and their health behavior. On the other hand, the school-focused study (3) was an exploratory sequential mixed-methods study that integrated an online survey of N=118 biology and physical education teachers and six focus group interviews with teachers and students (N=34). The surveys covered questions about the equipment and use of digital media, digital health literacy, and potential barriers of mHealth intervention in the context of physical education. The insights gained from the meta-analysis (1) and cross-sectional mixed-methods studies (2 & 3) were integrated into a multi-arm randomized controlled trial (4), including a study protocol, to answer the fourth research question and to evaluate individualized, sensory mHealth interventions. The experimental study includes N=995 participants, randomized to multiple study-arms with different levels of individualization including sensor- and app-based biofeedback, health needs of each individual, vital signs, and behavioral patterns. The study includes three measurement points at intervals of 8 weeks, with primary outcomes defined as heart rate variability, behavioral change (HAPA), and physical activity.

Results: The systematic literature search yielded 1101 studies, of which 12 were included in the qualitative synthesis and 10 in the meta-analysis (1). Findings indicated that digital health applications can effectively address insufficient physical activity, but their effectiveness in mitigating sedentary behavior remains uncertain. Additionally, our analysis suggested that highly individualized digital interventions may produce larger effect sizes in the context of insufficient physical activity, and that age-related differences may exist with respect to the degree of individualization required to achieve optimal outcomes. Addressing early adolescent target group, the subsequent family focused mixed methods study (2) found differences in health goals among families. Qualitatively identified mHealth related goals in the areas nutrition, mindfulness, abstinence, organized activities, resilience, nature as well as physical activity and combined the health behavior index of participants in a multiple regression model. The results revealed resilience, physical activity, and nature to be significant predictors of health behavior. Additional multiple logistic regression models identified healthier eating habits, communal cooking, outdoor activities, learning exercises for on-the-go, spending time in nature, stress management, and dietary changes as primary goals in the field of mHealth that children and adolescents would undertake with their parents. Addressing mid adolescents, both studies in the school focused project (3) identified a lack of knowledge and media infrastructure. The target groups showed a high interest in and need for the enhancement of digital health literacy. Compared to teachers of other subjects, physical education teachers showed lower digital health literacy and less interest. The results highlight the need for an improved infrastructure (e.g., access to Wi-Fi) and the exacerbated need for digital health literacy promotion in the school setting. In the randomized controlled trial focusing on late adolescents and adults (4), 170 of 995 eligible participants (26%) completed the post-measurement. MANOVA indicated small to moderate time*group interaction effects with physical activity-related outcomes of moderate to vigorous physical activity and inactivity-disruption counts in the app focused study-arms, but not for step counts and inactivity. Stress-related HRV parameters did not change over time. Despite high dropout rates and a complex study design, individualized interventions revealed initial effects on physical activity but not the expected effects on stress-related outcomes.

Discussion: The aim of this dissertation was to investigate the impact of individualization on the effectiveness of mHealth interventions for children and adolescents at different developmental stages. The results revealed that each developmental stage of children has unique requirements. For instance, in early childhood and adolescence, the involvement of the social environment of the family was shown to be beneficial, whereas in middle adolescence, the development of health literacy for independent use of mHealth interventions obtains amplified relevance. In late adolescence, individualization of interventions through biofeedback or more complex methods such as machine learning becomes significant. Despite several limitations, the individualized mHealth interventions were found to affect the physical activity and health behaviors of children and adolescents more than non-individualized interventions, provided that they adequately address the digital health literacy according to the child's developmental stage, involve social systems, are based on central theories of health behavior change, and have an educational approach. Future approaches should focus on the appropriate use of health data to develop context-specific and relevant interventions that are adjusted according to gender, culture, and competence. Therefore, individualization alone appears to be a partial aspect of the effective application of mHealth interventions, but tackles many obstacles related to digital solutions for the reduction of insufficient physical activity and sedentary behavior as well as other health behaviors. These aspects are combined in the proposed Youth mHealth Behavior Change Model, which combines the HAPA model with the self-Efficacy model and the presented study findings of this dissertation, providing a framework for physical activity related health behavior change for children and adolescents via mHealth interventions.

ZUSAMMENFASSUNG

Einleitung: Unzureichende körperliche Aktivität wurde als signifikanter Risikofaktor für nicht-übertragbare Krankheiten identifiziert und erhöht das Risiko für Erkrankungen wie Herz-Kreislauf-Erkrankungen, Bluthochdruck, Diabetes, Demenz, Fettleibigkeit sowie Brust- und Darmkrebs. Regelmäßige körperliche Aktivität hingegen hat positive Auswirkungen auf den Stressabbau und damit verbundene Gesundheitsrisiken. Die Vorteile von körperlicher Aktivität sind insbesondere für Kinder und Jugendliche von Bedeutung, da Verhaltensänderungen während der Adoleszenz bis ins Erwachsenenalter hineinreichen können. Die Prävalenz von unzureichender körperlicher Aktivität und sitzendem Verhalten bei Jugendlichen weltweit steigt jedoch stetig an, möglicherweise aufgrund der zunehmenden Digitalisierung und erhöhten Bildschirmzeit. Überraschenderweise gibt es jedoch laut longitudinalen und repräsentativen Daten aus der KIGGS-Studie keinen Zusammenhang zwischen Bildschirmzeit und reduzierter körperlicher Aktivität bei Kindern. Um die digitalen Realitäten der modernen Kindheit und Adoleszenz zu adressieren, könnten digitale Gesundheitsinterventionen (z.B. mHealth) einen lebensrelevanten und motivierenden Einstiegspunkt für die Veränderung von Verhaltensweisen im Zusammenhang mit körperlicher Aktivität bieten. Zahlreiche Meta-Analysen haben die Wirksamkeit von mHealth Interventionen bei Jugendlichen gezeigt, auch wenn die Effektstärken gering waren. Als mögliche Gründe werden der Mangel an wissenschaftlichen Grundlagen des Inhalts, inhaltsunspezifische Ansätze, unzureichende Altersangemessenheit, geringe Individualisierung und dürftige Nutzbarkeit genannt. Daher sind innovative Ansätze erforderlich, um die Wirksamkeit und Einhaltung digitaler Gesundheitsinterventionen bei Kindern und Jugendlichen zu erhöhen, die auf evidenzbasierten Techniken zur Verhaltensänderung (z.B. Gamification, Zielsetzung), altersgerechten Entwicklungsmodellen, motivationalen Aspekten und mehrstufiger Individualisierung basieren. Aus diesem Grund konzentriert sich diese Dissertation auf folgende Forschungsfragen: (1) Wie beeinflussen Individualisierung und Alter als Moderatoren die Wirksamkeit von mHealth-Interventionen zur Reduzierung unzureichender körperlicher aktivität und von sitzendem Verhalten bei Kindern und Jugendlichen? (2) Was sind realisierbare mHealth-basierte Aktivitäts- und Gesundheitsziele, die im familiären Kontext mit frühadoleszenten Jugendlichen umgesetzt werden können? (3) Wie kann die digitale Gesundheitskompetenz im Schulsetting gefördert werden, um einen reflektierten und verantwortungsbewussten Einsatz von mHealth-Anwendungen bei Jugendlichen in der mittleren Adoleszenz zu fördern? (4) Wie beeinflusst Individualisierung die Wirksamkeit von auf körperlicher Aktivität basierenden mHealth-Interventionen bei Jugendlichen in der späten Adoleszenz und im Erwachsenenalter?

Methodik: Eine kumulative Dissertation, bestehend aus sieben vorregistrierten Publikationen in nationalen und internationalen peer-reviewed Journals, wurde entwickelt, um diese Forschungsfragen zu adressieren. Um die erste Forschungsfrage zu beantworten, wurde eine systematisches Review gefolgt von einer Meta-Analyse (1) durchgeführt, um die Wirksamkeit von digitalen Gesundheitsinterventionen zur Prävention von unzureichender körperlicher Aktivität und sitzendem Verhalten bei Kindern und Jugendlichen in verschiedenen Entwicklungsstadien zu bewerten und individualisierte Interventionen mit nicht-individualisierten Interventionen zu vergleichen. Um die nächsten beiden Forschungsfragen zu beantworten, die auf den Ergebnissen der genannten Literaturarbeit basieren, wurden zwei Mixed-Methods-Querschnittsstudien durchgeführt, um die Voraussetzungen für die Förderung digitaler Gesundheit bei Kindern und Jugendlichen im (2) familiären und (3) schulischen Setting zu untersuchen. Qualitative Teilstudien wurden mit MAXQDA analysiert, während quantitative Teilstudien mit SPSS, R-Studio und JASP analysiert wurden. Die auf die Familie ausgerichtete Studie (2) war eine explanativ-sequentielle Mixed-Methods-Studie, die durch Interviews mit N=60 Eltern und Fokusgruppen mit N=120 Jugendlichen gemeinsame Familien-Gesundheitsziele identifizierte. Die anschließende quantitative Teilstudie befragte bundesweit N=1008 Familien nach ihrem Interesse an den identifizierten Familien-Gesundheitszielen und ihrem Gesundheitsverhalten. Die auf die Schule ausgerichtete Studie (3) war hingegen eine explorativ-sequentielle Mixed-Methods-Studie, die eine Online-Umfrage von N=118 Biologie- und Sportlehrern und nachfolgend sechs Fokusgruppeninterviews mit Lehrern und Schülern (N=34) integrierte. Die Interviews enthielten Fragen zur Ausstattung und Nutzung digitaler Medien, digitaler Gesundheitskompetenz und potenziellen Barrieren von mHealth-Interventionen im Kontext des Sportunterrichts. Die Erkenntnisse aus der Meta-Analyse (1) und den Querschnittsstudien (2 & 3) wurden, einschließlich eines Studienprotokolls, in eine multizentrische randomisierte kontrollierte Studie (4) integriert, um die vierte Forschungsfrage zu beantworten und individualisierte und sensorgestütze mHealth Interventionen zu evaluieren. Die experimentelle Studie umfasst N=995 potentielle Teilnehmer, die auf mehrere Studienarme mit unterschiedlichen Graden der Individualisierung, einschließlich sensor- und app-basierter Biofeedbacks, Gesundheitsbedürfnissen jedes Einzelnen, Vitalparameter und Verhaltensmustern, randomisiert wurden. Die Studie umfasst drei Messzeitpunkte im Abstand von 8 Wochen, wobei die primären Ergebnisse als Herzfrequenzvariabilität, Verhaltensänderung (HAPA) und körperliche Aktivität definiert sind.

Ergebnisse: Die systematische Literatursuche ergab 1101 Studien, von denen 12 in die qualitative Synthese und 10 in die Meta-Analyse (1) aufgenommen wurden. Die Ergebnisse zeigten, dass digitale Gesundheitsanwendungen zur Reduktion unzureichender körperliche Aktivität beitragen, aber ihre Wirksamkeit bei der Reduzierung von sitzendem Verhalten unklar ist. Die Analysen legten außerdem nahe, dass hoch individualisierte digitale Interventionen im Kontext unzureichender körperlicher Aktivität größere Effektstärken zeigen und dass altersbedingte Unterschiede in Bezug auf den Grad der Individualisierung vorhanden sein können, um optimale Ergebnisse zu erzielen. Die auf die frühe Adoleszenz ausgerichtete Familien-Studie (2) ergab Unterschiede in den Gesundheitszielen der Familien. In einer

multiplen Regressionsanalyse wurden qualitativ identifizierte mHealth-bezogene Ziele in den Bereichen Ernährung, Achtsamkeit, Abstinenz, organisierte Aktivitäten, Resilienz, Natur sowie körperliche Aktivität kombiniert und der Gesundheitsverhaltensindex der Teilnehmer ermittelt. Die Ergebnisse zeigten, dass Resilienz, körperliche Aktivität und Natur signifikante Prädiktoren für das Gesundheitsverhalten sind. Zusätzliche multiple logistische Regressionsmodelle identifizierten zudem gesündere Essgewohnheiten, gemeinsames Kochen, Outdoor-Aktivitäten, Entspannungsübungen für unterwegs, Zeit in der Natur verbringen, Stressbewältigung und Ernährungsumstellungen als primäre Ziele im Bereich mHealth, die Kinder und Jugendliche mit ihren Eltern unternehmen würden. In Bezug auf Jugendliche in der mittlere Adoleszenz identifizierte die Mixed Methods Studie im schulischen Kontext (3) einen Mangel an digitaler Gesundheitskompetenz und Medieninfrastruktur. Die Zielgruppen zeigten jedoch hohes Interesse und Bedarf an der Verbesserung ihrer digitalen Gesundheitskompetenz. Im Vergleich zu Lehrern anderer Fächer zeigten Sportlehrer eine geringere digitale Gesundheitskompetenz und weniger Interesse. Die Ergebnisse betonen die Notwendigkeit einer verbesserten Infrastruktur (z.B. Zugang zum Wi-Fi) in Sporthallen und einer verstärkten Förderung der digitalen Gesundheitskompetenz im schulischen Kontext. In der randomisierten kontrollierten Studie, die sich auf Jugendliche in der späten Adoleszenz und Erwachsene (4) konzentrierte, beendeten 170 von 995 berechtigten Teilnehmern (26%) die Postmessung. Eine MANOVA zeigte signifikante Zeit-Gruppen-Interaktionseffekte in Bezug auf die aktivitätsbezogenen Parameter „mäßige bis intensive körperlicher Aktivität“, sowie „Inaktivitäts-Unterbrechungen“ in den auf die App fokussierten Studienarmen, nicht aber für die Parameter „Schritte“ und „Inaktivität“. Stressbezogene HRV-Parameter änderten sich im Laufe der Zeit nicht. Trotz hoher Dropoutrate und eines komplexen Studiendesigns zeigten individualisierte Interventionen erste Auswirkungen auf die körperliche Aktivität, jedoch nicht die erwarteten Auswirkungen auf stressbezogene Parameter.

Diskussion: Das Ziel dieser Dissertation war es, den Einfluss der Individualisierung auf die Wirksamkeit von mHealth-Interventionen für Kinder und Jugendliche in verschiedenen Entwicklungsstadien zu untersuchen. Die Ergebnisse zeigen, dass jedes Entwicklungsstadium von Kindern einzigartige Anforderungen aufweißt. Zum Beispiel wurde gezeigt, dass in der Kindheit und frühen Adoleszenz die Einbeziehung des sozialen Umfelds der Familie vorteilhaft ist, während in der mittleren Adoleszenz die Entwicklung der Gesundheitskompetenz für die unabhängige Nutzung von mHealth-Interventionen verstärkt relevant wird. In der späten Adoleszenz gewinnt die Individualisierung von Interventionen durch Biofeedback oder komplexere Methoden wie z.B. maschinelles Lernen an Relevanz. Trotz einiger Einschränkungen wurden bei den getesteten individualisierten mHealth-Interventionen positive Effekte auf das Aktivitäts- und Gesundheitsverhalten von Kindern und Jugendlichen im Vergleich zu nicht-individualisierten Interventionen festgestellt. Allerdings nur unter der Prämisse, dass die Interventionen die digitale Gesundheitskompetenz entsprechend des Entwicklungsstandes des Kindes angemessen

berücksichtigen, soziale Systeme mit einbeziehen, auf zentralen Theorien der gesundheitlichen Verhaltensänderung basieren und einen pädagogischen Mehrwert aufweisen. Zukünftige Ansätze sollten sich auf den angemessenen Einsatz von Gesundheitsdaten konzentrieren, um kontextspezifische und relevante Interventionen zu entwickeln, die entsprechend dem Gender, der Kultur und der Kompetenz angepasst sind. Daher scheint die Individualisierung nur ein Teilaspekt der effektiven Anwendung von mHealth-Interventionen zu sein, behebt aber viele Hindernisse im Zusammenhang mit digitalen Lösungen zur Reduzierung von unzureichender körperlicher Aktivität und sitzendem Verhalten sowie anderen Gesundheitsverhaltensweisen. Diese Aspekte sind im vorgeschlagenen Youth-mHealth-Behavior-Change Modell kombiniert, welches den Health Action Process Approach mit dem Self-Efficacy Modell und den dargestellten Studienergebnissen dieser Dissertation verbindet und einen Rahmen für den gesundheitliche Verhaltenänderung im Zusammenhang mit körperlicher Aktivität für Kinder und Jugendliche durch mHealth-Interventionen bietet.

1 INTRODUCTION

This thesis delves into the potential of individualized mHealth interventions in the promotion of physical activity (PA) and reduction of sedentary behavior among children and adolescents. The introductory section provides a thorough theoretical foundation, encompassing the trends in insufficient physical activity and sedentary behavior, the effects of physical activity on noncommunicable diseases, and the underlying health behavior change theories, such as the Health Action Process Approach and the Self-Efficacy Model. Additionally, the theoretical background section sheds light on the leisure activities and screen time of children and adolescents, culminating in an interim summary of the relevant literature. The second section of this thesis focuses on the current state of research on mHealth interventions. This includes the evidence on the effectiveness of such interventions for all populations and their applicability to children and adolescents. Moreover, the section explores the different developmental stages of children and adolescents and their corresponding digital health literacy. Additionally, the section investigates the impact of social systems, such as family dynamics, school, and peer group, on the effectiveness of mHealth interventions. Pedagogical approaches and behavior change techniques are also presented in the context of mHealth interventions. Lastly, this section highlights the importance of context and preferential adjustment, particularly individualization and adaptive assessment, and just-in-time interventions. The third section of this thesis outlines the research questions and hypotheses, leading into the cumulative part of the dissertation, which comprises seven published studies that serve as the foundation for the present work. The studies delve into the impact of individualization and age as moderators on the effectiveness of mHealth interventions for reducing sedentary behavior, the feasible mHealth-based physical activity and health objectives that can be accomplished within the family framework involving early adolescents, the promotion of digital health literacy within the school setting, and the effect of individualization on the effectiveness of physical activity-based mHealth interventions. The final section of this thesis synthesizes the findings and results of the studies, followed by a discussion of their strengths and limitations. The conclusion highlights the theoretical and methodological developments that have emerged and identifies further areas of differentiation for future research.

1.1 THEORETICAL BACKGROUND ON HEALTH BEHAVIOUR CHANGE

1.1.1 Trends in insufficient physical activity and sedentary behaviour

Inactivity has been described as a prevailing epidemic of the 21st century (Hall et al., 2021). Therefore, insufficient physical activity and sedentary behavior are major public health concerns for children and adolescents (Chaput et al., 2020). For example, a 2020 pooled analysis of 298 population-based surveys with 1.6 million participants found that 80% of adolescents aged 11 to 17 years did not meet the minimum recommended levels of physical activity (PA) in 2016, an increase of 78% in 2001 (Guthold et al., 2020). The global prevalence of insufficient physical activity (IPA), defined as failure to meet the World Health Organization (WHO)-specific guidelines for physical activity (Tremblay et al., 2017), is over 80% among children and adolescents worldwide, predominantly resulting from extended periods of sedentary behavior. This phenomenon has shown a persistent increase over the past decades (Guthold et al., 2018), despite a well-established association between at least 60 minutes of moderate to vigorous physical activity, defined as any activity with a metabolic equivalent of task (MET) value between 3 and 5.9, and vigorous physical activity as ≥6 MET, per day on average for children and adolescents, and several health benefits (Tremblay et al., 2014).It is noteworthy that although sedentary behaviour (SB; defined as any waking behavior characterized by an energy expenditure ≤1.5 metabolic equivalents of task [METs] while in a sitting, reclining, or lying posture (Tremblay et al., 2014; Tremblay et al., 2017)) and IPA are often used interchangeably and refer to the same energy expenditure spectrum by definition, they are independent constructs and do not necessarily correlate with each other (van der Ploeg & Hillsdon, 2017), but both behaviors have significant health implications (Biddle & Asare, 2011).

Another review Dumith et al. (2011) found that PA levels decline during adolescence, particularly among girls. Within the national context of Germany, only 13.1% of girls and 17.4% of boys adhered to the recommended 60 minutes of moderate-to-vigorous physical activity (MVPA) per day (Jekauc et al., 2012). Compliance rates were notably lower among older individuals of both genders, with the sharpest decline occurring among age groups transitioning from primary to secondary school (Schmidt et al., 2020). Screen time has also been on the rise in recent years, with a study showing that 56% of children aged 6 to 11 years and 66% of those aged 12 to 15 years exceeded the American Academy of Pediatrics' recommendation of no more than 2 hours of screen time per day in 2009-2010 (Fakhouri et al., 2013). Internationally, there have been efforts to promote PA and combat SB in children and adolescents. For example, the 2016 PA and Fitness in China-The Youth Study found that PA levels had improved in Chinese children and adolescents compared to previous studies, but that obesity rates had also increased (Dong et al., 2019). Moreover, the COVID-19 pandemic had a significant impact on PA levels among children and adolescents, with many experiencing decreased PA and increased SB due to social distancing and school closures (Dunton et al., 2020). To combat the negative effects of IPA, the PA Guidelines for Americans recommend that children and adolescents aged 6 to 17 years engage in at least 60 minutes of MVPA each day (Piercy et al., 2018). Meeting these guidelines has been associated with lower cardiometabolic risk factors in children and adolescents, including lower blood pressure, cholesterol, and insulin resistance (Ekelund et al., 2012). The precise effects of PA on non-communicable diseases, as well as the health risks associated with IPA, will be detailed in the next chapter.

1.1.2 Effects of physical activity on noncommunicable diseases

Regular PA is associated with numerous health benefits for children and adolescents, including a reduced risk of developing noncommunicable diseases (NCDs) (Hallal et al., 2006; Reiner et al., 2013). The scientific evidence supports the positive effects of PA for cardiovascular health (Kelley et al., 2022), glucose regulation (King et al., 2007), bone health (Borer, 2005), and mental health (Biddle & Asare, 2011), and highlights the importance of promoting PA as a preventative health measure:

- Reduced risk of obesity: PA helps to maintain energy balance by increasing energy expenditure and reducing sedentary time, which can prevent the development of obesity . Several studies have shown that higher levels of PA are associated with lower body mass index (BMI) and reduced risk of obesity in children and adolescents (Telama et al., 2014). In addition, PA can improve body composition by increasing lean muscle mass and decreasing fat mass (Lazaar et al., 2007)
- Improved cardiovascular health: Regular PA can improve cardiovascular health by increasing cardiac output and reducing blood pressure, resting heart rate, and arterial stiffness (Kelley et al., 2022). PA also improves blood lipid profiles by increasing high-density lipoprotein (HDL) cholesterol and decreasing low-density lipoprotein (LDL) cholesterol and triglycerides, which are risk factors for cardiovascular disease (Woodcock et al., 2011). Several studies have shown that PA is associated with reduced risk of cardiovascular disease and improved cardiovascular function in children and adolescents (Andersen et al., 2011).
- Reduced risk of type 2 diabetes: PA can improve glucose regulation by increasing insulin sensitivity and reducing insulin resistance, which can prevent the development of type 2 diabetes (King et al., 2007). Several studies have shown that PA is associated with reduced risk of type 2 diabetes and improved glucose regulation in children and adolescents (Li et al., 2014).
- Improved bone health: PA can improve bone mineral density and bone strength, which can reduce the risk of osteoporosis and fractures in later life (Kemper et al., 2000). Weight-bearing activities such as jumping and running are particularly beneficial for bone health, as they create an osteogenic stimulus that promotes bone growth and remodeling (Borer, 2005). Several studies have shown that PA is associated with improved bone mineral density and reduced risk of fractures in children and adolescents (Fuchs et al., 2001).
- Improved mental health: PA can have numerous mental health benefits, including reducing symptoms of anxiety and depression (Biddle & Asare, 2011), improving mood and self-esteem, and enhancing cognitive function (Fox, 1999). Several studies have shown that PA is associated with improved mental health in children and adolescents, and that exercise interventions can be effective in treating and preventing mental health disorders (Janssen & Leblanc, 2010a).

Yet, it is important to distinguish between IPA and SB in children and adolescents in the context of NCD prevention. For instance, children and adolescents may exhibit prolonged sitting time (e.g., riding to school in a car, sitting in class all day, and playing video games in the evening) while simultaneously adhering to recommended guidelines for PA (e.g., one hour of soccer practice in the evening). In this case, the negative health consequences of prolonged sitting would still manifest, even if the level of PA is adequate (Biddle & Asare, 2011). Moreover, if behaviors such as physical inactivity and SB are strongly entrenched in childhood and adolescence, it is expected that these patterns will persist into adulthood (Telama et al., 2014). Therefore, from a global perspective, it is necessary to address these behavioral patterns, particularly in young populations, in the context of primary prevention and thus stimulate lasting health behaviour changes. While PA is widely recognized as a key determinant of health and well-being, sustaining behavior change can be challenging. Thus, understanding the theoretical underpinnings of health behavior change is crucial for promoting long-term adherence to healthy lifestyle habits. In this context, various theoretical frameworks have been proposed to explain and predict health behavior change, which will be the focus of the next section.

1.1.3 Comprehensive Overview on Health behaviour change theories

Health behavior change theories provide a framework for understanding how individuals adopt and maintain healthy behaviors (Nieuwenhuijsen et al., 2006). These theories explain why people may engage in unhealthy behaviors and how they can be motivated to change these behaviors. The most commonly used health behavior change theories are:

- Theory of Planned Behavior (TPB): TPB posits that behavior is driven by an individual's intentions, which are influenced by their attitudes towards the behavior, subjective norms, and perceived behavioral control. The attitudes refer to an individual's positive or negative evaluation of the behavior, the subjective norms refer to the individual's perception of social pressure to engage in the behavior, and the perceived behavioral control refers to the individual's perception of their ability to perform the behavior (Ajzen, 1991).
- Transtheoretical Model (TTM): The TTM proposes that individuals go through a series of stages when engaging in behavior change, including pre-contemplation, contemplation, preparation, action, and maintenance. The model also incorporates constructs such as self-efficacy, decisional balance, and processes of change to explain behavior change (Prochaska & Velicer, 1997).
- Health Belief Model (HBM): The HBM posits that behavior change is influenced by an individual's perception of the threat of a particular health problem and the perceived benefits and barriers to taking action to reduce that threat. Other constructs included in the HBM are cues to action and self-efficacy (Rosenstock, 1974).

- Social Cognitive Theory (SCT): The SCT suggests that behavior change is influenced by the interaction between individual factors (such as self-efficacy and outcome expectancies), environmental factors, and the behavior itself. The theory also incorporates observational learning and reinforcement as mechanisms for behavior change (Bandura, 1995).
- Self-Determination Theory (SDT): The SDT posits that individuals have innate psychological needs for autonomy, competence, and relatedness, and that these needs must be met in order to facilitate behavior change. The theory also proposes that behavior change is more likely to be maintained when it is driven by intrinsic rather than extrinsic motivations (Ryan & Deci, 2000).
- The Health Action Process Approach (HAPA): According to the HAPA, behavior change unfolds in two stages, namely, the motivational phase and the volitional phase. During the motivational phase, individuals form intentions to adopt or modify a specific health behavior. The volitional phase then involves the translation of intentions into actual behavior change through the implementation of action plans and coping strategies. This approach offers a valuable framework for understanding and predicting behavior change processes and has been applied successfully in various domains of health behavior change research (Schwarzer, 2008).

Overall, these theories provide useful frameworks for understanding and promoting health behavior change. By targeting the key constructs involved in each theory, interventions can be tailored to the individual's needs and increase the likelihood of successful behavior change. Among the various theoretical models of health behavior change, the HAPA has gained increasing attention in recent years., as it provides a comprehensive theoretical framework that takes into account both motivational and volitional aspects of behavior change and has been successfully applied to various health behaviors and populations (Schwarzer & Luszczynska, 2008). In the following section, we will provide an overview of the key components and stages of HAPA and discuss its implications for promoting sustained behavior change.

1.1.3.1 Health action process approach

The Health Action Process Approach (HAPA) is a comprehensive theoretical framework for understanding and promoting health behaviors (Schwarzer & Luszczynska, 2008). It was developed by Ralf Schwarzer and colleagues in the 1990s and has been used to explain a wide range of health behaviors, including exercise, diet, smoking cessation, and cancer screening. It consists of three stages: pre-intentional, intentional, and post-intentional and thus distinguishes between preintenders, intenders and actors (see figure 1).

The HAPA distinguishes itself from other health behavior change models by proposing a two-stage process for behavior change that incorporates both motivational and volitional phases. The motivational phase involves the formation of an intention to change one's behavior and developing the necessary motivation to do so. This phase is similar to the first stage in other models, such as the Theory of Planned Behavior (TPT) or the Transtheoretical Model (TTM). However/ Additionally, the HAPA also includes a volitional phase, in which an individual must translate their intentions into action by developing and implementing a plan. In contrast, other models often focus on identifying the key constructs that influence behavior change (such as attitudes, self-efficacy, and social norms) but do not provide as much guidance on how to put those constructs into action. The HAPA addresses this gap by emphasizing the importance of planning and self-regulation in achieving behavior change. Furthermore, the HAPA emphasizes the role of self-efficacy in both the motivational and volitional phases, as individuals must believe in their ability to both form an intention and carry out the behavior change plan. This focus on self-efficacy aligns with other models such as Social Cognitive Theory (SCT), which also highlights the importance of individuals' beliefs in their ability to successfully engage in behavior change.

Overall, the HAPA's emphasis on planning and self-regulation in both the motivational and volitional phase, along with its focus on self-efficacy, distinguishes it from other health behavior change models and thereby making it a useful framework for designing effective behavior change interventions.

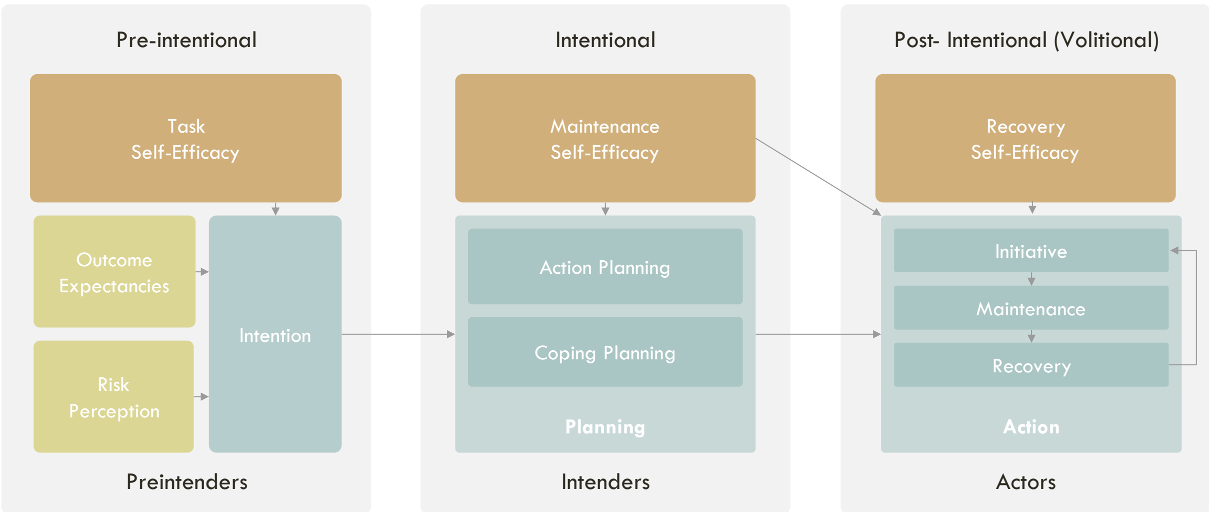

Figure 1: Visually adapted representation of the social-cognitive process model of health behaviour ("Health Action Process Approach", HAPA (Schwarzer, 2008), own illustration.

Following the HAPA framework, the pre-intentional stage involves the formation of an intention to engage in a health behavior. In this stage, individuals assess the benefits and costs of the behavior, as well as their confidence in their ability to perform it. Two key constructs involved in this stage are outcome expectancies and self-efficacy. Outcome expectancies refer to an individual's beliefs about the outcomes associated with a particular behavior. Positive outcome expectancies increase the likelihood of forming an intention to engage in the behavior, whereas negative outcome expectancies decrease this likelihood. Self-efficacy, on the other hand, refers to an individual's belief in their ability to perform the behavior. Higher levels of self-efficacy are associated with a greater likelihood of forming an intention to engage in the behavior (Schwarzer & Luszczynska, 2008). The intentional stage involves the translation of the intention into action. In this stage, individuals plan and implement the behavior. Three main constructs involved in this stage are action planning, coping planning, and self-monitoring. Action planning refers to the process of planning when, where, and how to perform the behavior. Coping planning refers to the process of planning how to overcome barriers and obstacles that may arise when trying to perform the behavior. Self-monitoring involves tracking and evaluating one's progress towards the behavior change goal (Schwarzer & Luszczynska, 2008). The post-intentional stage involves the maintenance of the behavior change. In this stage, individuals continue to engage in the behavior and may encounter challenges that threaten to derail their progress. The constructs involved in this stage include self-efficacy, outcome expectancies, coping planning, and maintenance self-efficacy. Maintenance self-efficacy refers to an individual's belief in their ability to sustain the behavior change over time (Schwarzer & Luszczynska, 2008).

Overall, the HAPA provides a comprehensive framework for understanding the process of behavior change and for designing interventions to promote health behaviors. By targeting the key constructs involved in each stage of the process, interventions can be tailored to the individual's needs and increase the likelihood of successful behavior change. One way do address this, is the use of various health behaviour change techniques. The taxonomy of behavior change techniques (BCTs) suggested by Michie et al. (2013) outlines specific strategies that can be used to facilitate behavior change. BCTs are organized into categories such as goal setting, self-monitoring, social support, feedback, and reward systems (Michie et al., 2013). These techniques can be integrated into the HAPA framework to provide a more comprehensive approach to behavior change. BCTs can be applied in both phases of the HAPA framework to facilitate behavior change. For example, goal setting can be used in the motivational phase to establish an intention to engage in PA, and self-monitoring can be used in the volitional phase to track progress and maintain behavior change. By integrating BCTs into the HAPA framework, a more comprehensive approach to behavior change can be developed, which can enhance the effectiveness of intervention (Wang et al., 2017).

To conduct a more detailed investigation of the potential for individualization within HAPA, it is essential to undertake a nuanced differentiation of the self-efficacy aspect. This will allow for a deeper understanding of the role of self-efficacy in the health behavior change process and how it can be leveraged to enhance the efficacy of interventions aimed at promoting healthy behavior.

1.1.3.2 Self-Efficacy model

Self-efficacy is important in the HAPA because it refers to an individual's belief in their ability to successfully engage in and complete (health) behaviors (Bandura, 1977). When individuals have high self-efficacy, they are more likely to initiate and maintain healthy behaviors, as they believe they have the skills and abilities necessary to do so (Schwarzer, 2008). In the HAPA, self-efficacy is seen as a crucial determinant of behavior change, and interventions aimed at increasing self-efficacy are often incorporated in the process of promoting healthy behaviors. For example, if someone has high self-efficacy beliefs for exercising regularly, they are more likely to set and achieve goals for PA, overcome barriers to exercise, and persist in their behavior even in the face of setbacks. On the other hand, if someone has low self-efficacy for exercise, they are expected to be less likely to start an exercise program or to stick with it over time. Therefore, high self-efficacy is essential in the HAPA as it can lead to greater motivation, goal attainment, and long-term maintenance of healthy behaviors. By fostering self-efficacy, individuals can be empowered to take control of their health and make positive changes that can impact their psychological well-being (Luszczynska et al., 2011).

In 2018, Picha and colleagues developed a self-efficacy model within the HAPA framework, which posits that self-efficacy is a mediating variable between action planning and behavior change (Picha & Howell, 2018). The model proposes that self-efficacy is influenced by outcome expectations, thusthe perceived benefits and consequences of engaging in a specific behavior, and self-regulatory processes, such as self-monitoring and self-reflection and is based on the work of Bandura (1977). The model also highlights the importance of context-specific self-efficacy, thus an individual's confidence in their ability to perform a behavior in a specific situation. According to the model, individuals with higher levels of self-efficacy are more likely to engage in health-promoting behaviors, while those with lower self-efficacy may be less likely to engage in such behaviors or may require additional support to do so. Individuals with low self-efficacy can therefore be supported by several sources of self-efficacy: Performance outcomes, vicarious experiences, verbal persuasion and physiological feedback (see figure 2). The model emphasizes the importance of tailoring interventions to individuals' specific self-efficacy beliefs and contextual factors to maximize the likelihood of behavior change. In a metanalysis, several studies have demonstrated the utility of the self-efficacy model in predicting health behavior change (Sheeran et al., 2016). For example, a study of PA behavior among adolescents found that self-efficacy was a significant predictor of PA intentions and behavior (Reyes Fernández et al., 2014). The self-efficacy model within the HAPA model provides a valuable framework for understanding the role of self-efficacy in health behavior change and for tailoring interventions to individuals' specific needs and contextual factors.

The self-efficacy model posits that there are four primary sources of self-efficacy: mastery experiences, vicarious experiences, verbal persuasion, and emotional and physiological states (Picha & Howell, 2018):

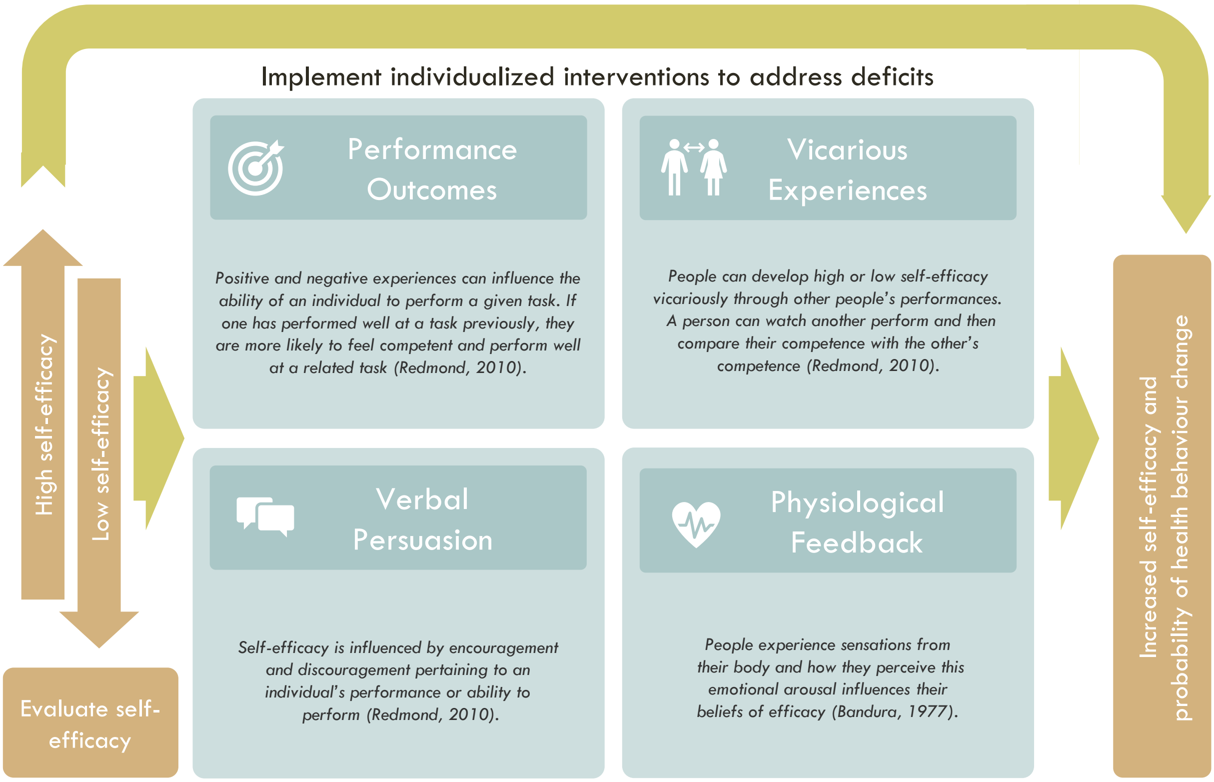

Figure 2: Self-Efficacy Model (Picha et al. 2018), own illustration

1. Mastery experiences: This source of self-efficacy is based on an individual's past performance and experiences. Success in completing a task increases an individual's confidence and belief in their ability to perform similar tasks in the future. In contrast, failure can decrease self-efficacy. Research has shown that successful experiences with PA can increase self-efficacy and adherence to exercise regimens (Maddux, 2009)
2. Vicarious experiences: Observing others successfully performing a task can also increase self-efficacy. Seeing others who are similar to oneself accomplishing a task can be particularly effective in enhancing self-efficacy. For example, research has shown that observing peers who are physically active can increase self-efficacy and PA behavior in adolescents (Bandura, 2004).
3. Verbal persuasion: Encouragement and positive feedback from others can also increase self-efficacy. Hearing supportive words from someone who is trusted and respected can be particularly effective in increasing self-efficacy (BarNir et al., 2011). In a study by Bandura (1995), verbal persuasion was found to be an effective source of self-efficacy in promoting exercise behavior.
4. Emotional and physiological states: This source of self-efficacy is based on an individual's emotions and physiological responses to a task. Positive emotions, such as enthusiasm and excitement, can increase self-efficacy, while negative emotions, such as anxiety and fear, can decrease it. Similarly, physical sensations such as fatigue and pain can lower self-efficacy, while feelings of energy and vigor can increase it (Bandura, 2004).

Overall, self-efficacy plays an important role in motivating and maintaining PA behavior. By understanding and utilizing the four sources of self-efficacy, health professionals can help individuals develop greater confidence in their ability to engage in PA and adhere to exercise regimens. Self-efficacy refers to an individual's belief in their ability to execute and accomplish specific tasks or behaviors in order to reach their desired outcomes. Research has shown that increasing self-efficacy can have a positive impact on behavior change in various health contexts, including PA, healthy eating, and disease (Luszczynska et al., 2005). One way to implement self-efficacy into interventions is individualization.

> *Within the realm of mHealth interventions, individualization is characterized as an accommodation to the unique requirements or circumstances of an individual, and is identified as a primary impediment to patients' adoption of health behaviors (Chen et al., 2021; Ebrahimi et al., 2021). Individualized interventions, sometimes also referred to as adaptive, user-centered, needs-specific, target group–specific, or tailored interventions, represent a potential avenue for providing person-centered care by adjusting to varying levels of individual needs and empowering individuals to actively monitor their health (Tong et al., 2021). Although non-mHealth interventions have employed individualized one-on-one meetings, which have shown high effectiveness, they are often deemed resource-intensive and time-consuming (Kereiakes et al., 2007; Mistry et al., 2012). As such, this approach has faced criticism for its burden on resources. Apps can implement this approach in a more ecologically sound manner, as they are easily accessible to a diverse range of populations (Baumann, Fiedler, et al., 2022).*

Individualization of interventions involves tailoring the intervention to the individual's unique needs, preferences, and characteristics. This approach has been shown to enhance the effectiveness of interventions, particularly for behavior change (Michie et al., 2014). The relationship between self-efficacy and individualization is evident in that individualized interventions can help to enhance an individual's self-efficacy. By tailoring the intervention to the individual's unique needs and preferences, they may feel more confident in their ability to successfully execute the recommended behaviors or tasks, which can in turn lead to greater behavior change success (Michie et al., 2014). For example, a study of a home-based cardiac rehabilitation program found that individualization of the exercise prescription based on patient preferences and abilities led to greater improvements in self-efficacy and exercise adherence (Varnfield et al., 2014). In a study by Barkley and Fahrenwald (2013) a self-efficacy coaching intervention with cardiac rehabilitation patients that included all four sources of self-efficacy was found to be effective. Overall, the individualization of interventions can help to enhance an individual's self-efficacy, which in turn can lead to greater success in behavior change (Young et al., 2020).

To foster PA among children and adolescents by enhancing their self-efficacy, individualization strategies should be employed. To achieve this, an initial analysis of the leisure activities engaged in by children and adolescents is necessary to tailor interventions to their specific context. When designing interventions to promote PA and reduce SB in children and adolescents, it is crucial to take into account their specific types of leisure time activities.

1.1.4 Leisure activities and screen time of children and adolescents

Children and adolescents participate in a diverse range of leisure activities, which are influenced by factors such as age, gender, culture, socioeconomic status, and personal interests. However, empirical evidence indicates that six particular leisure activities dominate a considerable proportion of their leisure time:

1. Active play: Active play has been found to promote physical fitness and reduce the risk of obesity and other health problems among children and adolescents (Janssen & Leblanc, 2010b). It also helps to develop gross motor skills, coordination, and balance (Guram & Heinz, 2018).
2. Creative activities: Engaging in creative activities, such as drawing, painting, and music, can improve children's cognitive and emotional development (Eisenberg et al., 2006) These activities promote creativity, self-expression, and problem-solving skills.
3. Reading: Reading has been found to improve literacy skills, vocabulary, and critical thinking abilities among children and adolescents (Krashen, 2011). It also promotes empathy and social skills (Mar & Oatley, 2008).
4. Socializing with friends: Socializing with peers helps to develop social skills, emotional intelligence, and a sense of belonging (Kucaba & Monks, 2022). Peer relationships can also provide emotional support and help children and adolescents navigate the challenges of adolescence (Collins & Steinberg, 2007).
5. Gaming: Video gaming can provide entertainment and a sense of accomplishment, but excessive gaming can have negative effects on physical health, mental health, and academic performance (Granic et al., 2014). Moderation and age-appropriate content are key to ensure that gaming remains a healthy leisure activity.
6. Television and media consumption: Some media consumption can be educational and entertaining, but excessive media consumption can have negative effects on physical and mental health (Guram & Heinz, 2018). It is important to set limits on screen time and monitor content to ensure that media consumption is healthy and age appropriate.

Furthermore, a study byAuhuber et al. (2019) emphasizes the growing importance of screen-based media in the lives of children and adolescents, suggesting that excessive media use may replace mor active leisure activities. The study highlights the extensive use of mobile phones in girls and populations of children from lower social strata, who are less physically active. The study found a decline in arts and music-related leisure activities, but social contacts and PA remained unchanged and had a positive interaction. As mobile phone use has significantly increased between 2011 and 2017 (Auhuber et al., 2019), continued monitoring is essential and promoting health-conscious behaviors, such as sufficient PA and limited screen time, at an early stage of child development can prevent the development of harmful habits that can negatively impact leisure activities in adulthood.

This above-described study highlights that screen-based media and especially smartphones have become ubiquitous in modern society and are increasingly being used by children and adolescents, while gradually displacing other children's leisure activities. Studies have shown that excessive smartphone use can lead to negative mental health outcomes in children and adolescents, including increased levels of depression, anxiety, and stress (Elhai et al., 2017). Additionally, smartphone use before bedtime has been linked to poor sleep quality, shorter sleep duration, and increased sleeping problems (Cain & Gradisar, 2010; Exelmans & van den Bulck, 2016). There is also evidence to suggest that excessive smartphone use can lead to addiction, particularly in children and adolescents who are more vulnerable to addictive behavior (Billieux et al., 2015; Panova & Carbonell, 2018). However, it is important to note that the effects of smartphone use in children and adolescents are not entirely negative. Smartphone use can also have positive effects on socialization, particularly for those who may have difficulty connecting with peers in person. It has been suggested that smartphones can help to bridge social gaps and reduce feelings of isolation (Campbell, 2015). Smartphones can also provide opportunities for enhanced learning and educational experiences, particularly through the use of educational apps and resources (Zydney & Warner, 2016).

While there are both positive and negative effects of smartphone use in children and adolescents, it is essential for parents and educators to monitor and regulate children's smartphone use to ensure healthy and responsible usage. By promoting responsible smartphone use, children and adolescents can reap the benefits of technology while avoiding the negative consequences. A potential strategy for addressing the alterations in the leisure activities of children and adolescents, and to develop a health psychology approach to this age group, is to utilize smartphone-based mobile health (mHealth) interventions to facilitate the initiation of health behavior modifications. Occasionally, it has been mentioned that the use of mHealth could lead to further increases in the already high screen time of children and adolescents, (Carson et al., 2016; Csibi et al., 2021) which should be taken into account when planning and implementing mHealth applications. However, while mHealth may increase screen time, this is not necessarily the case: The representative and longitudinal MoMo study demonstrated that increased screen time is not correlated with minutes of PA, providing various possibilities for digital interventions and potential avenues for novel approaches to target IPA and SB in children and adolescents (Pearson et al., 2014; Schmidt, Anedda, Burchartz, Kolb, Oriwol, & Woll, 2019)

1.1.5 Interim summary of the theoretical background

In summary, the theoretical background highlights that IPA and SB are major public health concerns for children and adolescents worldwide (Guthold et al., 2018). The COVID-19 pandemic has further exacerbated the problem, with many experiencing decreased PA and increased SB due to social distancing and school closures (Woods et al., 2020). Regular PA has numerous health benefits for children and adolescents, including a reduced risk of developing noncommunicable diseases (Hallal et al., 2006; Reiner et al., 2013). To promote long-term adherence to healthy lifestyle habits, it is important to understand the theoretical underpinnings of health behavior change. Various theoretical frameworks have been proposed to explain and predict health behavior change, with the HAPA being a comprehensive theoretical framework that has been successfully applied to various health behaviors and populations (Barg et al., 2012). The HAPA emphasizes the importance of planning and self-regulation in achieving behavior change, as well as the role of self-efficacy in both the motivational and volitional phases (Schwarzer & Luszczynska, 2008). Health professionals can help individuals develop greater confidence in their ability to engage in PA and adhere to exercise regimens by understanding and utilizing the four sources of self-efficacy.

The preceding chapter has emphasized the significance of comprehending the fundamental principles of health behavior change, especially in the context of PA promotion and SB reduction among young individuals. In the current era of technological advancements, mobile health (mHealth) interventions have surfaced as a promising approach for fostering PA and healthy lifestyle behaviors (Schoeppe et al., 2017). mHealth interventions offer several advantages, including increased convenience, affordability, and accessibility, for promoting PA and healthy lifestyle behaviors in children and adolescents(Dugas et al., 2020). They also allow for personalized and tailored interventions, increasing the likelihood of successful behavior change (Chen et al., 2021). The next chapter aims to furnish a comprehensive account of the present state of research on mHealth interventions for PA promotion among children and adolescents. Furthermore, it intends to deliberate on the prospective benefits and limitations of employing mHealth interventions to instigate behavior change and offer insights for future research endeavors in this domain.

1.2 CURRENT STATE OF RESEARCH ON MHEALTH INTERVENTIONS

1.2.1 Evidence on mHealth interventions for all populations

mHealth interventions employ mobile technology to convey health-related guidance, support, and information, and have demonstrated effectiveness in improving health outcomes across diverse populations (Direito et al., 2017). The salient benefit of mHealth interventions lies in their accessibility and convenience, as they can be conveniently accessed and utilized by young people in their daily lives. mHealth interventions have demonstrated effectiveness and suitability in reducing SB and IPA in both children and adolescents (Schoeppe et al., 2017) and adults (Mönninghoff et al., 2021). A paradox arises in that smartphone use is criticized for exacerbating inactivity but also enables activity (Glauner, 2021).

However, a closer look at the content of mHealth interventions reveals that text messaging has been the most commonly used method for delivering mHealth interventions (Whittaker et al., 2016), which has recently been criticized (Walthouwer et al., 2015). Instead, more individualized approaches should focus on appropriately responding to the realities of daily life, while taking into account the diversity of modern societies (Davis et al., 2020). Empirically supported aspects of effective mHealth interventions include:

- Integration of behavior change techniques (Michie et al., 2011), particularly addressing specific stages of behavior change (Schwarzer, 2008) and self-efficacy (Picha & Howell, 2018).
- Interventions based on existing theoretical approaches in motivational psychology (Fiedler et al., 2020)
- Temporal and spatial adaptation of the intervention time, e.g. just-in-time-adaptive-Interventions (JITAI) (Fiedler et al., 2023; Hardeman et al., 2019)
- Integration of interactive features and gamification techniques (King et al., 2013)
- Individualization of interventions based on biofeedback (Davis et al., 2020)
- Integration of multiple co-acting behavior change mechanisms (Dugas et al., 2020)

However, there are currently only few interventions with these evidence-based features. Chen and colleagues point out that the design of mHealth interventions often lacks a theory-driven approach and places little emphasis on evidence-based content (Chen et al., 2021; Han & Lee, 2018) A further challenge associated with mHealth interventions emerges when meta-analyses condense prior research, which highlights outcomes that are deemed supplementary rather than integral to the intervention (Copas et al., 2018).

In summary, mHealth interventions have been shown to be effective in improving health outcomes in a variety of populations. The accessibility and convenience of mobile technology make it an ideal platform for delivering health-related information. While some have criticized the use of smartphones for exacerbating inactivity, mHealth interventions have shown promise in promoting healthy behaviors. Empirically supported aspects of effective mHealth interventions include the integration of behavior change techniques, motivational psychology theories, JITAI, interactive features and gamification techniques, individualization based on biofeedback, and the integration of multiple co-acting behavior change mechanisms (Fiedler et al., 2020) . However, there is a lack of theory-driven approaches and evidence-based content in many mHealth interventions (Böhm et al., 2019).

As mHealth interventions demonstrated effectiveness in improving health outcomes across diverse populations, it is important to consider the specific needs and characteristics of different age groups. In particular, mHealth interventions for children and adolescents require a tailored approach that takes into account their unique developmental stage and daily life experiences (Schoeppe et al., 2017). Therefore, this section will focus on the evidence and challenges of implementing mHealth interventions for children and adolescents.

1.2.2 Evidence on mHealth interventions for children and adolescents

There are currently more mHealth interventions for healthy adults aimed at reducing IPA and SB than for healthy children and adolescents (Böhm et al., 2019; Mönninghoff et al., 2021). In one of the few reviews on mHealth for healthy children and adolescents, Schoeppe and colleagues (2017) found an overall moderate quality of health apps, but a positive correlation between app quality, the number of app functions, and integrated behavior change mechanisms. Future apps should therefore aim to engage users, be tailored to specific populations, and be based on theories of health behavior change (Schoeppe et al., 2017). Böhm and colleagues additionally criticize the quality of mHealth interventions for children and adolescents and suggest that more age-appropriate solutions are needed (Böhm et al., 2019). The results of other reviews suggest that smartphone-based mHealth interventions (particularly apps) are a versatile strategy for increasing PA and steps in children and adolescents (He et al., 2021). For example, Laranjo et al. (2021) found an average increase of 1850 steps per day after an mHealth intervention. Another randomized controlled trial conducted by Lubans et al. (2016) showed that an mHealth intervention using a smartphone app significantly increased PA levels and reduced SB in adolescent boys. An additional randomized controlled trial by Feter et al. (2018) found that a web-based mHealth intervention combined with pedometer use was effective in increasing PA levels in sedentary adolescent girls.

Overall, there is growing evidence supporting the effectiveness of PA-focused mHealth interventions in children and adolescents (Dawson et al., 2020). A systematic review and meta-analysis by Peng et al. (2020) found that mHealth interventions, including smartphone apps and wearable devices, can significantly increase PA levels in children and adolescents. A further systematic review by He et al. (2021) also reported positive outcomes of mHealth interventions on PA in children and adolescents, with particular emphasis on smartphone-based apps. However, further research is needed to explore the long-term effectiveness of these interventions and to identify the most effective intervention components for different populations. Eckert et al. (2022) suggest four key elements for the further development of mHealth interventions for children and adolescents to improve their effectiveness and sustainability (figure 3):

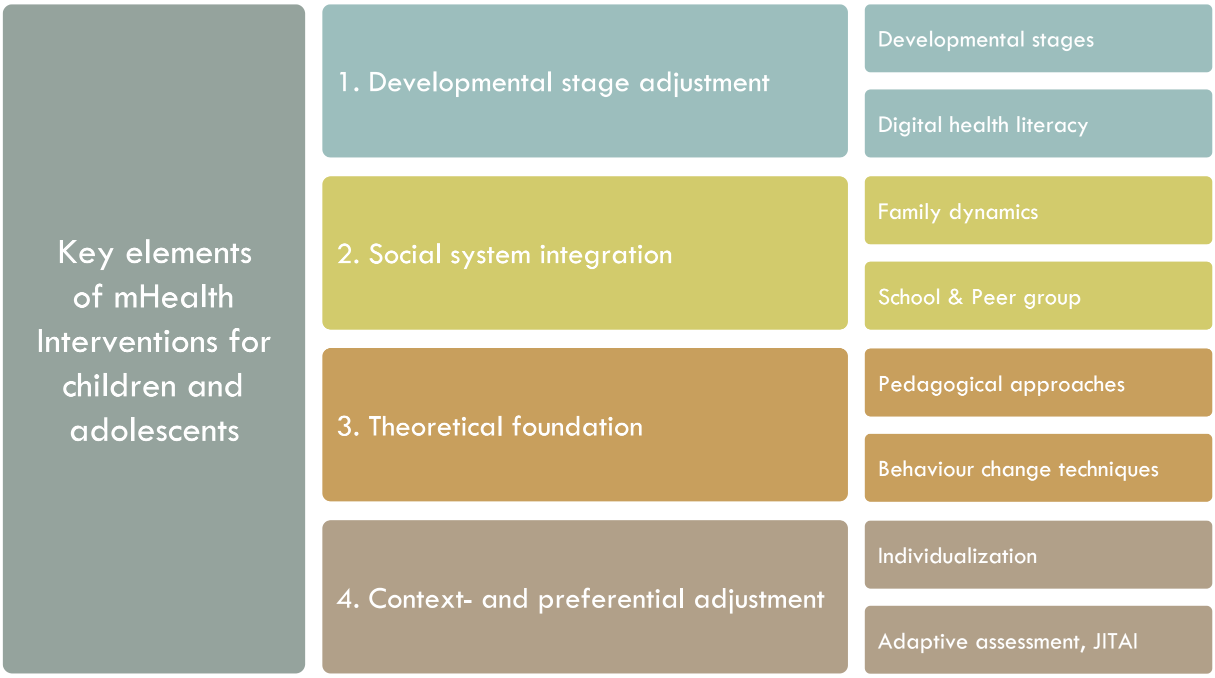

Figure 3: Key elements for the development and implementation of mHealth interventions to promote physical activity in children and adolescents (Eckert et al., 2022) (simplified, adapted and translated illustration)

These four areas (Developmental stage adjustment, social system integration, theoretical foundation as well as context and preferential adjustment) represent developmental domains for mHealth interventions, where research is still in its infancy and essential research gaps exist. The following chapters serve to systematically identify these gaps by subdividing the four core elements into various subcategories. The "Developmental Stage Adjustment" - domain focuses on the development stage and the cultivation of digital health literacy at each stage. The "Social System Integration" - domain subdivides into family, school, and peer groups, each bringing unique dynamics. The "Theoretical Foundation" - domain addresses pedagogical approaches and evidenced-based behavior change techniques. Finally, the "Context- and Preferential Adjustment" - domain highlights new research areas such as JITAI, adaptive assessment, and individualization of mHealth interventions for children and adolescents. These categories systematize current research gaps yet remain subsidiary towards a PA-related behavioral health change in children and adolescents through participation in mHealth interventions.

1.2.3 Importance of developmental adjustment of mHealth interventions

Developmental stage adjustment is important in mHealth for children and adolescents because their cognitive, emotional, and social development influences the individuals capacity to understand and engage with health information and technology (Diviani et al., 2016). Children and adolescents have different levels of digital health literacy and technological skills, depending on their age and developmental stage (Taba et al., 2022). Thus, interventions that do not consider developmental differences may not be effective in promoting health behaviors or may even be harmful (Latkin & Knowlton, 2015). For instance, if an mHealth intervention is designed for adolescents but not adapted to their cognitive abilities, it may use complex language or irrelevant content, resulting in disengagement or even negative outcomes. Therefore, by considering the developmental stage of children and adolescents, mHealth interventions can be tailored to meet their specific needs and increase the chances of successful outcomes.

1.2.3.1 Importance of developmental stages for of mHealth interventions

Younger children may have limited attention spans and may require simpler and more interactive interventions that incorporate gamification and visual aids to enhance their engagement. Adolescents, on the other hand, may desire more autonomy and control over their health information and may benefit from interventions that incorporate social media and peer support (Chung et al., 2021). Table 1 summarizes the different stages of child development from infancy to late adolescence (0-21 years) with a focus on physical, cognitive, and social/emotional development. It also highlights the role of the family in shaping a child's development, including their impact on a child's self-esteem, emotional regulation, socialization, identity formation, and decision-making skills. The table includes references for further reading and acknowledges that the family's role in child development is multifaceted and influenced by cultural and societal factors. In the process of childhood development, individuality only emerges when a child recognizes contextual influences on their own behavior and perception of others and begins to qualify their own characteristics, such as when prompted to describe themselves (Harter, 2003). The concept of self-efficacy (Bandura, 1977), which is also integrated into existing models of behavior change (e.g., the HAPA model) (Schwarzer & Luszczynska, 2008), plays a special role in this process. The development of a child's individuality is not fully realized until late adolescence (Table 1), with personality traits manifesting in grades 7 to 9. Adolescents typically describe themselves in specific contexts, leading to inconsistencies in their self-concept. Recognizing contradictory contents in their self-concept is a common source of stress during these years, but this inner stress can benefit adolescents by promoting structural psychological development (Harter & Monsour, 1992).

Table 1: Developmental stages of Children and Adolescents

Age Group	Physical Development	Cognitive Development	Social and emotional Development	Role of Family	References
Infancy (0-2 years)	Growth in weight and height, motor development, sensory development	Preverbal skills, object permanence	Attachment, development of emotions	Primary caregiver for support, affection, and stimulation	Berger, K. S. (2020). The developing person through the lifespan.
Childhood (3-8 years)	Slower growth, improvement in coordination, fine motor skills, sensory development	Symbolic thinking, language development, imagination	Self-concept, moral reasoning, peer relationships	Emotional support, supervision, socialization	Berk, L. E. (2002). Child development.
Early Adolescence (9-12 years)	Growth spurt, puberty, changes in body coordination	Abstract thinking, logical reasoning	Identity, self-esteem, emotional instability	Emotional support, parental monitoring, modeling of behavior	Santrock, J. W. (2017). Life-span development.
Mid Adolescence (13-17 years)	Continued growth spurt, sexual maturation	Hypothetical thinking, future planning, identity consolidation	Peer relationships, romantic relationships, risk-taking behavior	Emotional support, autonomy support, monitoring, guidance	Arnett, J. J. (2016). The Oxford handbook of emerging adulthood.
Late Adolescence (18-21 years)	Physical maturation, completion of puberty	Abstract thinking, logical and critical thinking	Identity formation, emotional stability, independence	Emotional support, guidance, financial support, transition to adulthood	Erikson, E. H. (1969). Identity: Youth and crisis.

A research gap therefore exists in addressing this stress and determining when and in what form the individualization of mHealth interventions is appropriate. While there has been progress in research on mHealth development in children and adolescents, there are still research gaps regarding the adaptation of mHealth interventions to the different developmental stages:

- An important research gap is the development of evidence-based mHealth interventions that take into account the specific needs and preferences of different age groups. There are concerns regarding the development of mHealth interventions that may not be tailored to the abilities and cognitive developmental stages of children and adolescents.
- Another research gap is the need for better validation of mHealth interventions across different age groups. It is important that mHealth interventions are not only culturally validated but also age-appropriately validated to ensure that they are effective and safe.

- Finally, there is also a need for improved collaboration between mHealth intervention developers and clinical professionals to ensure that the interventions are aligned with the needs of children and adolescents.

Overall, the challenge is to design mHealth interventions that are not only effective but also tailored to the developmental needs of children and adolescents. However, with the increasing use of digital technologies in healthcare, young people need to be able to navigate these tools effectively to make informed decisions about their health and critically reflect on that (Taba et al., 2022).

1.2.3.2 Importance of digital health literacy for mHealth interventions

Digital health literacy refers to the ability to find, understand, evaluate, and use digital health information to make informed health decisions. In children and adolescents, digital health literacy can manifest itself in various ways over time as they grow and develop (Dadaczynski et al., 2021).

Paige et al. (2018) found that in infancy and early childhood, children are exposed to digital health information through media and their parents. At this stage, they may develop basic skills in using technology, such as touch screens and voice commands, to access health-related content. They may also learn about health and safety practices through interactive games and videos designed for young children. In middle childhood, children become more independent in using technology and may begin to search for health information online. They may also start to develop critical thinking skills to evaluate the credibility of digital health information and understand the potential risks and benefits of certain health behaviors. During early adolescence, adolescents may become more curious and interested in health-related topics, such as puberty, sexuality, and mental health. They may use social media and other online platforms to seek information and connect with peers who share similar concerns. At this stage, digital health literacy can help adolescents navigate conflicting information and identify reliable sources of health information.

In mid-adolescence, adolescents may become more engaged in managing their own health, such as making appointments with healthcare providers, accessing their medical records, and using health-related apps to monitor their physical and mental health. Digital health literacy can help adolescents make informed decisions about their health and well-being and communicate effectively with healthcare providers. In late adolescence, young adults may face new health challenges, such as transitioning to independent living, managing chronic conditions, and making decisions about sexual and reproductive health. At this stage, digital health literacy can help young adults access and use online resources to support their health and well-being (Paige et al., 2018).

The state of research on digital health literacy among children and adolescents is still emerging, but it is increasingly recognized as an important area of study in the field of health communication and education. This is due to the widespread use of digital technologies in healthcare, and the need for children and adolescents to be able to navigate and make informed decisions about their health in these contexts (Sørensen et al., 2012). Recent studies have highlighted the challenges that children and adolescents face in developing digital health literacy. For example, research has shown that many young people lack the skills to critically evaluate health information on digital platforms, such as social media and health apps (Diviani et al., 2016; H. Kim & Xie, 2017). They may also struggle with understanding technical language or medical terminology used in digital health resources (Reen et al., 2019). Moreover, young people may not always have the support or guidance they need to develop DHL from parents, teachers, or healthcare providers (Stellefson et al., 2011). Lastly, digital health literacy can empower children and adolescents to take an active role in managing their health and prevent them from engaging in risky behaviors, such as using unverified health products or misinformation (Stassen et al., 2020).

To promote digital health literacy among children and adolescents, interventions are needed that target the specific challenges and needs of this population (Kayser et al., 2018). Such interventions may include educational programs that teach digital health literacy skills, as well as the development of digital health resources that are designed to be accessible and comprehensible to young people (Diviani et al., 2016). Additionally, it is important to involve parents, teachers, and healthcare providers in promoting digital health literacy among young people. In conclusion, digital health literacy is an important area of research and practice in promoting the health and well-being of children and adolescents. Further research is needed to identify effective interventions that promote digital health literacy among this population. While there has been increasing research attention on digital health literacy among children and adolescents in recent years, there are still several research gaps that exist in this area:

- The need to explore developmental differences in digital health literacy is supported by previous research, such as the study by Paige et al. (2018), which found that adolescents had higher digital health literacy scores than younger children.
- The role of parents and caregivers in children's digital health literacy is highlighted in the literature, as in the study by Diviani et al. (2016) which identified parents as key influencers on children's health-related Internet use.
- The need to explore digital health literacy in low-income communities is supported by several studies, such as the systematic review by Diviani et al. (2016), which found that individuals from low-income backgrounds had lower levels of digital health literacy (Norman & Skinner, 2006).

- The methods by which digital health literacy can be effectively fostered within the school environment, with the aim of promoting reflective and responsible use of mHealth applications among mid-adolescents, remain unclear.

Understanding developmental stages and digital health literacy in children and adolescents is important for designing effective interventions to promote health behavior change. However, social systems such as the family, peers, and school also play a critical role in shaping health beliefs and behaviors of children. Hence, it is essential to explore the role of social systems in engaging with mHealth interventions, which is the focus of the next section.

1.2.4 Importance of social systems for mHealth interventions

Integrating mHealth interventions for children and adolescents into social systems, such as families, peers, and schools, is important as social systems play a crucial role in shaping health beliefs, behaviors, and outcomes in this population (Ryan, 2009). By involving social systems in mHealth interventions, children and adolescents may receive more support, motivation, and reinforcement to engage in health behaviors and adopt healthy habits. For example, if an mHealth intervention is integrated into the school curriculum, it may provide children and adolescents with opportunities to learn and practice healthy behaviors in a supportive and structured environment. Likewise, if parents are involved in the design and implementation of an mHealth intervention, they may provide guidance and support to their children, promote the use of the technology, and reinforce positive health behaviors. Moreover, involving social systems in mHealth interventions may enhance the sustainability and scalability of the intervention, as it may leverage existing networks and resources. Therefore, integrating mHealth interventions for children and adolescents into social systems can enhance the effectiveness, acceptability, and sustainability of the intervention and ultimately lead to better health outcomes.

1.2.4.1 Importance of family dynamics for mHealth Interventions

As highlighted in table 1 , families have a significant impact on the health and well-being of children and adolescents. Research has consistently shown that family factors, such as parenting practices, family functioning, and family environment, are strongly associated with children's physical, emotional, and cognitive development (Fiese et al., 2000; Grolnick & Pomerantz, 2009). For instance, family involvement in PA has been associated with higher levels of PA and better health outcomes among children and adolescents (Dunton et al., 2015). Additionally, the family environment, such as the availability of healthy food choices, has been linked to the development of healthy eating habits and reduced risk of obesity in children (Cullen et al., 2001). Understanding the role of family in children's health and well-being is crucial for developing effective health interventions and promoting healthy behaviors. By addressing family and social factors, health interventions can be tailored to the unique needs and contexts of children and adolescents, leading to improved health outcomes and reduced health disparities (Brownson et al., 2009) In summary, the family as a social systems plays a critical role in the development of children and adolescents and has significant implications for their health and well-being, but further research is needed to effectively include families into mhealth interventions for children and adolescents:

- There is a lack of clarity on the optimal ways to involve families in mHealth interventions. Although there is evidence that involving families can enhance the effectiveness of mHealth interventions, there is still limited understanding of the optimal ways to involve families in these interventions (Hynynen et al., 2016).
- The understanding of the mechanisms through which family involvement influences health outcomes is limited. While it has been shown that involving families can lead to better health outcomes for children and adolescents (Carman et al., 2013; Carter, 2002), there is still limited understanding of the mechanisms through which family involvement influences these outcomes.
- There is a need for more culturally sensitive and contextually relevant mHealth interventions that take into account the diverse needs and preferences of families from different backgrounds.

1.2.4.2 Importance of school & peer groups for of mHealth interventions

Similarly, to families, other social systems, including peers, schools, and community resources, play a crucial role in shaping children's health behaviors and outcomes (Bronfenbrenner, 1994). Several studies have investigated the integration of school and peer groups in mHealth interventions for children and adolescents. School-based mHealth interventions have been found to be effective in promoting healthy behaviors (Sallis et al., 2000), such as PA and healthy eating habits, through the provision of tailored and interactive content that can be accessed through mobile devices (Hynynen et al., 2016). Moreover, peer-based interventions have been shown to be effective in promoting positive health behaviors and providing social support (Golsteijn et al., 2017). For example, a study conducted in the Netherlands found that a school-based intervention that used peer influence to promote PA among adolescents was effective in increasing their MVPA levels (Golsteijn et al., 2017). Additionally, the use of social media platforms, such as Facebook and Twitter, has the potential to enhance the reach and impact of mHealth interventions among school-aged children and adolescents by providing a platform for social support, communication, and engagement (Hynynen et al., 2016). While there is promising evidence on the integration of school and peer groups in mHealth interventions for children and adolescents, there are also several research gaps that need to be addressed:

- One major research gap is the need for more rigorous and standardized evaluation of these interventions, including the use of larger sample sizes and more comprehensive outcome measures.

- Additionally, there is a lack of research on the potential negative effects of school and peer-based mHealth interventions, such as increased screen time and social comparison.
- Another gap is the need to explore the optimal strategies for engaging and motivating school and peer groups to participate in these interventions, as well as the sustainability of their effects over time.

The integration of social systems, such as families, peer groups, and schools, has been identified as a critical factor in the success of mHealth interventions for children and adolescents (Kruk et al., 2022). However, while incorporating these systems into intervention design holds promise for improving outcomes, there is a need for an increased focus on the theoretical underpinnings of mHealth interventions. In particular, incorporating established models and theories from relevant fields such as health behavior and communication can help to ensure the effectiveness and sustainability of mHealth interventions. Therefore, the next chapter will explore the importance of integrating scientific theory and models into the development and implementation of mHealth interventions for children and adolescents.

1.2.5 Importance of theoretical foundation of mHealth interventions

Incorporating established models and theories from relevant fields such as health behavior and communication can help to ensure the effectiveness and sustainability of mHealth interventions for children and adolescents. Models and theories provide a framework for understanding the underlying mechanisms of health behaviors,for identifying the most effective strategies for promoting behavior change and for increasing the likelihood of lasting effects. However, research is needed for understanding the most effective ways to translate these theories into practice and on how to tailor interventions to specific populations, as well as how to effectively engage and motivate individuals to use these interventions over time. In the context of mHealth interventions for children and adolescents, the following two sections hapters explore strategies for integrating evidence-based pedagogical approaches and implementing behavior change techniques, including goal setting, in order to promote effective intervention outcomes.

1.2.5.1 Importance of pedagogical approaches for mHealth interventions

mHealth applications use various pedagogical approaches depending on their intended purpose and target audience. Some of the commonly used approaches include behaviorism, cognitivism, constructivism, and social learning theory.

Behaviorism focuses on observable behavior and external stimuli that shape behavior through reinforcement and punishment. Many mHealth interventions for behavior change, such as smoking cessation or weight management, use behaviorism principles to reinforce positive behaviors and discourage negative ones . For example, the Quit Genius app uses behavioral strategies like positive reinforcement and cognitive restructuring to help users quit smoking (Abroms et al., 2017). Cognitivism emphasizes the internal thought processes of learners and the role of mental structures in acquiring and organizing knowledge. Many educational apps that aim to enhance cognitive skills, such as memory, attention, and problem-solving, use cognitivist approaches (Harasim, 2017). For example, the Lumosity app uses games and challenges to improve cognitive skills by targeting specific mental processes (Fisher et al., 2014). Constructivism views learning as an active process where learners construct meaning from their experiences and interactions with the environment (MacLeod et al., 2022). Many mHealth apps that focus on patient education and self-management use constructivist approaches. For example, the My Asthma app uses a constructivist approach to teach asthma management by allowing users to create an individualized asthma action plan based on their symptoms and triggers (Strickland et al., 2017). Social learning theory emphasizes the importance of social interactions and modeling in learning (Chuang, 2021). Many mHealth interventions that target social support and behavior change use social learning theory principles. For example, the Fitbit app uses social support and accountability features to encourage PA and healthy habits (Lyons et al., 2014). Overall, pedagogical approaches used in mHealth interventions play a crucial role in achieving their intended outcomes and are rarely addressed in existing mHealth interventions for children and adolescents. This is a relevant consideration to bear in mind with regards to the customization of mHealth applications. By incorporating evidence-based pedagogical principles, mHealth interventions could effectively promote health behavior change and improve patient outcomes.

While there is some research on the use of evidence-based pedagogical approaches in mHealth interventions for children and adolescents, several research gaps exist:

- There is a need for further research on how to adapt and implement pedagogical strategies in ways that are engaging and effective for younger populations, while also accounting for the unique features and limitations of digital platforms.
- More research is needed to assess the impact of using evidence-based pedagogical approaches on behavior change outcomes and long-term health outcomes for children and adolescents participating in mHealth interventions.
- Furthermore, there is a research gap in identifying which of the described pedagogical approaches work best or whether a combination of approaches is more effective.

Having discussed various pedagogical approaches in mHealth interventions for children and adolescents in the previous section , we now turn to the behavior change mechanisms that underlie effective mHealth interventions. By examining the specific BCTs ((Michie et al., 2014) used in these interventions, we can gain a deeper understanding on how mHealth technology can be leveraged to promote positive behavior change and improve health outcomes in children and adolescents.

1.2.5.2 Importance of behavior change techniques for mHealth interventions

Integrating behavior change techniques (BCTs) into mHealth interventions for children and adolescents is crucial for improving health outcomes in this population. Research has shown that BCTs are effective in promoting behavior change and can be delivered through mHealth technology to enhance intervention effectiveness. For example, a systematic review of mHealth interventions for obesity prevention in children and adolescents found that interventions that incorporated BCTs, such as self-monitoring, goal setting, and feedback, were more effective in promoting healthy behaviors than interventions that did not include these techniques (Chen et al., 2015) Furthermore, the use of mHealth technology allows for the delivery of tailored and personalized feedback and support, which can enhance the effectiveness of the intervention. This can be particularly important in children and adolescents, as compared to adults they may require different types of support and feedback to facilitate behavior change (Michie et al., 2013). In addition, establishing healthy behaviors during childhood and adolescence can have long-term implications for health outcomes in adulthood. Therefore, promoting healthy behaviors early in life through mHealth interventions that incorporate BCTs can have a significant impact on improving overall health outcomes (Paige et al., 2018). To summarize, integrating BCTs into mHealth interventions for children and adolescents is an evidence-based approach that can promote behavior change and improve health outcomes in this population.

Although the use of BCTs in mHealth interventions for children and adolescents has shown promise in promoting positive behavior change and improving health outcomes, there are still some research gaps in this field.

- One research gap is the need for further development and validation of mHealth interventions that incorporate BCTs for specific health behaviors like PA in children and adolescents.
- Another research gap is the need to examine the optimal delivery methods and formats for BCTs in mHealth interventions for children and adolescents. For example, while some interventions have used text messaging or smartphone apps to deliver BCTs, other modes of delivery, such as virtual reality or social media, may be more effective for certain populations or health behaviors.
- There is a need to identify the key factors that influence the effectiveness of BCTs in mHealth interventions for children and adolescents. This includes examining how factors such as age, gender, cultural background, and socioeconomic status may impact the uptake and effectiveness of BCTs in this population.

- The specific physical activity and health goals that can be realistically achieved within a family-oriented framework involving children and adolescents are yet to be clearly defined.

By leveraging the unique capabilities of mHealth technology, healthcare professionals and developers can provide tailored and personalized interventions that are effective in promoting healthy behaviors.

1.2.6 Importance of context and preferential adjustment for mHealth interventions

1.2.6.1 Importance of individualization for mHealth interventions

A potential approach to addressing IPA and SB in children and adolescents is through the individualization of digital health applications, which are also referred to as adaptive, differentiated, needs-specific, audience-specific, tailored, or personalized interventions (Chen et al., 2021). In the educational setting, individualization has long been practiced under the term "Inner Differentiation" (Klafki & Stöcker, 1976; Trautmann & Wischer, 2009) to address the heterogeneity of school classes. In the context of mHealth, individualization is defined as the adaptation to the needs or special circumstances of an individual and the lack of individualization has been identified as one of the main barriers that prevent children and adolescents from changing their health behavior (Chen et al., 2021; Maron et al., 2010)

Individualized interventions offer a way to conduct person-centered interventions by varying individual needs. Examples for individualization are: Personalized feedback (providing tailored guidance based on users' specific health goals, physical activity levels, and preferences), Goal-setting (establishing individualized, SMART goals to increase motivation and adherence to the intervention), Gamification (Incorporating game-like elements to enhance user engagement and motivation), personalized reminders (Delivering context-specific reminders to engage in physical activity and other health-promoting behaviors) anyy many more (Tong et al., 2021). The higher effectiveness of individualized interventions compared to non-individualized interventions has been repeatedly demonstrated in various populations, particularly in adults (Broekhuizen et al., 2012; Laranjo et al., 2021), but not yet in children and adolescents, although several randomized controlled studies on this topic exist. For instance, the MOPO study examined the effects of a gamified and individualized mHealth intervention and has not been cited in any known meta-analyses to date (Pyky et al., 2017). Another example is the intervention by Moreau and colleagues (Moreau et al., 2015), which is a fully automatic, theory-guided tailored intervention. However, it should be noted that individualization in the context of child development means something different than in adults. Unlike adults, children have distinct physical, cognitive, and emotional developmental stages that must be taken into consideration. For example, younger children may require more guidance and support from their social enviroment to engage in physical activity, while older children may exhibit greater autonomy and self-motivation. The use of individualization in mHealth interventions for children and adolescents is an emerging area of research, and there are several research gaps that need to be addressed in this field:

- One research gap is the need for further development and validation of individualized mHealth interventions for specific health behaviors and outcomes in children and adolescents. While some studies have shown promising results for certain health behaviors, such as PA, more research is needed to determine the most effective strategies for tailoring interventions to individual characteristics and preferences.
- The specific type and intensity of individualization required to optimize the effectiveness of physical activity-based mHealth interventions remain unclear.
- Another research gap is the need to identify the most effective methods for individualizing mHealth interventions for children and adolescents. This includes examining the role of different types of data, such as self-reported information or sensor-based data, in developing and refining individualized interventions.
- Further research is needed to find the optimal balance between standardization and individualization in mHealth interventions for children and adolescents and to investigate the potential plateau effect of integrating individualized elements into mHealth interventions.
- The extent to which individualization is required, and how this need may differ across different age groups, in order to optimize the effectiveness of mHealth interventions aimed at reducing SB and increasing PA in children and adolescents remains unclear.

Adaptive assessment and JITAI are advanced forms of individualization in mHealth interventions for children and adolescents. Adaptive assessment allows for personalized assessment and monitoring of health behaviors and outcomes, while JITAI provide tailored support and guidance in real-time based on individual needs and preferences (Hardeman et al., 2019).

1.2.6.2 Importance of adaptive assessment for mhealth interventions

Adaptive assessment and JITAI are promising approaches in mHealth interventions for children and adolescents (Fiedler et al., 2023). Adaptive assessment involves tailoring the intervention to the specific needs and characteristics of each individual, while JITAI deliver support at the moment of need. A meta-analysis by Wang and Miller (2020) found moderate to large effect sizes for JITAI and identified two aspects of tailoring, namely: (1) tailoring to what (i.e., tailoring to both people's previous behavioral patterns and their current need states; with these effects additive) and (2) approach to tailoring (i.e., both using a human agent and an algorithm to determine the tailored feedback; with these effects additive), to be significantly associated with greater JITAI effectiveness (Wang & Miller, 2020).

Since adaptive assessment and JITAI in mHealth interventions for children and adolescents is a relatively new field, there are still many research gaps:

- For example, it is unclear whether data-based triggers for interventions can trigger stress and overwhelm children and adolescents.
- In addition, research is needed to determine what types of health data provide the best foundation for adaptive assessment and JITAI
- Further development of algorithms is needed to achieve context and preference-specific adjustment tailored to the individual.

1.3 Research question and hypotheses

The objective of this chapter is to address the research gaps identified in the preceding chapter by investigating the influence of mHealth interventions on diverse age groups and developmental stages. The inquiry encompasses factors such as effectiveness, family integration, individualization, and digital health literacy, as depicted in figure 3. The chapter centers on the research questions and hypotheses of this thesis that explores the factors pertinent to the individualization of mHealth interventions for children and adolescents and employs a graphical representation of the theoretical background, current state of research, and research gaps in this field. Figure 4 represents a visualization of the research project presented in this thesis, which aims to explore the factors relevant to mHealth interventions for children and adolescents. The figure provides a graphical representation of the theoretical background, the current state of research, and the research gaps in this area. The factors relevant to mHealth interventions for children and adolescents include effectiveness, family integration, individualization, and digital health literacy. To better understand the impact of these, the literature references across different age and developmental stages were analyzed and mapped. The figure shows that the research project comprises four research questions. The first research question seeks to investigate the influence of mHealth interventions on children and adolescents within the age range of 0 to 21 years. The focus of the inquiry is to evaluate the effectiveness of mHealth interventions across various age groups, highlighting the importance of integrating families into such interventions, tailoring them to individual needs, and fostering digital health literacy development. The second research question focuses on children and early adolescents aged 8-12 years. This phase is characterized by the increasing potential effectiveness of mHealth interventions, while individualization is still of little importance. Family involvement is particularly important in this phase, resulting in a zone of desired effects that is addressed in this study. The third research question pertains to target groups in middle adolescence aged 13-17 years. This phase is characterized by increasing independence from the family, increasing individuality, and digital health skills. The fourth and final research question relates to late adolescence or adulthood. In this phase, the need for individualization due to complex everyday realities and simultaneously high digital health literacy exceeds the effectiveness, creating another zone of desired effects.

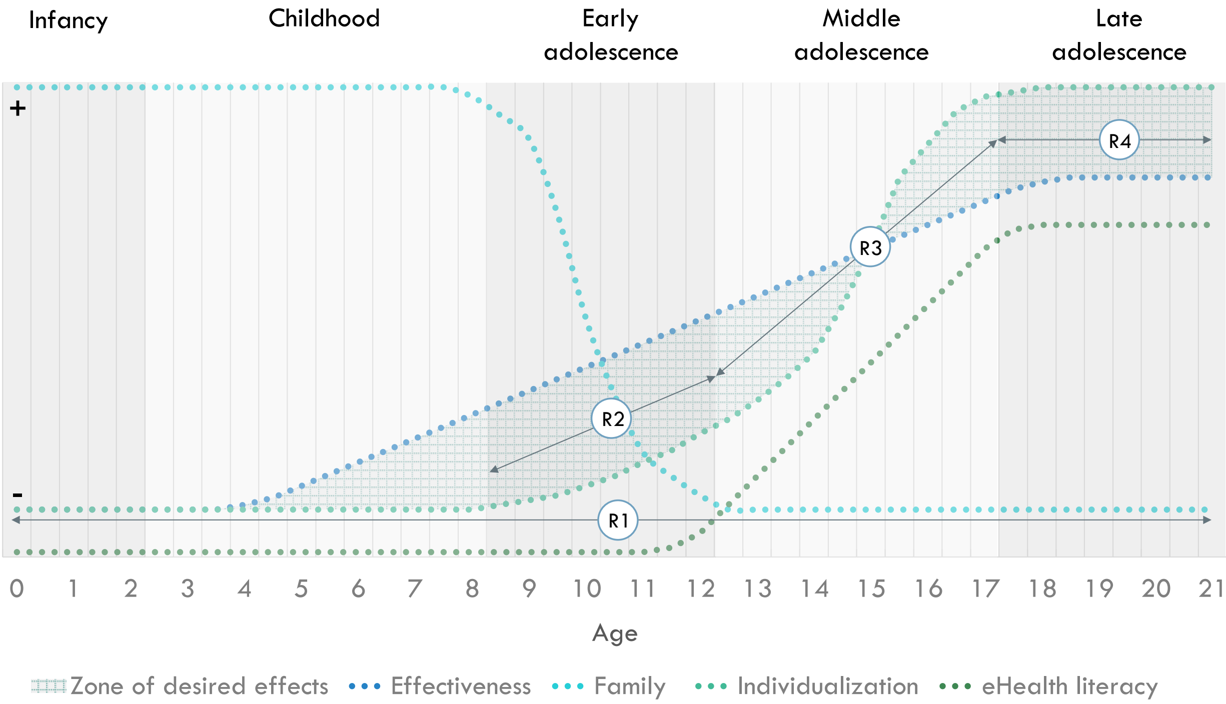

Figure 4: Proposed research question model to illustrate the assumed temporal course of effectiveness of mHealth interventions, the relevance of involving the family environment, the need for individualization, and the manifestation of digital health competence, categorized according to childhood developmental stages. The model includes arrows indicating the age groups to which the individual research questions refer.

R_1: What is the impact of individualization and age as moderators on the effectiveness of mHealth interventions for reducing SB and IPA in children and adolescents?

- **$H_{1.1}$:** The effectiveness of mHealth interventions for children and adolescents increases with age.
- **$H_{1.2}$:** Individualization is not as crucial for the effectiveness of mHealth interventions in children and early adolescents as it is in mid-adolescents and late adolescents.

R_2: What are the feasible mHealth-based physical activity and health objectives that can be accomplished within the family framework involving early adolescents?

- **$H_{2.1}$:** Parental and early adolescent physical activity and health goals partially intersect.
- **$H_{2.2}$:** Social systems engagement, particularly family, is more appropriate and beneficial for infants, children and early adolescents rather than for mid and late adolescents.

R$_3$: How can digital health literacy be promoted within the school setting to ensure reflective and responsible use of mHealth applications among mid adolescents?

- **H$_{3.1}$:** Both physical education teachers and mid adolescent students show digital health literacy deficits.
- **H$_{3.2}$:** Given the high proportion of practical elements and facilities required, the conditions for teaching digital health literacy in physical education differ considerably compared to other disciplines.

R$_4$: How does individualization affect the effectiveness of physical activity-based mHealth interventions?

- **H$_{4.1}$:** Individualized mHealth interventions show higher effectiveness on late adolescents and adults compared to non-individualized interventions.
- **H$_{4.2}$:** Promoting physical activity effectively with Individualized mHealth interventions benefits various other health outcomes.

2 CUMULATIVE PART OF THE DISSERTATION

2.1 WHAT IS THE IMPACT OF INDIVIDUALIZATION AND AGE AS MODERATORS ON THE EFFECTIVENESS OF MHEALTH INTERVENTIONS FOR REDUCING SEDENTARY BEHAVIOR AND INSUFFICIENT PHYSICAL ACTIVITY IN CHILDREN AND ADOLESCENTS?

The following publication has been published in relation to this research question:

Baumann, H., Fiedler, J., Wunsch, K., Woll, A., & Wollesen, B. (2022). MHealth Interventions to Reduce Physical Inactivity and Sedentary Behavior in Children and Adolescents: Systematic Review and Meta-analysis of Randomized Controlled Trials. *JMIR MHealth and UHealth*, *10*(5), e35920. https://doi.org/10.2196/35920

2.1.1 Introduction

Children and adolescents increasingly do not meet PA recommendations. Hence, IPA and SB among children and adolescents are relevant behavior change domains for using individualized mobile health (mHealth) interventions. Although several review papers (Böhm et al., 2019; He et al., 2021; Lee et al., 2019; Schoeppe et al., 2017) have been published on health-related PA promotion in the context of mHealth for children and youth, none of these works focus on reducing physical inactivity and SB in children and youth. The article discusses the prevalence of IPA in children and adolescents worldwide, which is mainly due to time spent on SB such as sitting and playing video games. This trend has negative health consequences and is expected to persist into adulthood. The article suggests mobile health interventions as a way to reduce physical inactivity and SB.

The authors emphasize the importance of personalized approaches and the integration of behavior change techniques. The quality of mobile health interventions for children and adolescents is criticized, and the authors suggest that more age-appropriate solutions are needed. The article also mentions the possibility for increased screen time with the use of mobile health interventions, but also highlights that there is evidence that this may not necessarily be the case. The authors' final assertion underscores the significance of tailored interventions that can be customized to an individual's unique requirements. Such interventions serve to empower individuals to proactively monitor their health.This review and meta-analysis investigated the effectiveness of mHealth interventions on IPA and SB, with a special focus on the age and level of individualization.

2.1.2 Methods

We used a database search and contacted study authors to obtain data if it was not available in the original manuscripts. The extracted data was then weighted by sample size and converted into an effect size (Cohen d) before being integrated into a meta-analysis using the RevmanWeb calculator. The meta-analysis used a random-effects model and effect sizes were interpreted as large (>0.50), moderate (0.50 to 0.30), small (0.30 to 0.10), or trivial (<0.10). Test for for heterogeneity, overall effects, and subgroup differences were performed using RevmanWeb. To assess for publication bias, funnel plots were created using RevmanWeb. The authors used the Grading of Recommendations, Assessment, Development, and Evaluations approach to provide certainty of the evidence, examining factors such as individual study limitations, inconsistency of results, indirectness of evidence, imprecision, and publication bias. An additional meta-regression was performed to relate the estimated effect sizes to the mean age of the samples. The study protocol was prospectively registered on PROSPERO.

2.1.3 Results

Out of 828 identified studies, a total of 11 (1.3%) were included for the qualitative synthesis and 10 (1.2%) for the meta-analysis based on the inclusion criteria. Trials included 1515 participants (mean age 11.69, SD 0.788 years; 65% male and 35% female) with self-reported (3/11, 27%) or device-measured (8/11, 73%) health data on the duration of SB and IPA for an average intervention period of 9.3 (SD 5.6) weeks (excluding follow-ups). Studies with high levels of individualization decreased IPA levels significantly (Cohen d=0.33; 95% CI 0.08-0.58; Z=2.55; P=.01), whereas those with low levels of individualization (Cohen d=−0.06; 95% CI −0.32 to 0.20; Z=0.48; P=.63) or addressing SB (Cohen d=−0.11; 95% CI −0.01 to 0.23; Z=1.73; P=.08) indicated no overall significant effect. Heterogeneity was moderate to low, and a test for subgroup differences indicated significant differences between trials with high and low levels of individualization (χ^2 1=4.0; P=.04; I2=75.2%). Age as a moderator variable showed a minor moderating effect (figure 5); however, the results were not significant, which might have been due to underpowering.

Table 2: Individualized elements of existing physical activity-related mHealth interventions for children and adolescents, categorized based on self-efficacy components (Yellow=mastery experience, Blue=vicarious experience, Orange=verbal persuasion, Green=direct biofeedback).

Author	Intervention	Individualized elements	Score	Level
Chen et al.	Fitbit-App & Facebook	Competitions with community or friends, individual goal setting, task adjustment in relation to BMI, direct biofeedback, real time coaching, goal specific motivational coaching, personalized advice, and guidance	6	High
Nyström et al.	MINISTOP-App	Individual feedback	1	low
Direito et al.	Zombies, Run! -App (1)	Audio instructions, missions and defense bases, virtual races	2	low
	Get-Running-App (2)	Human voice coach, training path, friend integration, low threshold approach, recovery periods, individual music	6	high
Downing et al.	Mini Movers SMS-based-Intervention	individual goal setting, goal specific feedback, tailored SMS, just in time delivery of SMS based on preferred time, date, and activity	4	high
Fassnacht et al.	SMS-based-Feedback-Intervention	individual goal setting, task adjustment in relation to BMI, tailored feedback messages, goal specific motivational coaching	4	high
Gaudet et al.	FitBit-App immediate intervention	Competitions with community or friends, individual goal setting, task adjustment in relation to BMI, direct biofeedback and real time coaching, goal specific motivational coaching, personalized advice, and guidance	6	high
	FitBit-App delayed intervention	Competitions with community or friends, individual goal setting, task adjustment in relation to BMI, direct biofeedback and real time coaching, goal specific motivational coaching, personalized advice, and guidance	6	high
Hammersley et al.	Time2b-Healthy Facebook and Online	Tailored reminder emails, Facebook group with, individual goalsetting, goal specific motivational coaching	4	high
Mendoza et al.	Fitbit-App & Facebook	Individual Awards in Facebook group, Competitions with community or friends, individual goal setting, task adjustment in relation to BMI, direct biofeedback and real time coaching, goal specific motivational coaching, personalized advice, and guidance	7	high
Pyky et al.	Clans of Oulu gamified App and online MOPO Portal	Stage of behavior change, individual feedback on physical activity and sitting time, GPS based tasks, competitions with community, peer-referenced comparison	5	high
Woudenberg et al.	App-based Social Network Intervention MyMovez	Content tailored to influential youth, comparing individual scores with others, individual rewards, individual identification with health behavior	4	high

2.1.4 Discussion

This study is the first to explore the effectiveness of mHealth interventions on reducing IPA and SB in children and adolescents, focusing on age- and individualization-dependent effects. The study findings support existing research that gamified approaches tend to be more effective in this population, but only if combined with individualization, theoretical foundation, and integration of BCTs. The most effective interventions are those that incorporate social components,community-based systems of social participation, and association with real-world physical activities in the surrounding environment. The study highlights the need for enhanced theoretical substantiation in the development of mHealth interventions, focusing on objective data and standardized outcome measures. The study found moderate effectiveness in reducing IPA, but no significant effect in reducing SB. The authors suggest that structural changes, such as educational policies for schools, are necessary to reduce SB. The study also showed that the effectiveness of mHealth interventions varies by age, with the highest effect sizes evident in adolescent age groups. Finally, the authors suggest that the use of mHealth interventions in childhood and adolescence requires careful consideration due to the potential shift in time resources and the need for individualization.

This study adds the following findings to the existing body of evidence:

Gamified mHealth interventions, combined with individualization and BCTs, effectively reduced IPA in children and adolescents, particularly in adolescents. Social components and community-based systems should be included, but no significant effect was observed in reducing SB. Structural changes are needed, and careful consideration is required for mHealth interventions due to the need for individualization and time resource shift.

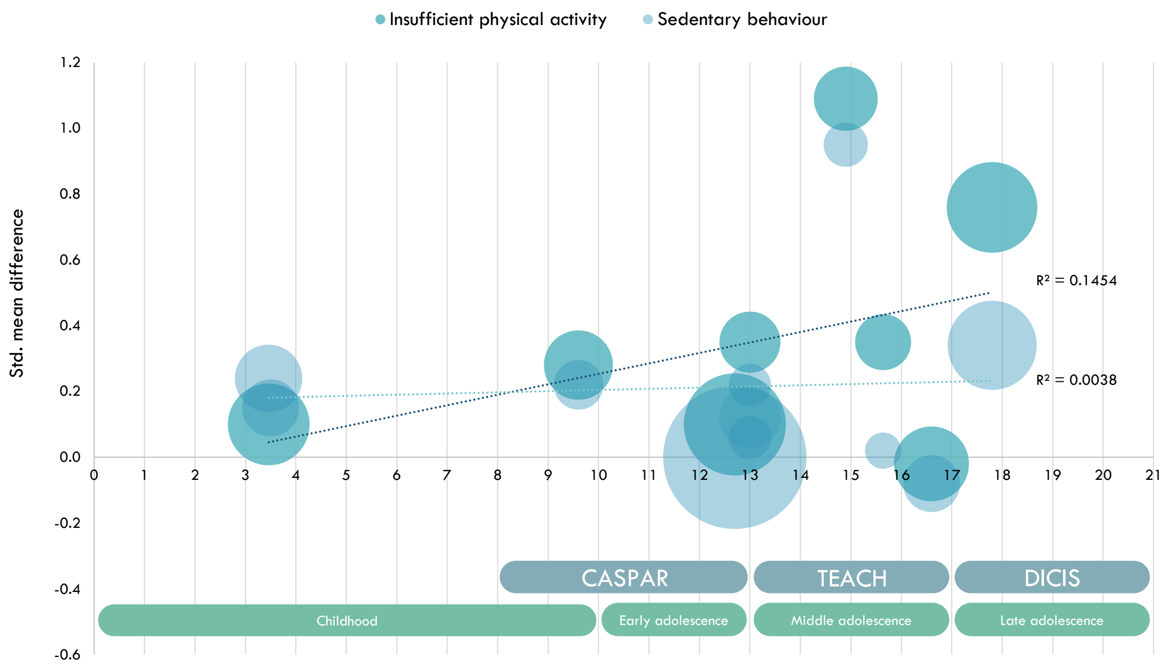

Figure 5: Grouped bubble plot of weighted standardized mean differences of individual trials and mean age of participants. Group differentiation based on the primary outcome (IPA and SB). High-individualized trials included only.

2.1.5 Authors contributions

The systematic review and meta-analysis wereconceptualized by Hannes Baumann, Janis Fiedler, Kathrin Wunsch, Alexander Woll, and Bettina Wollesen, while the methodology and formal analysis were carried out by Hannes Baumann, Janis Fiedler, Kathrin Wunsch. The investigation was conducted by Hannes Baumann, Janis Fiedler, and Kathrin Wunsch, with resources provided by Bettina Wollesen and Alexander Woll. Janis Fiedler and Kathrin Wunsch provided support in formulating the Prospero application, as well as in screening and evaluating the individual studies. The data curation was performed by Hannes Baumann, Janis Fiedler, and Kathrin Wunsch, while the original draft preparation was completed by Hannes Baumann and Janis Fiedler. The writing of the manuscript was reviewed and edited by Kathrin Wunsch, Janis Fiedler, Bettina Wollesen, and Alexander Woll, and the visualization was done by Hannes Baumann and Janis Fiedler. The project was supervised by Bettina Wollesen and Alexander Woll, and the project administration was handled by Bettina Wollesen. All authors have read and approved the published version of the manuscript.

2.2 What are the feasible mHealth-based physical activity and health objectives that can be accomplished within the family framework involving early adolescents?

The following three publications have been published in the context of this research question. However, additional analyses have been conducted as part of this PhD thesis. As all three publications have originated from the same project, this dissertation primarily consolidates partial results from these studies. Nevertheless, the emphasis is on the presented supplementary analyses, which have been based on a conglomerated dataset.

Meixner, C., Baumann, H., & Wollesen, B. (2020). Personality Traits, Gamification and Features to Develop an App to Reduce Physical Inactivity. *Information, 11(7),* 367.

Bischoff, L. L., Baumann, H., Meixner, C., Nixon, P., & Wollesen, B. (2021). App-Tailoring Requirements to Increase Stress Management Competencies Within Families: Cross-sectional Survey Study. *Journal of Medical Internet Research*, *23*(7), e26376. https://doi.org/10.2196/26376

Meixner, C., Baumann, H., & Wollesen, B. (2022). Gesundheitsbezogene Ziele der digitalen Prävention und Gesundheitsförderung in Familien. *Gesundheitswesen.* https://doi.org/10.1055/a-1860-0911

2.2.1 Introduction

The prevalence of obesity among adolescents and adults is increasing despite the availability of interventions (Guthold et al., 2018). This suggests a lack of tailored approaches to address the living environments of young people. Yeager et al. (2018) propose that tapping into adolescents' sensitivity to status and respect within social constructs could redirect them towards positive behavior change. Health-promoting family models, based on equal communication, are suggested by Michaelson et al. (2021) as useful tools for promoting health behaviors and PA among children and adolescents. When developing interventions, it is relevant to consider the living environments of both adults and adolescents. mHealth interventions, which are low-threshold and easily integrated, may be a potential solution, especially given the prevalence of smartphones among young people. Meta-analyses demonstrate that highly individualized mHealth interventions that integrate multiple behavior change mechanisms show the highest effectiveness for PA outcomes in children and adolescents (Baumann, Fiedler, et al., 2022; Böhm et al., 2019; Schoeppe et al., 2017). Interventions that integrate parental involvement may be beneficial for preadolescent populations as well. Social support and mHealth-based goal setting may represent two relevant health behavior change techniques for adolescents. Therefore, multiple behavior change mechanisms should be used in intervention planning, addressing different phases of the health behavior change process. Goal setting, especially when embedded in social settings, addresses the motivational phase, whereas embedding interventions in the family setting provides social support, incentives, and comparative regulators, reinforcing the post-intentional and volitional phases (Michie et al., 2011). Brown et al. (2020) have shown that establishing health goals in a family context improves health behavior and could be reinforced by mHealth applications. However, Colineau et al. (2011) have pointed out the interference between family and individual goals. Therefore, this paper aims to identify mutual health goals of different family members in the context of mHealth to initiate a long-term health behavior change process.

2.2.2 Methods

To answer the research question, an explanatory sequential mixed-methods study was conducted, in which adolescents in school settings and families were surveyed about their health behavior and jointly pursued health goals. Through 3 focus group interviews with school classes of different grades (N=120 adolescents, f=50.0%, m=50.0%, 3 age groups 11-12, 13-14 and 15-16 years) and 60 guideline interviews with parents (N=60 parents; f=41.7%, m=58.3%; Ø 42.4 age of parents), initial health goals were identified that children and adolescents would want to implement together with their parents. These goals were then quantified in a nationwide online survey (N=3795 participants (1008 families); f=50.4%, m=48.2%, d=1.7%; Ø 3.81 persons per household; 54% children (Ø 13.41 years); 46% adults (Ø 47.79 years)), along with sociodemographic variables such as age and gender. The questionnaire used a binary scale (interested/not interested) to measure interest in the health goals presented in table 3 in the prevention fields of activity, nutrition, and relaxation. Both studies were approved by the ethics committee of the University of Hamburg (reference number: AZ: 2019_270).

The analysis of both qualitative sub-studies was conducted through qualitative content analysis with MAXQDA, while the quantitative sub-studies of both projects were analyzed using SPSS and rStudio. To identify age-independent familial health goals, multiple binary logistic regression analyses were conducted.

Table 3: mHealth related health goals within the three dimensions of primary prevention

Health goals in the prevention area of physical activity	**Health goals in the prevention area of nutrition**	**Health goals in the prevention area of stress and relaxation**
Improvement of fitness	Healthier nutrition	Relaxation exercises in daily life
Building muscle mass	Weight change	Increase in resilience to stressors
Increasing flexibility	Dietary change	Practice of meditation exercises
Increasing endurance	Vegetarian diet	Practice of mindfulness exercises
More active lifestyle	Vegan diet	Practice of breathing exercises
Increasing performance	Communal cooking	Practice of yoga exercises
Participation in health courses	Trying new recipes	Spending time in nature
Conducting parent-child workouts	Seasonal, local & organic food intake	Wellness and sauna offerings
Outdoor activities	Knowledge about nutrient intake	Exercises for on-the-go
Membership in a sports club	Increase in fluid intake	Stress management strategies

2.2.3 Results

The structuring qualitative content analysis revealed thirty familial health goals (ten goals per field of behavior-related primary prevention) that the surveyed family members could imagine pursuing together. In the online survey, the greatest interest was shown for the following goals in the field of PA: "spending time in nature" (70%), "physical activity outdoors" (62%), and "improving fitness" (60%). However, the multiple binary logistic regression analysis showed significant age effects for twenty-four health goals. Six of the health goals showed no significant age effects (figure 6).

The intersection between children and adolescents and their parents is marked by green bars in figure 6. These variables do not show any age effects, meaning that the interest in the health goal does not vary significantly between individuals of different ages. This is paired with a high common interest (light blue bars) in identifying healthier eating habits, communal cooking, outdoor activities, learning exercises for on-the-go, spending time in nature, stress management, and dietary changes as primary goals in the field of mHealth that children and adolescents would undertake with their parents.

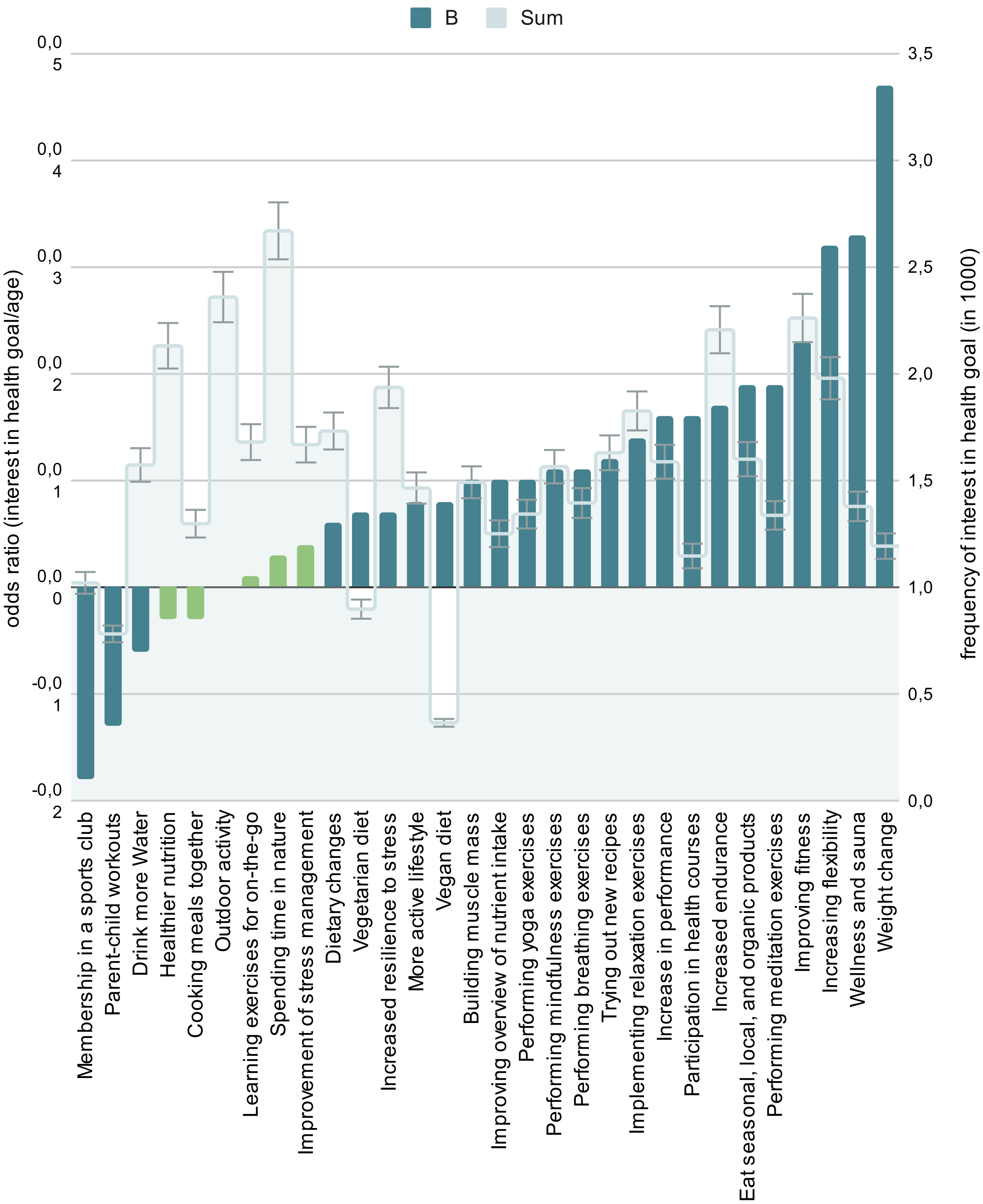

Figure 6: Combined bar chart displaying age dependence of health goals.

2.2.4 Discussion

Since the aim of the study was to identify familial health goals that are of high interest to all family members and show no age effects, not all of the qualitatively identified goals are relevant for family health promotion. Only the goals "integration of a healthier diet," "spending time in nature," and "physical activity outdoors" are both interesting to all members of the familys and are age independent. Integrating the study results into the context of Brand and Ekkekakis (2018) affective reflective theory of physical activity and exercise allows for theoretical embedding: multiplication of sport-related stimuli is necessary to stimulate type-1 processes and positive affect to convert them into type-2 processes, thereby promoting healthy habit formation. According to Grey et al. (2020), the family can therefore act as both a multiplier and a positive affect provider in addressing these goals in health interventions and thus positively influence the health behavior of adolescents in the long term.

This study adds the following findings to the existing body of evidence:

This study has identified age-independent health goals for parents and children, indicating that mHealth interventions targeting healthy diets or outdoor physical activities are more likely to be adopted within the family social system. Furthermore, the study highlights the benefits of using mHealth interventions within a family context, particularly for early adolescents.

2.2.5 Authors contributions

All three publications, originated in the same project (Caspar-Project), were initiated under the conceptualization of Bettina Wollesen, while the methodology and formal analysis were carried out by Hannes Baumann, Charlotte Meixner, and Bettina Wollesen. The investigation was conducted by Hannes Baumann and Charlotte Meixner with supervision of Bettina Wollesen. The resources for the study were provided by Bettina Wollesen, while the data curation was performed by Hannes Baumann, Charlotte Meixner, and Bettina Wollesen. Hannes Baumann performed an additional data analysis for the sake of this PhD thesis. The original draft of two manuscripts was prepared by Charlotte Meixner and one by Laura Bischoff, with subsequent review and editing of all three papers by Bettina Wollesen, Charlotte Meixner, and Hannes Baumann. The visualization aspects were taken care of by Hannes Baumann and Charlotte Meixner. The study was supervised by Bettina Wollesen, who was also responsible for project administration and funding acquisition. All authors have read and approved the final version of the manuscript for publication.

2.3 How can digital health literacy be promoted within the school setting to ensure reflective and responsible use of mHealth applications among mid adolescents?

The following publication has been published in relation to this research question:

Baumann, H.; Meixner, C.; & Wollesen, B. (2022): Voraussetzungen zur Vermittlung digitaler Gesundheitskompetenzen durch Sportlehrkräfte im Zuge der SARS-CoV-2-Pandemie: Eine explorative Mixed-Methods Studie im Schulkontext. In: *Zeitschrift für Studium und Lehre in der Sportwissenschaft - Themenheft Digitalisierung in der Sportlehrer*innenbildung* (5(1)), S. 5–18. DOI: 10.25847/zsls.2021.051.

2.3.1 Introduction

The Life World-related Setting Approach (Rosenstock, 1974), which can also be applied to the school setting, involves the age-appropriate participation of children and adolescents in measures to promote health and PA (Hanssen-Doose et al., 2018) The promotion of PA is in the foreground, while the teaching of health literacy (defined by Sørensen et al. (2012) as the abilities to find, understand, evaluate and apply health information for health-related decisions) is incorporated into the curricula of individual states (primarily in the subjects of sports, biology, and health) (Töpfer & Sygusch, 2014).

The pandemic conditions resulted in challenges to health promotion (e.g. the lack of sports and counseling options), which can be tackled more effectively with digital health literacy (e.g. targeted procurement of evidence-based health information, digital promotion of PA, use of digital applications for infection tracking) (Dadaczynski et al., 2021). However, there is still a lack of curricular integration of digital health literacy in most states in germany, which rapidly gained in importance during the nationwide lockdowns due to the SARS-CoV-2 pandemic (Crawford & Serhal, 2020). Furthermore, contact restrictions led to a reduction in social interactions, which required, among other things, digital solutions for the transfer of information in the school day. The previously presence-based teaching was transferred to homeschooling, a situation that overwhelmed many teachers, parents, and students (OECD, 2020). This resulted in socio-affective complications and IPA, particularly among socio-economically disadvantaged children (López-Bueno et al., 2021). Central changes for teachers included the needs-based use of digital teaching-learning platforms (e.g. Iserv and Commsy), digital conference tools (e.g. Zoom) or other forms of interaction with short preparation times to adapt the teaching material to digital formats. For example, students experience the lack of familiar daily structures of the school day as overwhelming (Magson et al., 2021; Naff et al., 2022). Homeschooling requires more self-management competencies by the students (e.g. ability to self-motivate, establish working structures, create daily plans) or support from parents. Furthermore, there is a lack of access to digital devices and the internet (Francis & Weller, 2022). Parents, teachers, and students are therefore faced with the task of jointly redesigning teaching-learning processes.

At the same time, the restricted possibilities for movement and interaction (Al-Oraibi et al., 2022) have an impact on physical and mental well-being, which is why digital health promotion is gaining more significance during periods of isolation. It is unclear how, especially in sports classes, the promotion of digital health literacy in distance learning situations can be integrated in such a way that the psychosocial dimension (e.g. the fostering of social skills, the building of social relationships) and the physical dimension (e.g. physical fitness, motor development) are not neglected. In this context, it is also necessary to develop and implement methods for the evaluation of the effectiveness and impact of digital health promotion measures.

2.3.2 Methods

To develop appropriate teaching-learning concepts for promoting digital health literacy among educators and students, this article examines the impacts of distance learning on both. The study also captures variations in digital health literacy among educators, depending on the subject they teach. The exploratory sequential mixed-methods approach consisted of an online survey with 118 teachers of health, biology, and physical education and six focus group interviews through Zoom, including teachers and students ($n=34$). The follow-up survey questions pertained to digital media infrastructure in schools, digital health literacy, and potential barriers to promoting digital health literacy in schools. The analysis involved frequency analysis and ANOVA, with qualitative analysis conducted using Mayring content analysis with MAXQDA 2020.

2.3.3 Results

Both studies revealed a shortage of digital literacy and media infrastructure. The target groups showed high interest in developing digital health literacy. Physical education teachers demonstrated lower digital health literacy compared to biology and health teachers ($F[2,99]=4.07$; $p=.020$; η^2 partial$=.107$). The results highlight the need for improved infrastructure (e.g. access to WLAN) and demonstrate a pressing need to promote digital health literacy in schools. Based on the analysis of both studies, four broad recommendations can be derived for successfully teaching digital health literacy: (1) basic infrastructural requirements, (2) content for teaching digital health literacy in physical education, (3) methodological implementation, and (4) further training for physical education teachers.

2.3.4 Discussion

Since the beginning of the pandemic, teachers and learners have been confronted with changes in the teaching-learning process that require digital competencies as well as digital health competencies. The overall goal of the study was to develop solutions and recommendations for the practical implementation of suitable teaching and learning concepts. The background of this is that teachers initially need to improve their own digital health competencies to subsequently act as multipliers for the digital health competencies of learners. The study identified infrastructure requirements and necessary competencies for digital teaching depending on the subjects taught (sports, biology, health), as well as the opinions of actors from multiple types of schools in focus groups. In addition, the study focused on the particular situation of sports teachers in order to provide recommendations for the implementation of digital teaching and learning projects and the future training of sports teachers. The study found a lack of mobile devices for implementing innovative digital teaching and learning projects to promote digital health competencies. Teachers' digital health competencies were also found to be deficient, particularly in the area of knowledge of physiological functions, their own health status, and risk factors. This suggests that the greatest challenges for implementing digital teaching and learning concepts may lie with sports teachers. However, it is unclear whether this is due to the self-concept or role perception of sports teachers. Furthermore, the functional feasibility of digital content in sports lessons needs to be considered, especially for primary and secondary level education, where sports halls as teaching venues have fewer media options than other subject rooms. Therefore, it appears that in the analog sports lesson, a focus on digital health competencies would initially reduce the time and intensity of movement. The study recommended careful selection of digital applications for promoting digital health competencies and the need for a pedagogical strategy for the use of mobile devices in sports lessons, as different conditions apply due to the high level of movement.

This study adds the following findings to the existing body of evidence:

Challenges in implementing digital health competency teaching in schools include a lack of mobile devices and digital literacy among teachers. Suitable apps can enable PA and digital health literacy education in homeschooling. Additionally, a lack of technological resources in gymnasiums hinders digital content implementation in physical education, highlighting the importance of targeted training for promoting digital teaching skills.

2.3.5 Authors contributions

This study was a collaborative effort by a team of researchers comprising Bettina Wollesen, Hannes Baumann, and Charlotte Meixner. The study's conceptualization and project idea (Teach-Project) was carried out by Bettina Wollesen, Hannes Baumann, and Charlotte Meixner, while Hannes Baumann, Charlotte Meixner, and Bettina Wollesen were responsible for the methodology and formal analysis.

Data collection was carried out by Hannes Baumann and Charlotte Meixner, with Bettina Wollesen providing the resources necessary for the study. Data curation was the responsibility of Hannes Baumann and Bettina Wollesen, while the original draft preparation of the manuscript was carried out by Bettina Wollesen and Hannes Baumann. The manuscript was subsequently reviewed and edited by Bettina Wollesen and Charlotte Meixner. Hannes Baumann was responsible for visualizing the data, while Bettina Wollesen provided supervision and project administration. The funding for the study was acquired by Bettina Wollesen. All authors have read and agreed to the published version of the manuscript.

2.4 How does individualization affect the effectiveness of mHealth interventions?

The following three publications have been published in connection with this research question:

Baumann, H., Heuel, L., Bischoff, L. L., Wollesen, B. (2023). mHealth interventions to reduce stress in healthcare workers (fitcor): study protocol for a randomized controlled trial. *Trials*, 24, 116.

Baumann, H., Heuel, L., & Wollesen, B. (2023). Efficacy of individualized sensory-based mHealth interventions to improve distress coping in healthcare professionals: A Multi-Arm Parallel-Group randomized controlled trial. *Sensors,* 23(4):2322. https://doi.org/10.3390/s23042322

2.4.1 Introduction

Occupational psychosocial stress is a significant risk factor for developing various diseases, including psychological, musculoskeletal, and cardiovascular diseases (Dragano, 2018; Järvelin-Pasanen et al., 2018). Healthcare professionals are particularly susceptible to high levels of stress due to recurring stressors, such as high work demands, leadership style, lack of appreciation, and work-family conflicts (McVicar, 2003; Moustaka & Constantinidis, 2010) which contributes to low heart rate variability. Chronically low heart rate variability is associated with impaired regulatory and homeostatic functions of the autonomic nervous system, which reduces the body's ability to cope with internal and external stressors (da Estrela et al., 2021). Resilience toward occupational stress can be improved through personal and organizational resources, and stress reduction interventions, such as mindfulness programs, PA, breathing exercises, progressive muscle relaxation, and yoga (Bischoff et al., 2019). To design effective interventions for healthcare professionals, it is essential to identify barriers, select appropriate intervention components, use theory, and engage end-users while considering the length and sustainability of interventions (Colquhoun et al., 2017). However, the evidence base for stress reduction interventions for health personnel is insufficient due to issues such as study rigor, high dropout rates, and a lack of appropriate study designs (Bischoff et al., 2019). Individual and organizational factors also make it difficult to implement effective interventions. Digital interventions, particularly mobile health (mHealth) interventions, have the potential to address these issues by offering low-cost, easy-to-implement, and need-individualized health promotion interventions (Stratton et al., 2017). mHealth interventions have been found to be effective in reducing stress and improving mental health outcomes among healthcare professionals (H.-G. Kim et al., 2018). Individualized interventions offer a potential way of delivering person-centered interventions, such as adapting intervention content to individual needs for behavior change, individual coaching based on intervention results, direct biofeedback via app and sensor interfaces, visualization of health data, and adaptation of content based on psychological characteristics (Chen et al., 2021). The present study aims to compare the effectiveness of web-based vs. app-based and individualized vs. non-individualized stress management interventions in improving distress coping in health professionals.

2.4.2 Methods

A multi-arm parallel group randomized controlled trial was conducted with five intervention groups, according to the CONSORT guidelines (Dwan et al., 2019), including necessary extensions (Juszczak et al., 2019; Schulz et al., 2010). All participants in the intervention groups received a digital intervention, and both questionnaire and sensory data were assessed at baseline (pre-intervention) and eight weeks (post-intervention). This paper only focuses on the sensory data. The five intervention groups were described as follows: Group 1 received a web-based digital stress management intervention with no additional features, Group 2 received a web-based need-oriented digital stress management intervention, Group 3 received a web-based need-oriented digital stress management intervention with telephone coaching, Group 4 received an app-based personality specific digital stress management intervention with sensory biofeedback, and Group 5 received an app-based personality specific digital stress management intervention with sensory biofeedback and a health report. The trial participants were healthcare professionals aged 18 years or older and fluent in German, with internet access via a smartphone. Random allocation was used to prevent selection bias. The participants were informed of their assigned intervention group and data collection was done via self-administered online questionnaires and sensors. There were five different intervention scenarios, each with various levels of individualization, with the app-based interventions featuring higher levels of personalization than the web-based ones. The sensors used were CM300, which includes an ECG circuit and various chips for measuring PA and stress levels. Demographic characteristics such as age, gender, and job hierarchy were also assessed. The focus of the study was on the sensory data in the stress and PA domains.

2.4.3 Results

The study aimed to evaluate the effectiveness of different intervention programs in promoting PA in small and middle-sized companies. The study was conducted among 995 participants from multiple institutions, of which 643 participants were assigned to the study groups and received interventions. However, due to various reasons such as lack of time, illness, and technological issues, a total of 170 participants were considered for analysis, resulting in a dropout rate of 74%. The participants were divided into five different study-arms with varied intervention programs and analyzed based on their assigned groups. The baseline data showed no significant differences in demographic characteristics between the intervention and control groups. The average age of the participants was 41.1 ± 10.9 years and the sample consisted of more female than male participants. The results of the statistical analysis (MANOVA) indicated significant time * group effects for the PA-related outcomes, including MVPA minutes and inactivity disruption counts. Post-hoc analysis revealed that the individualized app study-arms (4 and 5) were significantly different from the control group and less individualized web-based training study-arms (1, 2, and 3) in these outcomes.

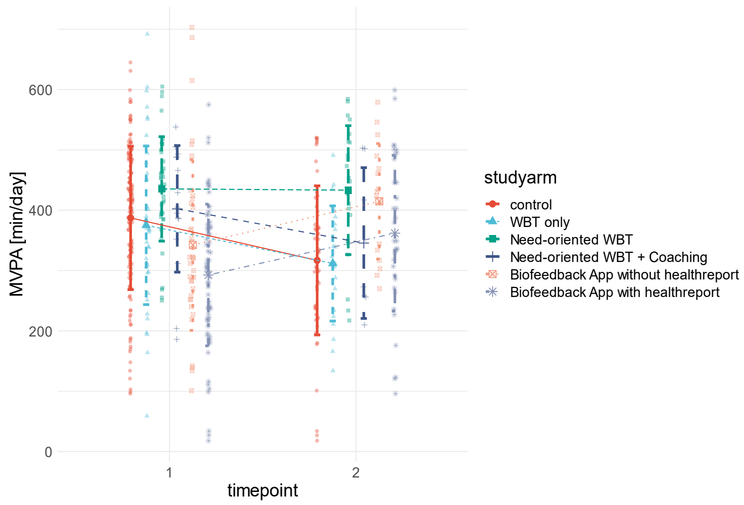

Figure 7: Grouped raincloud mean value plot of pre-post differences in moderate to vigorous physical activity [min/day] across study-arms and control group.

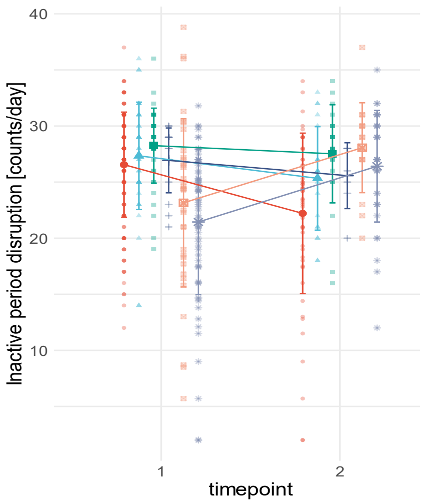

Figure 8: Grouped raincloud mean value plot of pre-post differences in inactive period disruption counts/day] across study-arms and control group.

Participants in study-arms 4 and 5 increased their activity time by 72.5 ± 45 minutes and 69.3 ± 11.7 minutes, respectively, while the activity time decreased in all other study-arms and the control group. Similarly, the number of inactivity disruptions per day increased significantly in the app trial in study-arms 4 and 5 but decreased in all other study-arms and the control group. However, no significant differences were observed in stress-related outcomes such as SDNN, RMSSD, LFHF, and the Beavsky Index, or in other PA-related outcomes such as steps and inactivity across measurement time points or among study-arms. Figures 3 and 4 illustrate the magnitude of the effects obtained from the study.

2.4.4 Discussion

This study was a multi-arm parallel randomized controlled trial aimed at exploring the effectiveness of different sensory-based mHealth interventions to enhance the coping of healthcare professionals with stress and PA. The interventions were designed to be individually tailored with the hypothesis that these interventions would result in small to moderate positive effects on PA and stress-related outcomes, while non-individualized interventions would be ineffective. Contrary to the expectations (Baumann et al., 2023), the results showed no significant improvement in stress-related heart rate variability (HRV) parameters over time, regardless of the level of individualization in the interventions. This is due to the fact that PA and stress perception are closely related, and specific and continuous training is necessary to achieve cognitive and psychophysical adaptations through PA. This was not achieved through the guidance provided in the mHealth interventions. Furthermore, an 8-week intervention may not be long enough to activate physiological mechanisms that have a stress-buffering effect (Gerber & Pühse, 2009). On the other hand, the interventions showed positive effects on PA outcomes, as measured by accelerometry, in the highly individualized app-based study-arms. The effects were seen in MVPA and inactivity interruptions, but not in steps taken and total inactivity. This could be due to the nature of the nursing profession and the fact that the intervention took place during work hours, leading to higher levels of MVPA and inactivity disruptions but also elevated, consistent step counts and inactivity levels. The findings suggest that the effectiveness of an app-based intervention is dependent on design aspects and user-centeredness. Although the study aimed to represent different levels of individualization across study-arms, it was not possible to determine which level of individualization was more effective. Both app-based interventions showed significant effects, but the sample size was not sufficient to show moderate effects. In conclusion, the findings highlight the importance of considering the context in which PA occurs and the need to differentiate between occupational and leisure time PA when studying the relationship between PA and stress. The results suggest that interventions aimed at increasing PA in a work setting may not necessarily reduce stress levels and that individualized app-based interventions may be more effective, but more research is needed to determine the optimal level of individualization and design (Holtermann et al., 2018).

This study adds the following findings to the existing body of evidence:

This study contributes to the existing evidence on mHealth interventions for stress reduction and PA promotion. It emphasizes the need for continuous training and supervision for sustainable cognitive and psychophysical adaptations through PA. Individualized app-based interventions with direct biofeedback and user-centered design are more effective, and long-term interventions may be necessary for addressing complex health issues. Technical issues contribute to high dropout rates, which could be minimized with additional attention to technical aspects.

2.4.5 Authors contributions

The randomized controlled trial, as well as the study protocol were conceptualized by Bettina Wollesen, who crafted the framework of the research design. Methodological and formal analytical rigor was ensured through contributions of Hannes Baumann, Luis Heuel, and Bettina Wollesen. The investigation was carried out by Hannes Baumann and Luis Heuel, with indispensable resource support from Bettina Wollesen. Hannes Baumann and Luis Heuel were responsible for data curation, while Hannes Baumann exhibited exemplary proficiency in crafting the original draft of the manuscript. The critical review and editing of the manuscript was accomplished by Bettina Wollesen, Laura L. Bischoff, and Luis Heuel, with Hannes Baumann ensuring apt visualization of the results. Supervision was provided by Bettina Wollesen, who also ensured efficient project administration and successful funding acquisition. All authors have meticulously reviewed and scrupulously approved the final version of the manuscript for publication.

3 OVERALL DISCUSSION

3.1 DISCUSSION OF RESEARCH QUESTIONS

The aim of this PhD thesis was to investigate the impact of individualization on the effectiveness of mHealth interventions for children and adolescents at different developmental stages. The results revealed that each developmental stage of children and adolescents has unique requirements. Utilizing the empirical outcomes of this study as a foundation, the research inquiries will be reiterated, and the findings will be scrutinized, culminating in evidence-based decisions regarding the hypotheses. Following this, a comprehensive assessment of the study's strengths and limitations will be conducted, and a conclusion will be drawn, accompanied by a prospective outlook on the theoretical, methodological, and differential advancement of mHealth interventions.

3.1.1 Moderators of mHealth effectiveness

R_1: What is the impact of individualization and age as moderators on the effectiveness of mHealth interventions for reducing SB in children and adolescents?

- **$H_{1.1}$:** The effectiveness of mHealth interventions for children and adolescents increases with age.
- **$H_{1.2}$:** Individualization is not as crucial for the effectiveness of mHealth interventions in children and early adolescents as it is in mid-adolescents and late adolescents.

The conducted systematic review and meta-analysis was the first to examine the age- and individualization-dependent effectiveness of mHealth interventions to reduce IPA and SB in children and adolescents and strengthens the evidence of moderate mHealth effectiveness. This is in line with existing research on PA relatedmHealth interventions for children and adolescents (Böhm et al., 2019; Schoeppe et al., 2017). One of the main qualitative results is, that gamified approaches tend to have a higher effect in this population, with several previous gamified interventions in this target group having already been shown to be effective (Sardi et al., 2017). The 18% (2/11) of trials showing the highest effectiveness in this meta-analysis (Fitbit and Facebook intervention by Chen et al. (2019) and the Clans of Oulu intervention by Pyky et al. (2017)) used this approach. However, it should be mentioned that the intervention Zombies, Run! by Direito et al. (2015), which showed a very low effect size, was also a gamified approach; however, it is hardly individualized and uses few BCTs. Therefore, the results suggest (in line with existing research by Khamzina et al. (2020)) that gamified approaches can be effective for children and adolescents but only if individualization, theoretical foundation, and integration of BCTs occur simultaneously. However, the two most effective interventions mentioned above share a distinguishing feature in addition to gamification. Both involve a social component and integrate community-based systems of social participation and association with real-world physical activities in the surrounding environment. Hammersley et al. (2017) and van Woudenberg et al. (2018) integrated similar approaches. This may suggest that friends, family, and surrounding environments are relevant determinants for children and adolescents in the context of mHealth and should be considered in the development of mHealth interventions to reduce IPA and SB. This review also demonstrates that mHealth interventions for children and adolescents are rarely theory based (Direito et al., 2018; Fiedler et al., 2020; Han & Lee, 2018) although theories were occasionally mentioned, and therefore reiterates the need for enhanced theoretical substantiation in the development of mHealth interventions. The consequences of non–theory-based approaches include low effect sizes and methodological deficiencies, at least in self-developed interventions (Fassnacht et al., 2015; Nyström et al., 2017). No negative effect of missing theoreticity could be shown when already existing and evaluated apps (e.g., Fitbit app) were used (Gaudet et al., 2017; Mendoza et al., 2017). In this respect, another striking aspect of the results is that most of the considered interventions used commercially available apps (especially Fitbit models and the corresponding app) or self-developed approaches. Models from other well-known commercial providers were not used. Data transfer software was repeatedly cited as a reason by in some studies. From a scientific point of view, one of the problems may be that companies for exampleFitbit do not disclose the mechanisms and underlying theories behind their developments. Regarding the quality of the integrated data, it should be mentioned that many trials addressed multiple outcomes (Mayo-Wilson et al., 2017) and used questionnaire data as outcome parameters (Ferrari et al., 2020). A more appropriate approach would be to focus only on objective data or consider a combination of objective and subjective data, similar to the approach of Chen et al. (2019). The use of solely qualitative data can yield a problem if an objective comparison with WHO recommendations must be provided (Fiedler et al., 2021). Therefore, we encourage researchers in the field of mHealth to use accelerometry-based measurements and more standardized outcome measures in future intervention studies. Another key aspect of qualitative analysis is the individualization of the included mHealth interventions. It is noticeable that the type of individualization varies considerably between frequently used techniques that are frequently used (e.g., individual goal setting) and other techniques that are unique to one of the interventions (e.g., individualization based on the stage of behavior change). Similar to existing ideas in the field of behavior change mechanisms (Michie et al., 2013), a consistent taxonomy is needed and should be a part of future research.

Across all interventions, it appears that mHealth interventions to reduce IPA in children and adolescents showed an overall significant moderate effectiveness, whereas interventions to reduce SB showed no overall significant effect. Accordingly, it appears easier to change IPA than SB in children and adolescents. More structural changes are probably necessary to reduce SB, which may include educational policies for schools. For instance, it is more difficult to reduce sitting time in class, at lunch, at home while doing homework, or during transportation than it is to do another hour of sports in the evening. Potential ideas that could be implemented in the context of mHealth would be JITAI with reminders for small exercise breaks (Wunsch et al., 2022); in the school context, the use of automated standing desks to interrupt sitting times; or the assignment of physically activating homework that encourages children and adolescents to explore their invigorated environment. It should be further discussed that the considered mHealth interventions had no or even a small reverse effect on the reduction of SB. Although it has been shown that screen time and PA are independent constructs (Pearson et al., 2014; Schmidt, Anedda, Burchartz, Kolb, Oriwol, & Woll, 2019), it becomes evident that the use of apps leads an unchanged or slightly increased time spent in SB, although IPA decreases. Thus, there presumably is a shift in time resources among children and adolescents through the use of mHealth intervention. A similar finding emerged for the game Pokémon Go (Khamzina et al., 2020). The consequences of this finding are far-reaching and suggest that the use of mHealth in adolescence and childhood deserves careful consideration. For younger age groups in particular the use of an app as a family or with parental support could be feasible, yet so far result low effect sizes, as shown by 20% (3/15) of the considered interventions (Downing et al., 2017; Hammersley et al., 2019; Nyström et al., 2017)

Looking at the average age of the target groups in the interventions used in the meta-regression, it is noteworthy that the highest effect sizes were evident in the adolescent age groups. Therefore, it is reasonable to assume that participants in different age groups are differently impressionable by mHealth. There are multiple explanations for this finding. First, as children age, unhealthy behaviors may be established, and apps may need to become more individualized to be effective (Tong et al., 2021). Second, the more the child evolves into an individual, the more important it becomes to address their individuality within health interventions. The second hypothesis is supported by one of the key findings of the meta-analysis that individualized mHealth interventions to reduce IPA differ significantly from non-individualized interventions with the same objective. This is in line with previous research on other populations (Tong et al., 2021). However, it is interesting to note that interventions with the highest level of individualization, are not the most effective (Mendoza et al., 2017). Thus, more individualization does not necessarily lead to higher effectiveness; rather, the selection of particularly relevant parameters in combination with the rest of the intervention characteristics seems to result in an effective intervention. For example, the development of a new intervention could be accompanied by a kind of intervention mapping (Koutoukidis et al., 2018) which could beaccompanied by a target group analysis. Thereby the needs and requirements of the target group of an mHealth intervention would be revealed. Future research should aim to deepen these partially exploratory findings and identify the underlying psychological mechanisms. We hypothesize that there is a sweet spot at which the addition of further mechanisms for individualization and behavior change no longer leads to a larger effect, which would have profuse implications for the development of mHealth interventions. Furthermore, based on the results of this review, we would like to point out that the content and functions of mHealth interventions for children and adolescents should always be adapted to the age of the target group to avoid possible developmental psychological difficulties and associated low effect sizes. It should also be mentioned that the results of the meta-regression, as suggested in the introduction section, again indicate that SB and IPA are not correlated constructs. Therefore, PA promotion does not necessarily imply SB reduction and should hence be addressed separately. In summary, the systematic review and meta-analysis addthe followings aspect to the existing body of evidence:

1. Gamified approaches tend to have a higher effect in children and adolescents, but only if individualization, theoretical foundation, and integration of BCTs occur simultaneously.
2. The most effective interventions also involve the social component, integrate community-based systems of social participation and association with real-world physical activities in the surrounding environment.
3. mHealth interventions for children and adolescents are rarely theory-based, and this reinforces the need for enhanced theoretical substantiation in the development of mHealth interventions.
4. Most of the considered interventions used commercially available apps, especially Fitbit models and the corresponding app, or self-developed approaches, and data transfer software was cited as a reason in some studies.
5. mHealth interventions to reduce IPA in children and adolescents showed an overall significant, but moderate effectiveness, whereas interventions to reduce SB showed no overall significant effect.
6. It is probably harder to reduce SB in children and adolescents du to a lack of educational policies for schools.
7. The use of mHealth interventions can lead to a shift in time resources among children and adolescents, with an unchanged or slightly increased time spent in SB, although IPA decreases.
8. The use of mHealth in adolescence and childhood deserves careful consideration, and for younger age groups, the use of an app as a family or with parental support could be beneficial.
9. The effectiveness of mHealth interventions is moderated by individualization and age, with more individualization and higher age associated with higher effectiveness.

Based on the research question and underlying hypotheses, it can be concluded that age does not significantly moderate the effect of interventions. Therefore, hypothesis 1.1 is rejected, contrary to expectations. However, it was observed that mHealth interventions were more effective in addressing IPA than non-individualized interventions. Strong effect sizes were observed in interventions targeting age groups above 15 years, whereas interventions aimed at adolescents under the age of 10 years demonstrated minimal effectiveness. Consequently, hypothesis 1.2 can be accepted, although the supporting evidence base is inadequate and requires further randomized controlled trials.

3.1.2 Family health goals

R_2: What are the feasible mHealth-based physical activity and health objectives that can be accomplished within the family framework involving early adolescents?

- **$H_{2.1}$:** Parental and adolescent physical activity and health goals partially intersect.
- **$H_{2.2}$:** Social systems engagement, particularly family, is more appropriate and beneficial for infants, children and early adolescents rather than for mid and late adolescents.

The insights gained from this study illustrate the potential for digital measures in the prevention and promotion of health within families, highlighting areas of overlap in the content preferences of family members. It can be assumed that mHealth interventions for families are particularly suitable for families with children under the age of 13 years. Further research should identify usage preferences in a family health app, usage in different family constellations, and a family-oriented approach. Since the aim of the study was to identify familial health goals that are of high interest to all family members and show no age effects, not all of the qualitatively identified goals are relevant for family health promotion. In line with control theory, behavior change techniques, such as goal setting, have been associated with increased intervention effects (Michie et al., 2013; Strecher et al., 1995). For example, a study by Heber et al. (2016) evaluated a newly developed internet-based stress management intervention in a waitlist-controlled randomized trial that included principles for health behavior change such as goal setting, action planning, and coping planning for reducing stress. Their results showed significant effects between the intervention and waitlist control group. Goal-setting technique features might thus be promising for the individual needs. The additional analysis indicated that only family goals "integration of a healthier diet," "spending time in nature," and "physical activity outdoors" are both interesting to parents and children as well as independent of the age. Integrating the study results into the context of Brand and Ekkekakis' (2018) affective reflective theory of PA and exercise allows for theoretical embedding: multiplication of sport-related stimuli is necessary to stimulate type-1 processes and positive affect to convert them into type-2 processes, thereby promoting healthy habit formation. According to Grey et al. (2018), the family can therefore act as both a multiplier and a positive affect provider in addressing these goals in health interventions and thus positively influence the health behavior of adolescents in the long term (Sanders & Mazzucchelli, 2022). In summary, this study adds the followings aspect to the existing body of evidence:

1. It identifies age independent health goals for both, parents and their children. Thus, families mHealth interventions targeting a healthier diet or outdoor physical activities are most likely to be adopted within the social system of a family.
2. It identifies that the familial use of mHealth interventions is most beneficial for early adolescent age groups.

Hypothesis 2.1 can therefore be accepted. There is a partial intersect between parental and adolescent health goals, which can be integrated into mHealth Interventions for families. For PA focused interventions, outdoor activities are the lowest common denominator. Hypothesis 2.2 can only be partially confirmed, as infants and young children were not included in the study. However, as expected, there seems to be a point in child development where an implementation of health goals in the family context is no longer of interest to adolescents. Based on the study findings, this is estimated to occur around the age of 13 years, between early and middle adolescence. Thus, mHealth interventions for families should target families with children between 8-12 years of age. Further research is needed to confirm this age range and to identify specific developmental factors that influence the effectiveness of health interventions among adolescents. Additionally, it is recommended that interventions for families with older adolescents should focus on individualized approaches that consider the unique needs and preferences of each family member. Overall, these findings contribute to the growing body of research on family-based health interventions and highlight the importance of considering developmental factors when designing and implementing such interventions.

3.1.3 Digital health literacy

R_3: How can digital Health literacy be promoted within the school setting to ensure reflective and responsible use of mHealth applications among mid adolescents?

- **$H_{3.1}$:** Both physical education teachers and mid adolescent students show digital health literacy deficits.
- **$H_{3.2}$:** Given the high proportion of practical elements and facilities required, the conditions for teaching digital health literacy in physical education differ considerably compared to other disciplines.

Regarding the research question "How can digital health literacy be promoted within the school setting to ensure reflective and responsible use of mHealth applications among mid-adolescents?", it was found that there initially is a lack of mobile devices with which innovative digital teaching and learning projects to promote digital health literacy could be implemented. Consistent with previous research, a discrepancy between the existence of digital media and their active use in teaching was observed (Drossel et al., 2019). This could be due to outdated technological equipment or a lack of digital literacy among teachers (Baumgartner et al., 2016). One solution to obtain missing mobile devices would be to apply for funding from the Digital Pact School (BMBF, 2023). However, using private devices could exacerbate the existing "digital divide" (Ho & Tseng, 2006). There are options to integrate movement and health competency education in homeschooling. For example, the app "Teamfit" can induce step challenges between the class and the teacher. Careful selection of digital applications to promote digital health literacy is essential in this type of teaching integration (Stassen et al., 2020). In addition, there needs to be a pedagogical strategy for using mobile devices in physical education (Anastasopoulou et al., 2014), as the high level of PA requires different conditions than in other subjects.

Similar to surveys of students, teachers tend to underestimate their own digital health literacy (Dadaczynski et al., 2021). The results suggest a discrepancy in digital health literacy between biology/health and physical education teachers, particularly in the eHLQ dimension "knowledge of basic physiological functions, one's own health status, risk factors, and ways to avoid them". This is surprising, given that it is generally assumed that a sports degree includes basic knowledge of preventing various diseases. Additionally, the relevance of digital health literacy for teachers in all three subject areas is included in educational plans. It is possible that physical education teachers face the greatest barriers to implementing these teaching-learning concepts. It is unclear whether this is due to self-perception or the teachers' role in physical education. It is worth considering to what extent functional implementation of digital content is feasible in physical education, particularly in primary and secondary schools, since gymnasiums have fewer technological resources compared to other subject areas. Furthermore, focusing on digital health literacy in practical physical education would initially reduce movement time and intensity. Therefore, it seems that there is no place for digital health literacy in traditional physical education. Only when physical education is cancelled due to the COVID-19 pandemic (as demonstrated in the qualitative survey of this study), a time frame becomes available for developing movement-based teaching and learning concepts to promote digital health literacy. Existing innovative concepts include the integration of virtual reality content and 360-degree videos. However, the fact that digital content has only gained relevance in physical education due to pandemic-related constraints reveals long-standing structural methodological and didactic deficits in physical education. The overarching goal should thus be to catch up with other subject cultures regarding digitalization, to equip sports facilities with digital resources and to develop methodological-didactic approaches to using digital tools to promote movement time, even after the pandemic. Based on their pedagogical experience, the teachers selected a methodology that consciously aims to promote student responsibility, self-management, and time-management. The idea is to transfer the topics of digital health literacy promotion to cooperative and self-directed learning forms in physical education. This can lead to an improved ability to act in the fields of sports and health for sports teachers and potentially contribute to a more health-conscious lifestyle among learners.

The smartphone ban in schools is a further obstacle to implementing teaching-learning projects for digital health literacy. Although smartphones can impair interpersonal communication, distract from teaching, and enable cyberbullying, a deliberate and comprehensive promotion of responsible technology use is needed. Smartphones can provide an added value in physical education by having a motivating effect, increasing learning time, and promoting critical media use by adolescents. It is also useful to address the advantages and disadvantages of smartphone use in everyday school life and highlight its positive aspects for constructive media use. To avoid disturbances in smartphone use during teaching, binding rules for classroom use can help. Although smartphones are less used in physical education due to high movement components, there are potentials, such as smartphone-based motion analysis. However, schools should provide smartphones for this purpose. Learners can create their movement videos and identify relevant movement phases (e.g., throwing or swimming) with the help of relevant teacher guidance and receive direct visual feedback.

The study results illustrate implications for the teacher education program in sports as well as the urgent need to promote digital teaching skills among sports teachers. This need manifests itself, among other things, in the fact that the surveyed sports teachers have the lowest value in digital health literacy compared to expert colleagues. Since the promotion of health literacy is already located in the curricula of the individual federal states, the transfer of "lessons learned" from distance learning should be carried out in all practice-related modules during the preparatory service for teachers. This could be implemented with specific training modules on (1) technical possibilities of smartphones and tablets to support movement, motion analysis, and movement learning, (2) e- and mHealth possibilities, or (3) integration of age-specific aspects of digital health literacy, e.g., in dealing with suitable exercise programs in the event of school and sports club closures. It should be mentioned that the competence to conduct digitally supported teaching events in the field of sports, as well as the targeted use of methods for digital teaching of movement and, if necessary, movement competence, is a derivative product of digital health literacy of teachers. However, digital health literacy is just one aspect of successful digital teaching.

The situation during the pandemic highlighted the lack of digital health literacy among teachers and students, necessitating adjustments in the long-term digital orientation of physical education. Many new approaches have emerged in a short time, but they are currently only based on practical experience and require fundamental digital health literacy. Concepts for the teaching of digital health literacy are missing. By promoting these topics in teacher education programs, especially in physical education, teachers can benefit and handle distance learning situations better, as well as expand their methodological and didactic repertoire beyond the pandemic. In summary, this study extends the existing evidence with the following aspects:

1. A lack of mobile devices and digital literacy among teachers is preventing the implementation of digital health competency teaching projects in schools.
2. PA and digital health literacy education can be integrated into homeschooling using digital apps like "Teamfit," but careful selection of apps is crucial.
3. Teachers underestimate their digital health literacy, especially in the knowledge of basic physiological functions, their own health status, risk factors, and ways to avoid them, particularly in physical education teachers.
4. A lack of technological resources in gymnasiums poses a significant challenge in implementing digital content into physical education, highlighting the importance to catch up with other subject cultures regarding digitalization.
5. Smartphones can provide added value in physical education, but a smartphone ban in schools is an obstacle to implementing teaching-learning projects for digital health literacy.
6. The urgent need to promote digital teaching skills among sports teachers is essential, and it could be implemented with specific training modules on technical possibilities of smartphones, e- and mHealth possibilities, and age-specific aspects of digital health literacy.

Based on the research findings, hypothesis 1 can only be partially accepted, as the empirical approach to assessing the digital health literacy of children and adolescents was not sufficient. However, the qualitative responses strongly suggest that the hypothesis is likely to hold true. The results indicated a deficit in digital health literacy among teachers, particularly in the domain of physical education. Hypothesis 2, on the other hand, can be accepted, as both the interviews and the online survey revealed fundamentally different prerequisites for the transmission of digital health literacy in the field of sports. The identified infrastructure problems, such as the lack of Wi-Fi access, present a challenge, but also offer great potential for further development in this area.

3.1.4 Degree of individualization

R_4: How does individualization affect the effectiveness of physical activity-based mHealth interventions?

- **$H_{4.1}$:** Individualized mHealth interventions show higher effectiveness with late adolescents and adults compared to non-individualized interventions.
- **$H_{4.2}$:** Promoting physical activity effectively with individualized mHealth interventions benefits various other health outcomes.

To answer this question, the aforementioned multi-armed randomized controlled trial was conducted. Contrary to our expectations, stress-related HRV-parameters did not show significant improvements over time, regardless of the study-arm or the resulting level of individualization. Within this context, the stress buffering hypothesis assumes that PA and stress perception are closely related constructs (Gerber & Pühse, 2009). However, to achieve cognitive and psychophysical adaptations through PA, continuous, specific training according to exercise principles is necessary for sustainable effects (Borresen & Lambert, 2009; Herold et al., 2019). To gain a positive effect on HRV parameters or subjective reported stress, physical exercise such as yoga or endurance training needs to be performed on a regular basis (Bischoff et al., 2019). Aside from the challenges in obtaining the stress-related parameters, an 8-week intervention may in retrospect be insufficient to activate physiological mechanisms that have a stress-buffering effect. Long-term interventions may be necessary for addressing chronic stress symptoms or for addressing more complex health issues that require sustained support and intervention. An even stronger involvement of the participants would have been useful in terms of intervention mapping (Colquhoun et al., 2017). Moreover, the lack of supervision during the intervention in the mHealth interventions forced the participants to self-pace the intervention. This is a major disadvantage compared to supervised interventions (Chen et al., 2021; Fleischmann et al., 2018). Thus, it can be inferred that incorporating motivational elements and structured guidance for engaging in supplementary physical exercise alongside the utilization of the mHealth intervention is deemed imperative. In contrast to the results on the physiological HRV based stress parameters, the interventions show positive effects on the accelerometry-based measured PA related outcomes in high individualized app-based study-arms (app-based digital stress management interventions with sensory biofeedback with and without health report). Strikingly, the small to moderate effects in PA typical for mHealth interventions (Mönninghoff et al., 2021) could only be shown for the outcomes of MVPA and inactivity interruptions but not for those of steps and inactivity. Besides the fact that the considered interventions did not have steps and inactivity reduction as a primary goal, the nature of the nursing profession could be another possible explanatory mechanism: other studies indicate higher step counts in nurses than in other occupations (Chang & Cho, 2022) as well as long work commutes and night shifts with long inactive periods (Hazzard et al., 2013). Consequently, while a participant completes the intervention during working hours as instructed, this results in higher levels of MVPA and increased inactivity disruptions on the one hand; on the other hand, it inevitably results in an elevated, consistent step count due to patient work and elevated, unavoidable inactivity levels due to commutes and night shifts. The findings from our study suggest that the relationship between PA and stress may vary depending on the context in which the activity takes place. This supports the idea of the “physical activity paradox” (Coenen et al., 2018; Holtermann et al., 2018), which refers to the idea that the benefits of PA may depend on the specific circumstances in which it occurs. Our results suggest that PA may be perceived as more stressful when it is part of work, rather than leisure time, which suggests that interventions aimed at increasing PA in a work setting may not necessarily reduce stress levels. However, if PA is increased without also increasing stress, this could still be considered an improvement. Overall, these findings highlight the importance of considering the context in which PA occurs and the need to differentiate between occupational and leisure time PA when studying the relationship between PA and stress.

However, the effectiveness of an app-based intervention seems to be largely dependent on design aspects and user-centeredness. Despite all efforts to represent different levels of individualization across study-arms, it could not be clarified which level of individualization is more effective based on effect sizes, as only both of the app-based interventions were able to show significant effects. With respect to our initial hypothesis, we would have assumed that study-arm 1 (WBT only) failed to show effects due to a lack of individualization. This idea was supported by the results. It would have been reasonable to suspect that effectiveness would increase across the remaining four study-arms due to increasing individualization. However, no significant effects were found for study-arms 2 (need-oriented WBT) and 3 (need-oriented WBT and coaching). Study-arms 4 (biofeedback app without health report) and 5 (biofeedback app with health report) each indicated homogeneous effect sizes for the outcomes MVPA and inactivity disruption. Thus, it could be argued, that based on the results of this study, it seems to make no difference whether a health report is displayed or not. However, one possible reason for this result could also be the small sample size in the individual study-arms. Due to the high dropout rate, the number of subjects was insufficient to show the expected moderate effects according to the power analysis. The results should therefore be interpreted with caution. Nevertheless, the findings further indicate that individualized app-based interventions with direct biofeedback and differentiation by personality structure show better effectiveness than web-based trainings (WBT) accessed via the smartphone browser. However, one reason for the high dropout rate was technical complaints while using the app-based interventions. With additional effort in the technical aspects, this disadvantage could be minimized. Therefore, it remains unclear to what extent the need orientation or the coaching, which were exclusive for WBT, would have resulted in a further improvement of the effect size in the app-based interventions. One possible explanation for the limited effectiveness of our intervention, in addition to the high dropout rate, is the insufficient incorporation of health behavior change strategies. While our biofeedback app included both active and passive behavior change techniques and promoted stress management skills, some of the content proposed by Bischoff et al. (2021) was not implemented. Specifically, we applied individualization of app content, fulfilling common weekly goals and tasks, increasing knowledge about a healthy lifestyle, reminders for objectives, and controlling and checking progress but did not include many suggestions for activities with diaries for documentation and development of strategies or informational or instructional videos. The inclusion of these behavior change mechanisms could potentially enhance behavior change in future interventions. In summary, the following aspects are the most relevant to answer the research question and extend the existing body of evidence in this field of research:

1. App-based study-arms that are highly individualized exhibit favorable outcomes on accelerometry-based measures of physical activity.
2. Long-term interventions may be a requisite for addressing chronic stress symptoms or complex health issues that demand sustained support and intervention.
3. Sustainable cognitive and psychophysical adaptations through physical activity necessitate continuous, specific training based on exercise principles. The guidance of an app alone may not suffice in achieving these goals. The effectiveness of app-based interventions is primarily dependent on design aspects and user-centeredness.
4. Unsupervised mHealth interventions that mandate participants to self-pace the intervention may be significantly disadvantaged compared to supervised interventions.
5. The nursing profession's nature may serve as an explanatory mechanism for the modest to moderate effects of physical activity interventions.
6. The relationship between physical activity and stress may be subject to variability based on the activity's context, according to the findings.
7. Personalized app-based interventions that offer direct biofeedback and differentiation by personality structure present superior efficacy in comparison to web-based trainings accessed via the smartphone browser.

Technical grievances encountered during app-based interventions contributed to the high dropout rate. However, additional efforts in addressing the technical aspects could potentially mitigate this disadvantage.Thus, the research question can only be partially answered. Indeed, Individualization appears to influence the effectiveness of PA-based interventions, and individualized app-based interventions demonstrate the highest effect sizes compared to non-individualized interventions. However, effect sizes are only weak to moderate, and other health outcomes such as stress are not positively affected by it. The partial acceptance of Hypothesis 4.1 is warranted solely in light of the observed effects pertaining to app versus web-based interventions, whereas the nullification of Hypothesis 4.2 is justified, given the absence of positive stress-related outcomes. Nevertheless, additional inquiry is indispensable to explicate this matter.

3.2 Strength and limitations of this dissertation

This PhD thesis has several limitations, which are described in the subsequent paragraphs. Beginning with the systematic review, it is the first to differentiate between SB and IPA when considering the effects of mHealth on children and adolescents and contrast both study effects and bias. Moreover, no other review in the field to date includes a narrative analysis of individualized elements in mHealth interventions and relates them to intervention effectiveness. Another unique feature is the exploratory meta-regression. In addition to these strengths, the conducted review underlying this PhD thesis has numerous limitations, both at the study and review levels. At the study level, apart from the studies by von Pyky et al. (2017), van Woudenberg et al. (2018), and Nyström et al. (2017), the sample size was generally moderate to small, which may have biased the results. It should also be noted that most of the studies included multiple outcome parameters and that the primary objective of these studies was not to decrease IPA and SB. As a consequence, we assume that the observed effect sizes do not fully reflect the magnitude of the true effect. If all the included mHealth interventions were targeted at reducing IPA or SB alone, the results would certainly be more conclusive. Conspicuous among studies with small sample sizes compared with those with larger samples is the lower rating in the ROB assessment. In addition, there was a small number of included studies and partly considerable heterogeneity because of deviants, for example, the results of the study by Pyky et al. (2017). This could be because of the major variability in the study design or the diverse target and age groups. At the review level, the asymmetries observed in the funnel plot of the SB outcome indicate a publication bias. This is probably because of the study by Pyky et al. (2017), although the ROB assessment in this study was positive. Furthermore, it should be noted that the study results of Sirriyeh et al. (2010) could not be included in the meta-analysis because of a lack of reporting and as the authors did not provide any data when asked repeatedly. As the study was a 4-arm randomized controlled trial, this would certainly have been insightful for the review. In the included studies with several study-arms, such as the study by Direito et al. (2015), it was observed that the results of individual studies sometimes differed considerably. In this case, the immersive app Zombies, Run showed a substantially smaller effect than the nonimmersive app Get Running. Although other existing meta-analyses in the field of mHealth for children and adolescents similarly integrate multiple study-arms (e.g., He et al. (2021)) and we attempted to avoid potential overpowering by using the splitted shared group procedure (Rücker et al., 2017), this approach should be considered controversial. Arguably, one author team was responsible for an excessive degree of evidence. For example, if a study shows a high ROB and includes four study-arms, it leads to a globally insufficient certainty of evidence. As the only way to avoid this potential bias is to deliberately exclude existing evidence, further research should focus on minimizing the number of study-arms and developing new statistical methods to address this issue. Another limitation of this review was that follow-up data were not extracted. As mHealth in children and adolescents is still a relatively young field of research, we did not consider there to be enough studies with follow-up measurements for a meta-analysis and therefore decided not to include follow-up measurements for reasons of evidence comparability. However, concerning mHealth in adults, it has already been shown that the effects of the interventions decrease in the long term (Mönninghoff et al., 2021). If more mHealth trials with children and adolescents are published, we suggest replicating this review, including its follow-up effects. We assume that the long-term effects of mHealth induced behaviour change are considerably stronger in children and adolescents than in adults, as they may not yet be as well-established as for adults. In general, the results of this review and meta-analysis should be interpreted with caution, as only moderate to low certainty of evidence is warranted based on the grading of recommendations, assessment, development, and evaluations rating. In addition, many publications identified in the systematic literature screening were excluded as they were study protocols or small pilot studies. Therefore, this review should be updated at a later point in time. Furthermore, there is also limited comparability between the included studies, as the mechanisms of the considered mHealth interventions certainly move along disparate causal pathways in different age groups. In summary, despite some limitations, the conducted meta-analysis extends the existing evidence of a fledgling field of research by distinguishing IPA from SB, and by providing a detailed review and systematization of interventions as well as meta-regression and sets the groundwork for the further studies of this PhD thesis by specifically identifying research gaps.

The second research question, which led to three publications from a related research project, conducted a comprehensive survey on family health behavior in Germany. The study had a large sample size of 1008 families and 3794 participants, making it the most comprehensive survey on family health behavior in Germany. The study identified nature-based joint activities with the family as an area of exercise-related family health promotion which has not been the focus of mHealth interventions. The study also found that many existing family-based mHealth interventions do not demonstrate effectiveness due to a lack of overlap between parental and child/adolescent health goals. This study is the first to identify health goals beyond the current health status and examine the intersection between family members. However, the study has some limitations. The questionnaire used in the study only contained parts of validated questionnaires and was further developed and adapted to the needs and requirements of the health insurance company, which funded this study. If the entirety of the original questionnaires would have been used, it would likely have resulted in a significantly smaller sample size. Additionally, random sampling was limited as only insured persons from a German health insurance company were included, and response bias due to social desirability cannot be excluded. Furthermore, the lack of discourse on age-appropriate use of digital media is a limitation, and assessing more than one family member was not possible at this stage of the project. A holistic analysis of the requirements of an app that targets the entire family is needed, and the identification of the target group was only based on two items due to practical reasons and the length of the existing survey in a larger research project. The study's results can be regarded as exploratory and should be replicated using validated scales. Nonetheless, because of the large sample size, the study's findings support the idea of individualization in the development of mHealth interventions.

The next study focused on examining the digital health literacy of mid-adolescents, a topic that has gained significant relevance amidst the ongoing Covid-19 pandemic. Although the study had a slightly smaller sample size than some previous research, it was able to shed new light on the shortcomings of both physical education teachers and students in relation to digitization in the context of physical education. The study also emphasized the importance of digital health literacy in the current climate. However, the study had some limitations that should be addressed in future research. Firstly, the digital health literacy of students could not be fully assessed as standardized instruments for this target group were not available. Thus, future studies should develop and use validated tools to assess digital health literacy in adolescents. Additionally, the sampling technique used in the study was non-random, and the distribution of teachers in the groups was uneven, which limits the generalizability of the results. Future studies should ensure that random sampling techniques are employed to increase the external validity of the findings. Moreover, the study sample consisted of teacher education students, trainees, and certified teachers, all relatively young of age. While this allowed for diverse perspectives to be considered, the inclusion of older, more experienced teachers could have provided more detailed insight into the challenges faced in everyday school life. Future studies should aim to recruit a more diverse sample of participants. The study's validity was also affected by several factors. For instance, not all participating students had taught during the first lockdown, even though they had practical experience. Additionally, certain individuals dominated the discussion in focus group interviews, which only became apparent during the data analysis phase. To address this issue, future moderators of focus groups should employ measures to ensure equitable participation among participants. Finally, the study employed non-standardized measurement instruments, which may have resulted in selective item selection. Future studies should validate the measurement tools used or only use validated assessment instruments to ensure that the study results are comparable across different research settings. By addressing these limitations, future research can build upon the findings of this study and provide more comprehensive insights into the digital health literacy of mid-adolescents.

Finally, the strengths and limitations of the randomized controlled trial are presented. To the best of our knowledge, this is the first mHealth intervention of this quality and complexity in the healthcare setting, demonstrating initial effects in the area of physical effectiveness despite a small sample size and high dropout rates. Moreover, it is the first mHealth intervention including multiple study-arms with different levels of individualization demonstrating differences in effectiveness. However, the conditions of data collection were difficult, which may have contributed to the high dropout rates. The dropout rate of 74% was almost four times higher than expected due to the inability to establish personal contact with participants during the COVID-19 pandemic. Email-based communication appeared to be ineffective in the healthcare setting, resulting in the exclusion of 113 individuals due to non-response. A potential contributor to communication issues and technical inconsistencies was the low level of digital literacy among the nurses. Although these circumstances were considered when designing the intervention, pre-interventional training to develop digital literacy could be provided in future interventions. The intervention or measurement procedure may also have contributed to the high dropout rate. Excessive demands were placed on healthcare workers due to the numerous extensive questionnaires, autonomous sensor ordering, and proprietary installation of the app. Additionally, the app did not support push notifications, and synchronization problems between the app and sensor occurred frequently. In terms of the measurement procedure, it should be noted that the intervention had different initiation times and durations for all participants. Participants were instructed to wear the sensor during working hours and for at least 48 hours. The timing of sensor wearing, and vacation periods were not identifiable from the data. Within the scope of this dissertation, it would have been ideal to incorporate a study population exclusively comprising individuals in the late adolescent phase. However, due to the limitations imposed by the pandemic, this was only feasible to a certain extent. As a result, any inferences derived from the outcomes pertaining to late adolescent youths should be approached with prudence.

3.3 Conclusions and perspectives

The aim of this dissertation was to investigate the impact of individualization on the effectiveness of mHealth interventions for children and adolescents at different developmental stages. The results revealed that each developmental stage of children has unique requirements. For instance, in early childhood and adolescence, it is beneficial to involve the social environment of the family, whereas in middle adolescence, the development of digital health literacy for independent use of mHealth interventions becomes more relevant. In late adolescence, individualization of interventions through biofeedback or more complex methods such as machine learning becomes significant. The results obtained from the late adolescent population are likely transferable to adult populations, including healthcare professionals. Furthermore, the findings suggest the existence of an optimal level of individualization, beyond which the inclusion of additional individualized elements does not necessarily enhance the intervention's efficacy. Despite several limitations, the individualized mHealth interventions were found to influence the PA and health behaviors of children and adolescents more than non-individualized interventions, provided that they appropriately address the digital health literacy according to the child's developmental stage, involve social systems, and are based on central theories of health behavior change and have an educational approach. Future approaches should focus on the appropriate use of health data to develop context-specific and relevant interventions that act according to gender, culture, and digital health literacy. Therefore, individualization alone appears to be a partial aspect of the effective application of mHealth interventions, but it does not solve all problems. These aspects are combined in the proposed Youth mHealth Behavior Change Model, which combines the HAPA model with the self-Efficacy model and study findings, providing a framework for movement-related health behavior change for children and adolescents through mHealth interventions.

3.3.1 Theoretical development of mHealth interventions for children & adolescents

To further enhance the development of mHealth interventions, an advancement of existing theories like the self-efficacy model and the HAPA model as well as of the key findings of this Dissertation is provided. As introduced above, the self-Efficacy model emphasizes the crucial role of self-belief in predicting and changing health behaviors. It proposes that individuals with high self-efficacy for a specific behavior are more likely to initiate and maintain that behavior. On the other hand, the HAPA model identifies two distinct phases of behavior change: the motivational phase and the volitional phase. The motivational phase involves forming an intention to engage in a behavior, while the volitional phase involves translating that intention into actual behavior change. By integrating the Self-Efficacy and HAPA models along with key findings of this thesis, the proposed Youth mHealth Behavior Change Model (YMHBCM) (figure 9) provides a comprehensive framework for PA-related health behavior change in children and adolescents through mHealth interventions. This integrated framework offers a more thorough understanding of the processes involved in behavior change and provides an effective approach for designing mHealth interventions that encourage PA-related health behaviors in children and adolescents. This proposed model complements existing theories insofar as the sub-components for promoting self-efficacy are mapped to the stages of the HAPA model based on the study results, and relevant core elements for mHealth interventions for children and adolescents are extended on the various stages of behavior change.

Pre-intentional children and adolescents are best reached through verbal persuasion based on the results of the sub-studies, using pedagogical approaches and interventions that match the developmental stage. However, the challenge lies in translating intention into action. Here, the digital health literacy of children and adolescents, the social environment, and vicarious experiences are particularly important, as well as setting common goals. Intentional children and adolescents should therefore be encouraged by mHealth content tailored to their needs to actually implement and maintain their intention. Solely in the post-intentional phase it becomes relevant to integrate more complex mechanisms of physiological feedback such as biofeedback, JITAI, or machine learning content to ensure a long-term impact of the intervention.

The proposed YMHBCM has several potential implications for different target groups, including children and adolescents, parents, and mHealth intervention developers: For children and adolescents, the model suggests that mHealth interventions should be tailored to their developmental stage and digital health literacy and involve their social environment to provide support and motivation. The model also emphasizes the importance of setting common goals and providing interventions that match their specific needs to help them initiate and maintain behavior change. Therefore, mHealth interventions can be designed to effectively target and support children and adolescents in adopting PA-related health behaviors.

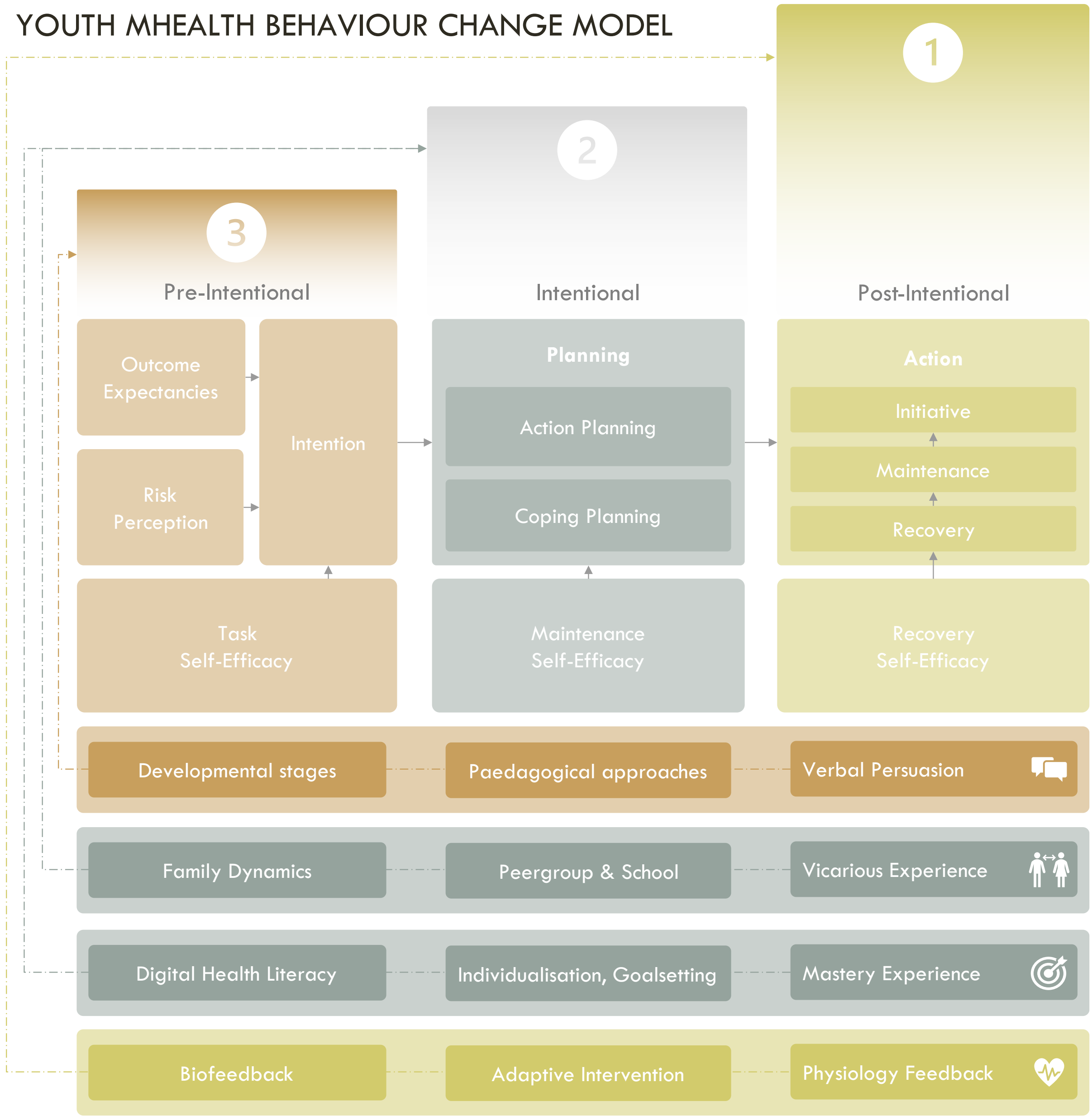

Figure 9: Suggested Youth mHealth Behavior Change Model (YmHBCM)

Parents can also benefit from the proposed model, as it highlights the importance of involving them in mHealth interventions and setting goals together with their children. Parents can play a significant role in providing support and motivation for their children and can be valuable partners in the process of behavior change. Additionally, parents can improve their own digital health literacy, which can have a positive impact on their children's health behavior. For mHealth intervention developers, the proposed model provides a comprehensive framework for designing effective interventions that promote PA-related health behaviors in children and adolescents. The model emphasizes the importance of tailoring interventions to the developmental stage of children and adolescents, as well as their digital health literacy, and involving the social environment to provide support and motivation. The model also highlights the importance of integrating more complex mechanisms of physiological feedback in the post-intentional phase to ensure long-term impact.

In summary, the proposed YMHBCM can help guide the development of effective mHealth interventions that target PA-related health behaviors in children and adolescents. It highlights the importance of considering the specific needs of different target groups and involving their social environment to provide support and motivation. By using this model, mHealth interventions can be individualized to effectively target and support children and adolescents in adopting and maintaining PA-related health behaviors.

3.3.2 Methodological development of mHealth interventions for children & adolescents

mHealth interventions for children and adolescents have the potential to provide efficient and accessible healthcare services. However, there are challenges associated with the design and implementation of these interventions and methodological advancements are necessary. Several strategies have been suggested to improve the methodological aspects of mHealth interventions for children and adolescents, including the use of mixed methods approaches, stakeholder involvement in the intervention development process, and rigorous testing and evaluation of the interventions (Schmidt et al., 2022). One promising avenue for methodological improvement in mHealth interventions is the use of user-centered design (UCD) principles (Boudreaux et al., 2014), which represent a special case of individualization. UCD emphasizes the involvement of end-users, including children and adolescents, in the design and development process to ensure that the interventions are tailored to their needs and preferences. The use of UCD has been shown to enhance the effectiveness and acceptability of mHealth interventions for children and adolescents (Boudreaux et al., 2014). Another methodological approach that could enhance mHealth interventions for children and adolescents is the use of more adaptive designs. Adaptive designs allow for modifications to be made to the intervention in response to participant feedback or changes in the study environment (Collins et al., 2004). This approach could enable the tailoring of interventions to individual needs and preferences, leading to increased engagement and effectiveness. Two special cases for this kind of individualization are JITAI or adaptive assessment (Hardeman et al., 2019). JITAI allows for interventions to be delivered at the right time and in the right context based on the individual's current situation and needs. Adaptive assessment, on the other hand, involves collecting data from multiple sources, such as wearable devices and smartphones, to provide a comprehensive understanding of the individual's behavior patterns. The use of JITAI and adaptive assessment can help mHealth interventions to better address the unique needs of children and adolescents by providing interventions that are tailored to their specific context, behavior patterns, and preferences (Nahum-Shani et al., 2018). For example, a JITAI intervention can deliver a reminder to a child to engage in PA when they are in a setting that is conducive to PA, such as a playground. Similarly, adaptive assessment can collect data on the child's PA patterns throughout the day and provide personalized feedback and recommendations for increasing PA.

Research has shown that the use of JITAI and adaptive assessment can lead to improved intervention outcomes and user engagement in mHealth interventions for children and adolescents (Lathia et al., 2017). Therefore, further development and integration of JITAI and adaptive assessment into mHealth interventions can enhance the effectiveness and usability of these interventions for promoting healthy behaviors among children and adolescents (Wang & Miller, 2020). Wunsch et al. (2022) proposed a conceptual framework for the integration of JITAI into mHealth interventions. The framework posits five factors that should be taken into consideration during the development of JITAIs, which include responsiveness in real-time, adaptability to input data, system-triggered responses, goal-oriented design, and customization to user preferences.

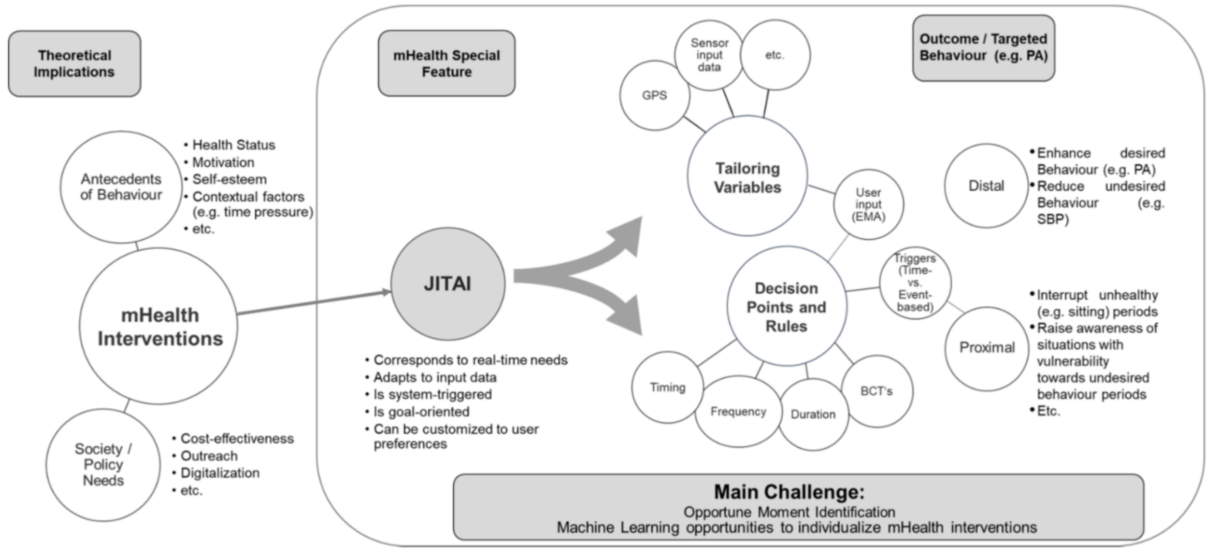

Figure 10: Conceptual framework of JITAIs: On the left, this figure indicates the theoretical Iimplications of mHealth for certain outcome variables (on the right). Here, just-in-time adaptive interventions (JITAIs) as an mHealth special feature are described thoroughly concerning their key facets tailoring variables and decision points and rules for targeted behaviour attainment. (Excerpted from Wunsch et al. 2022.)

These findings align with the primary findings of this dissertation (see figure 9) and once again highlight the need for individualization on various levels. Additionally, the framework identifies two significant challenges associated with JITAI interventions, namely the identification of opportune moments and the potential of machine learning approaches for further individualization of mHealth interventions.

As highlighted in the framework, machine learning (ML) as well as artificial intelligence (AI) algorithms have the potential to enhance the effectiveness of mHealth interventions for children and adolescents by enabling individualized and adaptive interventions (Khan & Alotaibi, 2020). ML and AI can be used to analyze data collected from the interventions, such as user engagement and activity levels, to optimize the intervention content and delivery in real-time (Triantafyllidis & Tsanas, 2019). By analyzing large amounts of data and identifying patterns, these tools can help to individualize interventions and improve their effectiveness. One way machine learning can enhance mHealth interventions is through its ability to predict and prevent relapses. By monitoring individual data patterns over time, machine learning algorithms can recognize patterns of behavior that precede relapse, enabling timely interventions to prevent relapse (Fond et al., 2019).

Another way in which machine learning can improve mHealth interventions is through its ability to identify individuals who are most likely to benefit from specific interventions. For example, in a study by Maniruzzaman et al. (2022), machine learning algorithms were used to predict which children with attention-deficit/hyperactivity disorder (ADHD) would benefit from a specific mHealth intervention. The results showed that children who were identified as likely to benefit from the intervention had significantly greater improvements in ADHD symptoms compared to those who were not identified as likely to benefit. In addition, machine learning algorithms can be used to improve the accuracy of diagnoses and identify comorbidities. In a study by Aleem et al. (2022), machine learning algorithms were used to predict which individuals with depression would also have anxiety disorders. The results showed that the algorithm was able to accurately identify individuals with comorbid anxiety disorders, demonstrating the potential for machine learning to improve the accuracy of diagnoses and identify comorbidities. This concept must be contextualized within the domain of PA. Overall, machine learning and algorithms have the potential to significantly enhance mHealth interventions for children and adolescents by individualizing interventions, predicting and preventing relapses, identifying individuals who are most likely to benefit from specific interventions, and improving the accuracy of diagnoses (Aleem et al., 2022; Maniruzzaman et al., 2022; Wunsch, K., Fiedler, J., Eckert, T., & Woll, A., 2022).

More recently, AI integrations into mHealth interventions have emerged, which can be used even more efficient to analyze large amounts of data collected from sensors and mobile devices, identify patterns, and provide personalized feedback to users (Khan & Alotaibi, 2020). It identifies individual health behavior patterns and provides tailored feedback and recommendations, which can improve the effectiveness of mHealth interventions as well as changes in health status. Moreover, itcan detect early signs of disease, and therefore alert healthcare providers when interventions may be needed (Kumar et al., 2022). Furthermore, AI can automate routine tasks and decision-making processes, thereby improving the efficiency of healthcare delivery and reducing the burden on healthcare professionals (Bohr & Memarzadeh, 2020). While there is great potential of these technologies for improving health outcomes, it is also important to consider potential risks and challenges. One key concern is the accuracy and reliability of AI algorithms, which can be influenced by biases in data collection and algorithm design (Belenguer, 2022). Additionally, the implementation of AI in healthcare settings may lead to issues with privacy and security, as well as ethical considerations surrounding data ownership and consent (Bélisle-Pipon et al., 2021)

Moreover, the integration of AI may exacerbate existing health disparities, as it may not be accessible or effective for all populations, particularly those with limited access to technology or resources (Chen, Joshi, Ghassemi, 2020). Therefore, while AI integration in mHealth interventions has the potential to revolutionize healthcare delivery, it is important to approach these innovations with a critical lens and consider the potential risks and challenges associated with their implementation. Both JITAIs and approaches utilizing AI and machine learning share a common objective of extracting meaningful utility from continuously gathered health data, thereby promoting individualization for the user/patient.

To ensure an even more precise utilization of health data, an additional critical component in the methodological advancement of movement-related mHealth interventions, apart from User-Centered Design (UCD), JITAIs, ML, and AI, is the quantification of PA. Contemporary methods depart from conventional metrics such as step count, MVPA, and SB, emphasizing a more comprehensive approach that scrutinizes the entire diurnal routine, including recovery periods: the 24-hour physical activity circle approach. This could be a promising method to develop mHealth interventions for children and adolescents, as it considers PA across the entire day, including both structured and unstructured activities, and SBs (Rosenberger et al., 2019). It has become more common to use this approach in research studies, but its implementation in clinical practice and public health initiatives is still limited. In some countries, such as Canada (CSEP, 2023) and Australia (Australian Government & Department of Health, 2023), the approach is consistent with PA guidelines and can be used to support policy development. It involves examining the full range of PA behaviors during the day, such as sleep, leisure time, active transportation, and school time, and implementing interventions that target different components of the PA circle (Rosenberger et al., 2019). A core component included in the 24-hour physical activity circle approach is the incorporation of recovery periods. This is also being reflected in newer parameters in the field of HRV (Schaffarczyk et al., 2022).

To further develop mHealth interventions using the 24-hour physical activity circle approach, researchers can utilize wearable technology and mobile applications to track and provide real-time feedback on PA behaviors as well as recovery periods throughout the day (Peterson et al., 2018). Additionally, interventions can be tailored to the specific needs and preferences of children and adolescents, incorporating fun and engaging activities to promote sustained participation (Leblanc et al., 2013). Collaboration with parents and schools can also enhance the success of interventions by promoting a supportive environment for PA across different settings (Jago et al., 2014).

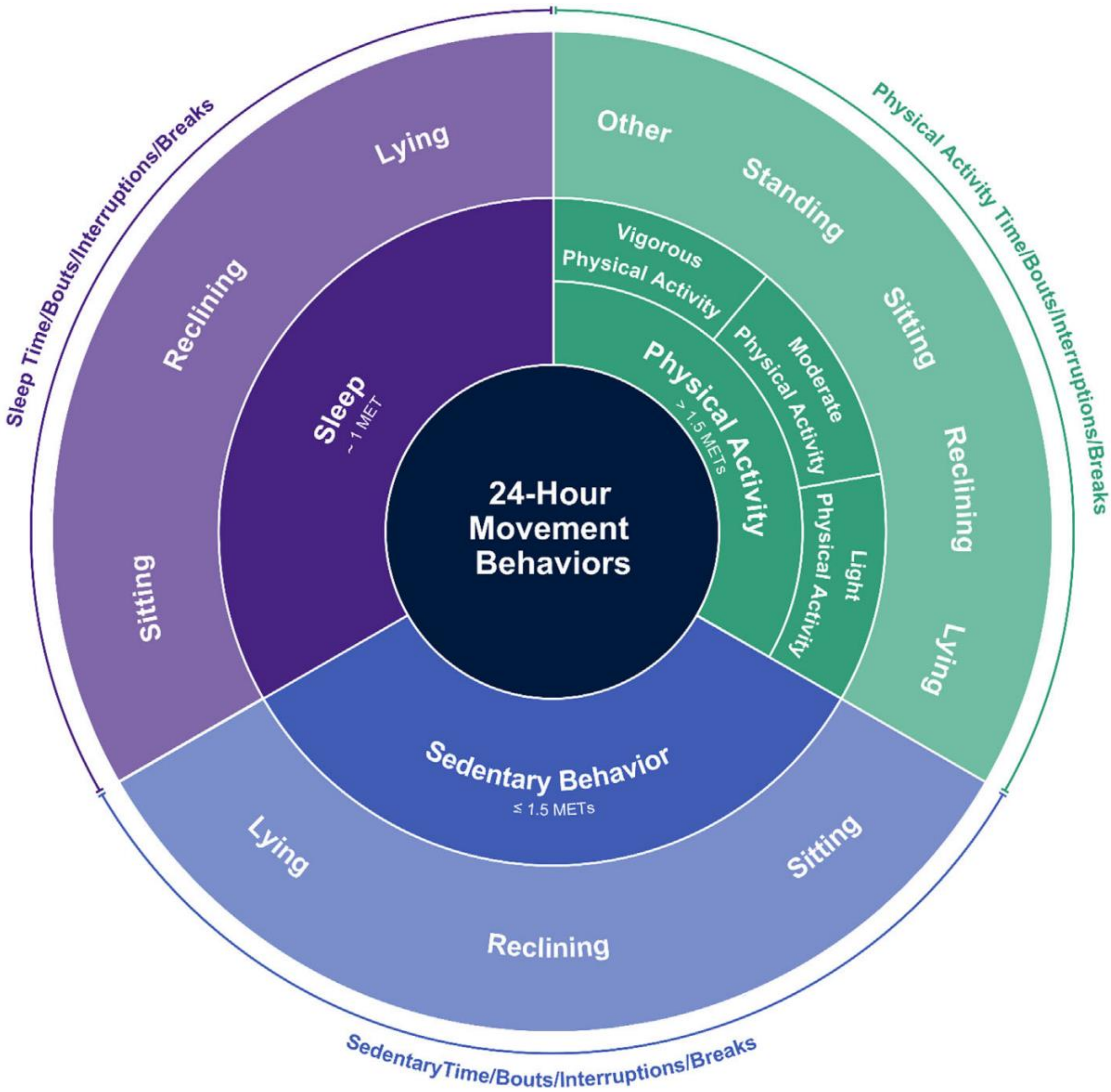

Figure 11: Illustration of the final conceptual model of movement-based terminology arranged around a 24-h period (Tremblay et al., 2017)

In conclusion, the 24-hour physical activity circle (Tremblay et al., 2017) approach provides a comprehensive perspective for developing effective mHealth interventions for children and adolescents. By considering the full range of PA behaviors and utilizing technology and tailored interventions, mHealth interventions can promote sustained PA and reduce SB among young people. The trend in the methodological advancement of mHealth applications for children and adolescents is moving towards more holistic approaches to human movement, in addition to the growing possibilities of individualization through complex techniques such as JITAI and gamification, as well as increasing automation through ML and AI.

3.3.3 Further differentiation of mHealth interventions for children & adolescents

Overall, a more differentiated approach like individualization to mHealth intervention development and implementation can help to address the diverse needs and preferences of children and adolescents and promote sustainable behavior change over time. This includes (1) adapting the complexity of mHealth interventions, as well as (2) accommodating diversity and heterogeneity, and (3) integrating children and adolescents into the development of mHealth interventions through participatory action research.

(1) Adaption of intervention complexity: It is important to adapt the content complexity of mHealth interventions for children and adolescents to ensure that they are appropriate and effective for this age group. Children and adolescents have different developmental needs and abilities compared to adults, and therefore, interventions designed for adults may not be suitable or engaging for young people. By adapting the content complexity, mHealth interventions can be tailored to the cognitive and emotional developmental stages of children and adolescents, making them more accessible, understandable, and engaging. This can increase the likelihood of successful behavior change and promote long-term adoption of healthy behaviors, leading to better health outcomes. For example, complex indices and health parameters may be difficult for younger children to understand and may not be motivating. To address this, the effectiveness of gamification elements is evident (Suleiman-Martos et al., 2021), as well as the use of avatars or particularly visual content. Special attention should also be given to educationally disadvantaged populations, where language barriers may exist, and the parents of children may only be able to provide limited support.
(2) Adaption to diversity and heterogeneity: Adapting mHealth interventions for children and adolescents to diversity and heterogeneity is important for several reasons. First, children and adolescents come from diverse backgrounds, including different cultures, socioeconomic status, and health conditions. Therefore, interventions need to be adapted to meet the unique needs and challenges of different subgroups within this population. Second, adapting mHealth interventions to diversity and heterogeneity can help to reduce health disparities and promote health equity. Certain populations may face greater barriers to accessing and utilizing mHealth interventions, such as language barriers, lack of technological access, or limited digital health literacy. Adapting interventions to address these barriers can improve the reach and effectiveness of interventions for these populations. Third, by adapting mHealth interventions to diversity and heterogeneity, interventions can be more engaging and relevant to the needs and interests of the target population. This can increase motivation and adherence to the intervention, leading to better health outcomes. From a differentiational perspective, the development of mHealth interventions for children and adolescents requires a focus on individual differences and the recognition that there is

no one-size-fits-all approach. Differentiation theory suggests that individuals have unique developmental trajectories, and therefore, interventions should be tailored to meet individual needs (Labouvie et al., 1991). One strategy to accomplish differentiation is through the implementation of adaptive interventions that are customized to suit the specific characteristics and requirements of each individual. Another approach to achieve differentiation involves emphasizing the heterogeneity of the intended audience. This could involve the use of culturally sensitive and linguistically appropriate interventions, as well as interventions that are tailored to specific sub-groups within the population (e.g., individuals with different levels of digital health literacy or those with different mental health needs). It is important to acknowledge that not all interventions are amenable to customization, as the process of tailoring interventions to accommodate the unique attributes and requirements of each individual is often laborious and resource intensive. Individualized interventions may require additional assessments and analyses to determine the most appropriate and effective strategies for each individual. This can increase the complexity and cost of the intervention, making it less feasible for some interventions or populations. However, as technology and data analytics continue to advance, there is increasing recognition of the importance of individualized interventions for maximizing effectiveness and promoting sustained behavior change. As such, efforts are being made to develop more efficient and cost-effective ways to individualize interventions and tailor them to the unique needs and characteristics of each individual.

(3) Participatory action research: This approach can be utilized in the development of mHealth interventions for children and adolescents and involves the active participation of stakeholders, including children and adolescents themselves, as well as parents, educators, and healthcare providers, in the development process. This approach can help ensure that the intervention is sensitive to the needs and preferences of the target population, particularly as children and adolescents are the end-users of these interventions. The involvement of children and adolescents in the development process can promote ownership and engagement with the intervention, increasing their motivation to use it and thus leading to better outcomes. Additionally, participatory action research can help identify and address potential barriers to implementation and uptake of mHealth interventions, including cultural, social, and technological factors that may influence their willingness and ability to use the intervention. By tailoring interventions to meet the unique needs of individuals and the diversity of the target population, mHealth interventions can be made more engaging and effective. In summary, utilizing a participatory action research approach in the development of mHealth interventions for children and adolescents can promote stakeholder involvement, increase motivation and ownership, and identify and address potential barriers to implementation and uptake. These efforts can lead to the development of interventions that are more tailored to

the needs of individuals and the diversity of the target population, improving the effectiveness of mHealth interventions for children and adolescents.

In conclusion and in addition to the study results, this thesis proposes a Youth mHealth Behavior Change Model that integrates the Self-Efficacy and HAPA models with key findings to provide a comprehensive framework for designing mHealth interventions that promote PA-related health behaviors in children and adolescents. The model emphasizes the importance of considering the specific needs of different target groups and involving their social environment to provide support and motivation and can guide the development of effective mHealth interventions. Additionally, the thesis suggests several methodological advancements for future mHealth intervention developments, including user-centered design principles, JITAI, machine learning algorithms, and a 24-hour PA circle approach. Collaboration with parents and schools can also enhance intervention success. To address the diverse needs and preferences of children and adolescents, a differentiated approach that adapts intervention complexity, accommodates diversity and heterogeneity, and involves children and adolescents in the development process through participatory action research is important. This approach can promote ownership and engagement, identify and address potential barriers, and lead to more tailored interventions that ultimately improve effectiveness.

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5 FURTHER PUBLICATIONS

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7 DECLARATION OF AUTHENTICITY

I hereby declare under oath that:

1. The dissertation submitted by me has not been the subject of any other examination procedure or evaluated as insufficient in such a procedure.
2. I have written the dissertation submitted by myself, have not used sources and aids other than those specified, and have not received any commercial doctoral consulting services. I have indicated any passages taken over literally or in content as such.

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(Place, Date) (Signature)

8 APPENDIX

8.1.1 Full version of the first publication (20 pages)

8.1.2 Full version of the second publication (18 pages)

8.1.3 Full version of the third publication (15 pages)

8.1.4 Full version of the fourth publication (9 pages)

8.1.5 Full version of the fifth publication (14 pages)

8.1.6 Full version of the sixth publication (18 pages)

8.1.7 Full version of the seventh publication (20 pages)

Review

mHealth Interventions to Reduce Physical Inactivity and Sedentary Behavior in Children and Adolescents: Systematic Review and Meta-analysis of Randomized Controlled Trials

Hannes Baumann[1,2,3*], MSc; Janis Fiedler[4], MSc; Kathrin Wunsch[4*], PhD; Alexander Woll[4*], PhD; Bettina Wollesen[1*], PhD

[1]Department of Human Movement, Faculty of Psychology and Human Movement Science, University of Hamburg, Hamburg, Germany

[2]Department of Biological Psychology and Neuroergonomics, Institute for Psychology and Occupational Science, Technical University Berlin, Berlin, Germany

[3]Department of Performance, Neuroscience, Therapy and Health, Faculty of Health Sciences, Medical School Hamburg, Hamburg, Germany

[4]Institute of Sports and Sports Science, Karlsruhe Institute of Technology, Karlsruhe, Germany

[*]these authors contributed equally

Corresponding Author:
Kathrin Wunsch, PhD
Institute of Sports and Sports Science
Karlsruhe Institute of Technology
Engler-Bunte-Ring 15
Karlsruhe, 76131
Germany
Phone: 49 721 608 454
Email: kathrin.wunsch@kit.edu

Abstract

Background: Children and adolescents increasingly do not meet physical activity (PA) recommendations. Hence, insufficient PA (IPA) and sedentary behavior (SB) among children and adolescents are relevant behavior change domains for using individualized mobile health (mHealth) interventions.

Objective: This review and meta-analysis investigated the effectiveness of mHealth interventions on IPA and SB, with a special focus on the age and level of individualization.

Methods: PubMed, Scopus, Web of Science, SPORTDiscus, and Cochrane Library were searched for randomized controlled trials published between January 2000 and March 2021. mHealth interventions for primary prevention in children and adolescents addressing behavior change related to IPA and SB were included. Included studies were compared for content characteristics and methodological quality and summarized narratively. In addition, a meta-analysis with a subsequent exploratory meta-regression examining the moderating effects of age and individualization on overall effectiveness was performed.

Results: On the basis of the inclusion criteria, 1.3% (11/828) of the preliminary identified studies were included in the qualitative synthesis, and 1.2% (10/828) were included in the meta-analysis. Trials included a total of 1515 participants (mean age (11.69, SD 0.788 years; 65% male and 35% female) self-reported (3/11, 27%) or device-measured (8/11, 73%) health data on the duration of SB and IPA for an average of 9.3 (SD 5.6) weeks. Studies with high levels of individualization significantly decreased insufficient PA levels (Cohen d=0.33; 95% CI 0.08-0.58; Z=2.55; P=.01), whereas those with low levels of individualization (Cohen d=−0.06; 95% CI −0.32 to 0.20; Z=0.48; P=.63) or targeting SB (Cohen d=−0.11; 95% CI −0.01 to 0.23; Z=1.73; P=.08) indicated no overall significant effect. The heterogeneity of the studies was moderate to low, and significant subgroup differences were found between trials with high and low levels of individualization (χ^2_1=4.0; P=.04; I^2=75.2%). Age as a moderator variable showed a small effect; however, the results were not significant, which might have been because of being underpowered.

Conclusions: Evidence suggests that mHealth interventions for children and adolescents can foster moderate reductions in IPA but not SB. Moreover, individualized mHealth interventions to reduce IPA seem to be more effective for adolescents than for children. Although, to date, only a few mHealth studies have addressed inactive and sedentary young people, and their quality of evidence is moderate, these findings indicate the relevance of individualization on the one hand and the difficulties in reducing SB using mHealth interventions on the other.

Trial Registration: PROSPERO CRD42020209417; https://www.crd.york.ac.uk/prospero/display_record.php?RecordID=209417

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KEYWORDS

health behavior change; individualization; sedentary behavior; physical activity; tailored interventions; personalized medicine; health app; mobile phone

Introduction

Rationale

"Inactivity is the epidemic of the 21st century" [1]. The prevalence of insufficient physical activity (IPA; defined as not meeting the specified physical activity [PA] guidelines [2]) in children and adolescents is >80% worldwide, which is mainly attributable to time spent on sedentary behavior (SB; defined as any waking behavior characterized by an energy expenditure ≤1.5 metabolic equivalents of task [METs] while in a sitting, reclining, or lying posture [2,3]) and has increased continuously over the past decades [4]. This trend remains unbroken, although the health benefits of at least 60 minutes of moderate to vigorous PA (MVPA; defined as any activity with a MET value between 3 and 5.9; vigorous-intensity PA is defined as ≥6 METs [5,6]) on average per day for children and adolescents are well-established [7].

Although SB and IPA may be used synonymously, and indeed by definition, they refer to the same energy expenditure spectrum, it should still be noted that they are not necessarily correlated [8], and both have severe health consequences [9]. For example, children and adolescents may exhibit high levels of SB (driving to school, sitting in class all day, and playing video games in the evening) while simultaneously meeting the recommended PA guidelines (going to soccer practice for an hour in the evening). In this case, the health consequences of SB time would be occurring, although the PA level is sufficient. If IPA and SB are performed in childhood and adolescence, it is assumed that these behavioral patterns will endure until adulthood [10], which is why, from a global perspective, it is important to target young populations with strong IPA and SB patterns in the context of primary prevention.

Given the increasing digitization in health care and the proliferation of smartphones [11], mobile health (mHealth) interventions have been shown to be effective and of scope in reducing IPA and SB in children and adolescents [12], as well as in adults [13]. A more detailed glance at the contents of mHealth interventions reveals that SMS text messaging interventions are one of the most common methods used for delivering mHealth interventions [14], which has been recently criticized [15]. Instead, personalized approaches should focus on responding appropriately to the realities of everyday life and addressing the diversity of modern societies [16]. Key facets of effective mHealth interventions depict the integration of behavior change techniques (BCTs) [17] and the foundation upon existing theoretical approaches [18]. Furthermore, there is empirical evidence that just-in-time interventions [19,20], individualized or tailored interventions [21], and interventions that incorporate multiple BCTs [22] show large potential in this respect. However, Chen et al [23] highlight that the design of mHealth interventions often lacks a theory-driven approach [24,25], and there is little emphasis on evidence-based content [26]. Another difficulty with mHealth interventions occurs when existing evidence is summarized in meta-analyses and refers to outcomes that are coreported as secondary outcomes but do not constitute the core of the intervention [27].

Until recently, there have been far more mHealth interventions for healthy adults aiming to reduce IPA and SB than for healthy children and adolescents [13,28]. In one of the very few reviews on healthy children and adolescent target groups, Schoeppe et al [12] demonstrated an overall moderate quality of health apps and found a positive correlation between app quality and the number of app features and BCTs, therefore suggesting that future apps should target user engagement, be tailored to specific populations, and be guided by health behavior theories. Böhm et al [28] furthermore criticize the quality of mHealth interventions for children and adolescents in this respect and suggest that more age-appropriate solutions are needed. The results of other reviews indicate that smartphone-based mHealth interventions (especially apps) are a versatile strategy for increasing PA and steps in children and adolescents [29]. For example, Laranjo et al [30] found an average increase of 1850 steps per day after an mHealth intervention. However, it is also occasionally mentioned that the use of mHealth could lead to a further increase in the already high screen time of children and adolescents [31,32], which needs to be taken into consideration when planning and implementing mHealth apps. Although mHealth can increase screen time, it may not necessarily do so. The representative and longitudinal Motorik-Modul study demonstrated that increased screen time does not correlate with PA minutes, opening various opportunities for digital interventions and potential ways for new approaches to target the IPA and SB of children and adolescents [33,34].

In the context of mHealth, individualization is defined as an adaptation to the needs or special circumstances of an individual and is cited as one of the main barriers that prevent patients from changing their health behavior [23,35]. Individualized interventions (sometimes also called adaptive, needs-specific, target group–specific, tailored, or personalized interventions) offer a potential way of delivering person-centered interventions by varying levels of individual needs and empowering individuals to monitor their health actively [21]. Non-mHealth interventions have sometimes used individualized one-on-one meetings, showing high effectiveness but consuming much time and resources. Therefore, this approach has been criticized as time consuming and resource burdening [36,37]. Apps can apply this approach in a much more ecological way by being easily accessible to a wide variety of populations. The enhanced efficacy of individualized interventions compared with nonindividualized interventions has been repeatedly demonstrated in various populations [30,38,39], especially in adults [40], but not yet in children or adolescents, although several randomized controlled trials address this matter. For example, the MOPO study examined the effects of a gamified and individualized mHealth intervention and has not been cited in any meta-analysis to date [41]. Another example of this is the intervention of Moreau et al [42], which is a fully automated, theory-driven, tailored intervention. In addition, there is no existing taxonomy for individualized app elements as there is, for example, for behavior change mechanisms [17], from which derives the urgent need for further systematic reviews and development of a taxonomy for individualized elements.

Objective

Although several reviews [12,28,29,43] have been published on mHealth-based PA promotion in children and adolescents, and some of them also include studies with IPA and SB as outcomes, none of the existing reviews ensures (1) a clear focus on the at-risk target group of children and adolescents with high IPA and SB levels and (2) a separate analysis of effects of mHealth on IPA and SB. Therefore, this review might contribute to a better understanding of the needs of children and adolescents who engage in IPA and high SB. For this reason, this review's aims were 3-fold.

First, there is a need to identify and describe existing SB and IPA mHealth interventions that address PA for children and adolescents. Second, this review sought to answer whether and how mHealth interventions are effective in reducing IPA and SB in healthy children and adolescents. Third, there is a need to explore whether age and individualization are moderators of the overall effectiveness of the mHealth interventions. This leads to the following main research questions:

1. What are the characteristics of effective existing mHealth interventions for children and adolescents to reduce SB and IPA?
2. How effective are existing mHealth interventions for children and adolescents in reducing SB and IPA?
3. What moderating effects do individualization and age have on the effectiveness of mHealth interventions for children and adolescents to reduce SB and IPA?

Methods

This systematic review and meta-analysis was conducted according to Cochrane methodology, and the results were reported following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 statement [44].

Eligibility Criteria

The criteria for eligible studies are defined in accordance with the population, intervention, comparison, and outcomes criteria [45] and are presented in Textbox 1. In line with World Health Organization (WHO) recommendations [5], IPA was defined as <60 minutes of MVPA per day or insufficient step count per day (<5000 steps per day) [46], and SB was defined as any waking behavior characterized by an energy expenditure of ≤1.5 METs while in a sitting, reclining, or lying posture [2,3]. Alternative measures can be screen time and sitting time.

Textbox 1. Summary of the population, intervention, comparison, and outcomes and eligibility criteria.

Participants and population

- Inclusion: healthy children and adolescents (aged 0-21 years) without physical or psychological morbidities that would influence the realization of behaviors targeted by the respective interventions and studies that include participants with any physical or psychological morbidities (eg, populations with obesity) and provides a subgroup analysis for the healthy population separately
- Exclusion: children and adolescents with any physical or psychological morbidities, populations with mean age >21 years, studies conducted within clinical settings, and studies focusing on populations whose insufficient physical activity (IPA) or sedentary behavior (SB) is influenced by disease-specific recommendations or health status

Intervention or interventions and exposure or exposures

- Inclusion: mobile health (mHealth) interventions with healthy children and adolescents where the primary or secondary outcome measure was IPA or SB, mixed interventions, and family-based interventions
- Exclusion: studies without mHealth interventions

Comparator(s) and control

- Inclusion: active or passive control groups
- Exclusion: studies without a control group

Outcomes

- Inclusion:
  - IPA, which is defined as <60 minutes of self-reported or accelerometry-measured moderate to vigorous physical activity per day or insufficient step count per day (<5000 steps per day); therefore, various physical activity measures (min/week of physical activity, steps, counts, metabolic equivalents of task [MET] minutes, screen time, and sitting time) need to be included
  - SB, which is defined as any waking behaviors characterized by an energy expenditure of ≤1.5 METs while in a sitting, reclining, or lying posture; alternative measures can be screen time and sitting time
- Exclusion: mHealth intervention studies that do not involve IPA or SB as a primary or secondary outcome

Types of study to be included

- Inclusion: randomized controlled trials (RCTs) that include individual or cluster randomization, clinical trials, feasibility studies with an RCT design, and just-in-time adaptive interventions; for a potential meta-analysis, only RCTs were included
- Exclusion: nonexperimental study designs (eg, observational or case studies, studies reporting prevalence or trend data, measurement studies, and theoretical papers), non–peer-reviewed studies, and nonprimary studies (eg, letters, comments, conference proceedings, reviews, and narrative articles)

Information Sources

After group discussion among the research team, a systematic search for randomized controlled trials in English between January 1, 2000, and January 29, 2021. was conducted using the 5 databases of PubMed, Scopus, Web of Science, SPORTDiscus, and Cochrane Library.

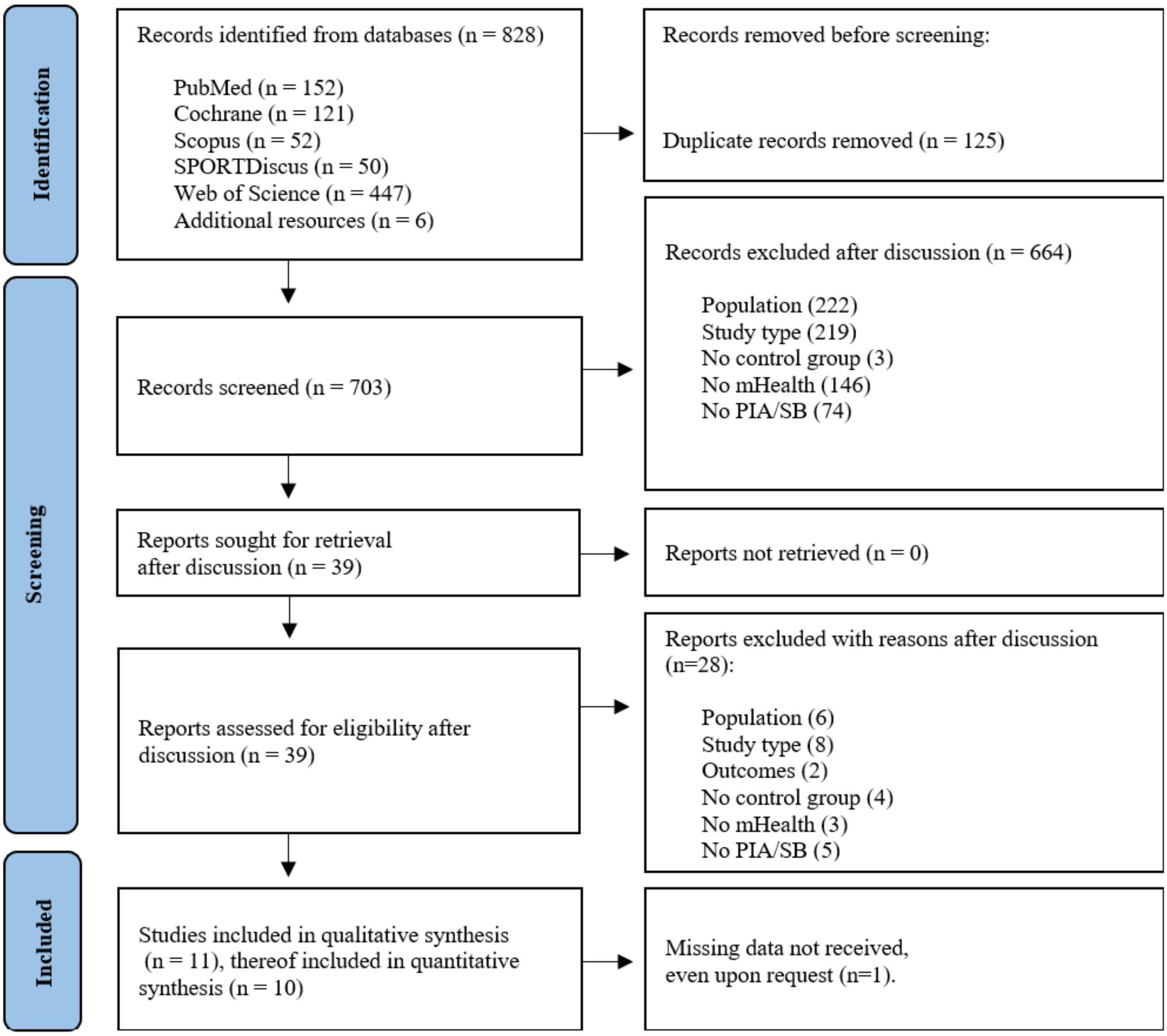
Search Strategy

The search terms were reviewed by 3 authors (HB, JF, and KW), and the search was conducted by 1 author (HB) in March 2021. The following vital constructs, as well as numerous synonyms, were used: (*children* OR *adolescents*) AND (*mHealth*) AND (*IPA* OR *SB*). The entire search strategy can be found in the *Availability of Data, Code, and Other Materials* section.

Selection Process

The identified literature was imported to the reference management software Zotero (Roy Rosenzweig Center for History and New Media). After removing duplicates, the first author (HB) and a coauthor (JF) screened titles and abstracts to identify all potentially eligible studies based on the inclusion and exclusion criteria (the detailed study flow is presented in the PRISMA flowchart in Figure 1). Full-text articles were retrieved for eligible abstracts and reviewed by the same 2 authors before inclusion in the review. The first author (HB) and a second reviewer (JF) independently assessed full paper copies of remaining potentially eligible studies to determine included studies, and if no consent was reached, a third reviewer (KW) resolved the disagreement by discussion and arbitration.

Figure 1. Flowchart and study selection process (adapted from Page et al [45]). IPA: insufficient physical activity; SB: sedentary behavior.



Data Collection Process and Data Items

On a study level, data, including the name of the author, year of publication, study type, study aim, information about the mHealth intervention, duration of intervention, follow-up period, target population or setting, integration of parents, country, sample size, age (range, mean, and SD), gender, IPA or SB criterion, relevant outcomes, measurement method, treatment effects, individualized elements, BCT elements, and theoretical foundation were extracted. To identify interventions with high and low levels of individualization, we quantified the individualized elements and defined *low level of individualization* as the number of individualized items below the IQR of the evaluated interventions and *high level of individualization* as the number of individualized items within or above the IQR of the evaluated interventions.

Study Risk of Bias Assessment

The risk of bias (ROB) in individual studies was evaluated independently by 2 reviewers (HB and KW) using the 5-dimensional ROB 2 tool [47]. In this procedure, the overall ROB is classified as low if all dimensions indicate low risk. Once ≥1 dimension is rated as unclear, the entire trial is rated the same way. Furthermore, if ≥1 dimension is classified as being high risk, the overall ROB is rated high. Disagreements between the authors concerning the ROB were resolved by discussion, with the involvement of another author where necessary.

Effect Measures

To perform a meta-analysis, the sample sizes, means, and SDs of measurement time points 1 and 2 were extracted from the intervention and control groups of all included studies (or study arms) for both IPA and SB. For reasons of comparability in the meta-analysis, follow-up data were not extracted, as not all studies included a third or fourth measurement point. When multiple primary outcome measures were presented, the most conclusive measure to our research questions was identified by JF and HB. Quality of information and the orientation toward WHO guidelines played a critical role in this process. It was defined that IPA was most likely to be modeled by *minutes of MVPA per day*, as suggested by the WHO, followed by *minutes of light MVPA per day*, *minutes of PA per day*, and *number of steps per day*. For SB, *minutes in SB per day* was preferred over the proxy measures of *minutes of sitting time per day* and *minutes of screen time per day*.

Synthesis Methods

If data for the meta-analysis were not available in the original manuscripts, the study authors were contacted. The last search was conducted in March 2021. Extracted data were then weighted by sample size (splitted shared group procedure was used in studies with multiple study arms to avoid unit of analysis error [48]), converted into Cohen *d*, and integrated into a meta-analysis with random effects using RevmanWeb [49] calculator. We used the following benchmark to interpret the effect sizes: effect sizes >0.50 are interpreted as large, effect sizes of 0.50 to 0.30 as moderate, and effect sizes of 0.30 to 0.10 as small or <0.10 as trivial [50]. Tests for heterogeneity, overall effects, and subgroup differences were also calculated using RevmanWeb.

Reporting Bias Assessment and Certainty Assessment

To assess publication bias, funnel plots were compiled using RevmanWeb to determine asymmetric shapes within the natural statistical dispersion [51]. If the plot is asymmetric because of many large effect sizes on one side of the mean, it strongly suggests unpublished or unconducted studies with contrary results. To provide certainty of the evidence, the Grading of Recommendations, Assessment, Development, and Evaluations approach [52] was used as an extension of the ROB assessment. The following five factors were examined to obtain a well-founded assessment: individual study limitations (ROB), inconsistency of results (heterogeneity), indirectness of evidence (external validity), imprecision (small sample size and wide CI), and publication bias.

Additional Analyses

An additional meta-regression was performed in R-Studio [53] using the *Metafor* package [54] to relate the estimated effect sizes to the mean age of the samples. We distinguished between primary outcome (IPA or SB) and level of individualization (low or high). The included trials (and their multiple arms) were divided into trials with high (number of individualized items within or above the IQR of evaluated interventions) and low levels of individualization (number of individualized items below the IQR of evaluated interventions) to conduct a meta-analysis. For both IPA and SB outcomes, a separate meta-analysis was conducted to provide the comparability of effects. To visualize the results, a grouped bubble plot was created in Microsoft Excel [55], plotting the weighted standardized mean differences of the individual trials and the average age of the participants. Group differentiation was based on the primary outcome (IPA and SB).

Registration and Protocol

The protocol for this systematic review and meta-analysis was prospectively registered on PROSPERO (International Prospective Register of Systematic Reviews) and can be accessed using registration number CRD42020209417.

Availability of Data, Code, and Other Materials

The search string (Medical Subject Headings) was as follows:

> *(Child [MeSH] OR Adolescent [MeSH]) AND (Health Promotion[MeSH] OR School Health Services[MeSH] OR Primary Prevention[MeSH] OR Health Behavior Change) AND (Telemedicine [MeSH] OR Patient-Specific Modeling[MeSH] OR Individuali* OR tailored Intervention OR digital health OR Mobile Applications[MeSH] OR mobile phone* OR smartphone* OR iPhone* OR iPad* OR tablet* OR android OR SMS OR text message* OR App OR Reminder Systems [MeSH]) AND (SB[MeSH] OR Physical Fitness[MESH] OR Exercise[MESH] OR energy expenditure) / Filter applied: years 2010-2020, only RCT and Clinical Trials*

Results

Study Selection

The initial database search generated 828 articles, of which 125 (15.1%) were duplicates (Figure 1), and the study screening identified 11 (1.35) studies as eligible for qualitative analysis and 10 (1.2%) articles for quantitative synthesis.

Study Characteristics

A total of 11 randomized controlled trials were included (n=10, 91%, parallel and n=1, 9%, crossover trial), with a duration of 9.3 (SD 5.6) weeks, of which 3 (27%) [56-58] included a follow-up measurement. Eligible trials included samples of 40 to 496 participants (mean 138, SD 145), with a mean age range of 3.5 to 17.8 years (Table 1). In 9% (10/11) of studies, both genders were approximately equally represented. A single study [41] only included male adolescents, resulting in an overall gender distribution of 975 boys and young men to 540 girls and young women. Approximately 27% (3/11) of trials with young children (aged <5 years) included parent integration, whereas others focused on children and adolescents only. The target population and study aims varied across studies, and the countries were exclusively Western nations. The mHealth interventions ranged from basic SMS text messaging interventions to web-based mobile interventions, individualized and gamified apps, and wearable interventions. In addition, of the 15 interventions, 3 (20%) used self-reported measures, and 8 (53%) interventions used device-based measures of health data on the duration of SB and IPA. Furthermore, it should be mentioned that not all studies focused on reducing SB or IPA as their primary objective. Approximately 45% (5/11) of studies aimed to promote PA [41,57-60], 9% (1/11) aimed to improve fat mass index [61], 9% (1/11) aimed to reduce BMI [62], and 9% (1/11) aimed to change behavior [56] as a primary study aim.

The quantitative results of the individual studies are presented in the forest plots in Figures 2 and 3. To describe each intervention (or study arm) in detail, the number and content of individualized elements, BCTs, and theoretical foundations are presented in Table 2.

Table 1. Study characteristics.

Study	Study type (duration in weeks)	Study aim	Description of mHealth[a] intervention	Population (setting), region, and country	Sample size (N)	Age (years)		SB[b] (unit) and IPA[c] outcomes (unit); measurement method
						Values, mean (SD)	Values, range	
Chen et al [62]	2-arm parallel RCT[d] with follow-up (12)	Decrease BMI	iStart Smart for Teens: a smartphone-based, culturally appropriate, and tailored educational program for weight management	Chinese American adolescents who are overweight, California, United States	40 (male 23 and female 17)	14.9 (1.67)	13-18	SB (hours per day) and PA[e] (days per week); questionnaire (California Health Interview Survey)
Nyström et al [61]	2-arm parallel RCT (24)	Reduce obesity (improve fat mass index)	Web-based app to deliver MINISTOP intervention, which provided an extensive program of information and behavioral support	Healthy children (preschool; parental support), Östergötland, Sweden	313 (male 170 and female 143)	4.5 (0.1)	4-5	SB (min/day) and MVPA[f] (minutes per day); ActiGraph wGT3x-BT accelerometer
Direito et al [58]	3-arm parallel RCT (8)	Improve PA levels in healthy young people who are insufficiently active	AIMFIT trial compared the apps “Zombies, run” and “Get Running” with a control group (device measured)	Healthy adolescents, Auckland, New Zealand	51 (male 22 and female 29)	15.67 (1.2)	14-17	SB (minutes per day) and MVPA (minutes per day); accelerometer (ActiGraph GT1M) and PAQ-A[g]
Downing et al [63]	2-arm pilot RCT (6)	Reducing children’s SB in early age	Mini-Movers: SMS text messaging intervention to provide information and practical support	Young children (playgroups; parental support), Melbourne, Australia	57 (male 26 and female 31)	3.05 (0.75)	2-4	Sitting time (minutes per day) and no IPA outcome; ActivePAL
Fassnacht et al [59]	2-arm parallel RCT (8) with 2 follow-ups (4 and 4)	Promote health behavior in school-aged children	Daily behavior reporting and feedback vis SMS text messaging	Healthy children (elementary school), Braga, Portugal	49 (male 23 and female 26)	9.6 (0.4)	8-19	Screen time (hours per day) and PA (hours per day); Family Eating and Activity Habits questionnaire
Gaudet et al [57]	Crossover RCT (6)	Increase PA in young adolescents	Wrist-worn PA tracker (Fitbit, model Charge HR)+web-based Fitbit user account	Young adolescents (school), New Brunswick, Canada	46, (male 22 and female 24)	13.0 (0.35)	13-14	SB (minutes per day) and MVPA (minutes per day); Actical accelerometer
Hammersley et al [64]	2-arm parallel RCT (11) with 2 follow-ups (12 and 24)	Reduce obesity behaviors in preschool children	Parent focused; Time2bHealthy Online Program with Fakebook integration	Children who are overweight (preschool; parental support), Wollongong, Australia	86 (male 43 and female 43)	3.46 (0.92)	2-5	SB (minutes per day) and MVPA (minutes per day); ActiGraph GT3X+ accelerometer
Mendoza et al [60]	2-arm parallel RCT (10)	Promote PA among adolescent and young adult survivors	Wearable PA-tracking device (Fitbit Flex) and a peer-based web-based support group (a Facebook group)	Childhood survivors of cancer, Seattle, United States	59 (male 24 and female 35)	16.6 (1.5)	14-18	SB (minutes per day) and MVPA (minutes per day); ActiGraph GT3X+ accelerometer
Pyky et al [41]	2-arm parallel RCT (6)	Promote PA and social activity	Game-based persuasion, for example, by physically moving within the districts of the city; players could earn points and claim areas for their clan in-game	Young adolescent men (military), Oulu, Finland	496 (male 496 and female 0)	17.8 (0.6)	16-20	SB (minutes per day) and MVPA (minutes per day); Polar Active Accelerometer

Study	Study type (duration in weeks)	Study aim	Description of mHealth[a] intervention	Population (setting), region, and country	Sample size (N)	Age (years)		SB[b] (unit) and IPA[c] outcomes (unit); measurement method
						Values, mean (SD)	Values, range	
Sirriyeh et al [56]	4-arm exploratory RCT (2)	PA behavior change	Daily SMS text messages, which included manipulations of affective or beneficial beliefs	Late adolescents (state schools), Yorkshire, United Kingdom	128 (male 38 and female 90)	17.3 (0.68)	16-19	IPAQ[h] questionnaire; no outcomes; time point 0 data missing
Van Woudenberg et al [65]	2-arm clustered RCT (10)	Promote PA	Smartphone-based SNI[i] with MyMovez2 Wearable Lab—a smartphone with a tailor-made research app	Influential adolescents (school), Venlo, Netherlands	190 (male 88 and female 102)	12.7 (0.50)	11-19	SB (minutes per day) and MVPA (minutes per day); accelerometer (Fitbit Flex)

[a]mHealth: mobile health.
[b]SB: sedentary behavior.
[c]IPA: insufficient physical activity.
[d]RCT: randomized controlled trial.
[e]PA: physical activity.
[f]MVPA: moderate to vigorous physical activity.
[g]PAQ-A: Physical Activity Questionnaire for Adolescents.
[h]IPAQ: International Physical Activity Questionnaire.
[i]SNI: social network intervention.

Figure 2. Forest plot for effect size comparison of high-individualized versus low-individualized mobile health interventions on decreasing IPA [42,58-63,66]. IPA: insufficient physical activity.

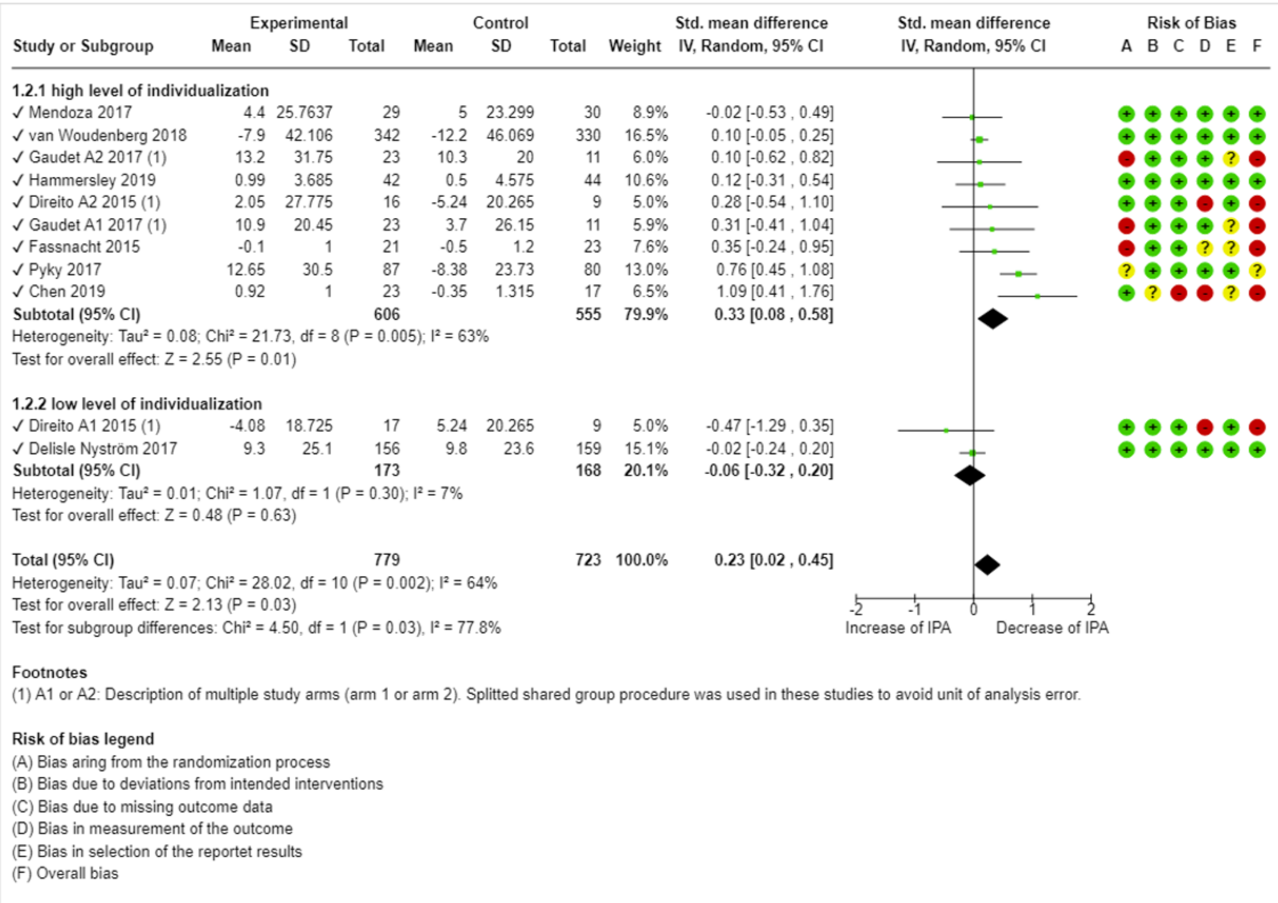
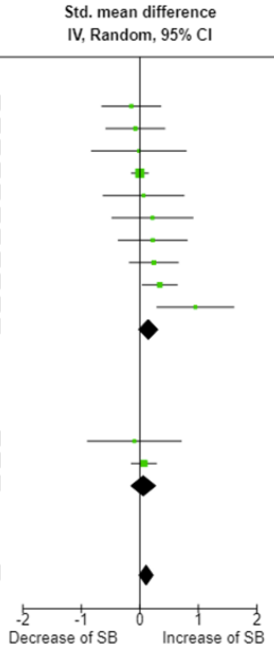


Figure 3. Forest plot for effect size comparison of high-individualized versus low-individualized mobile health interventions on decreasing SB [42,58-64,66]. RCT: randomized controlled trial; SB: sedentary behavior.

Study or Subgroup	Experimental Mean	Experimental SD	Experimental Total	Control Mean	Control SD	Control Total	Weight	Std. mean difference IV, Random, 95% CI	A	B	C	D	E	F
1.1.1 high level of individualization														
✓ Downing 2018	-24.8	145.28	30	-3.7	140.845	29	5.1%	-0.15 [-0.66 , 0.37]	?	+	+	+	+	?
✓ Mendoza 2017	-4.5	82.5491	29	1	56.5068	30	5.1%	-0.08 [-0.59 , 0.43]	+	+	+	+	+	+
✓ Direito A2 2015 (1)	16.99	96.19	16	18.75	94.375	9	2.1%	-0.02 [-0.83 , 0.80]	+	+	+	-	+	-
✓ van Woudenberg 2018	12.185	102533	352	21.44	111.31	330	32.5%	-0.00 [-0.15 , 0.15]	+	+	+	+	+	+
✓ Gaudet A1 2017 (1)	-21.3	75	23	-26.1	73.45	12	2.9%	0.06 [-0.64 , 0.76]	-	+	+	+	?	-
✓ Gaudet A2 2017 (1)	8.2	78.9	23	-8.5	69.1	12	2.8%	0.22 [-0.48 , 0.92]	-	+	+	+	?	-
✓ Fassnacht 2015	-0.3	0.75	20	-0.5	1	24	3.9%	0.22 [-0.38 , 0.81]	-	+	+	?	?	-
✓ Hammersley 2019	2.03	8.325	42	0.17	7.095	44	7.2%	0.24 [-0.19 , 0.66]	+	+	+	+	+	+
✓ Pyky 2017	26.47	137.25	87	-18.4	124.44	80	12.6%	0.34 [0.03 , 0.65]	?	+	+	+	+	?
✓ Chen 2019	0.97	0.715	23	0.08	1.1425	17	3.1%	0.95 [0.28 , 1.61]	+	?	-	-	?	-
Subtotal (95% CI)			**645**			**587**	**77.4%**	**0.14 [-0.02 , 0.31]**						
Heterogeneity: Tau² = 0.02; Chi² = 12.45, df = 9 (P = 0.19); I² = 28%														
Test for overall effect: Z = 1.70 (P = 0.09)														
1.1.2 low level of individualization														
✓ Direito A1 2015 (1)	8.59	110.1	17	18.75	94.375	9	2.2%	-0.09 [-0.90 , 0.71]	+	+	+	-	+	-
✓ Delisle Nyström 2017	3	48.5	156	-0.6	55	159	20.5%	0.07 [-0.15 , 0.29]	+	+	+	+	+	+
Subtotal (95% CI)			**173**			**168**	**22.6%**	**0.06 [-0.16 , 0.27]**						
Heterogeneity: Tau² = 0.00; Chi² = 0.14, df = 1 (P = 0.70); I² = 0%														
Test for overall effect: Z = 0.53 (P = 0.59)														
Total (95% CI)			**818**			**755**	**100.0%**	**0.11 [-0.01 , 0.23]**						
Heterogeneity: Tau² = 0.01; Chi² = 12.68, df = 11 (P = 0.31); I² = 13%														
Test for overall effect: Z = 1.73 (P = 0.08)														
Test for subgroup differences: Chi² = 0.38, df = 1 (P = 0.54), I² = 0%														



Footnotes
(1) A1 or A2: Description of multiple study arms (arm 1 or arm 2). Splitted shared group procedure was used in these studies to avoid unit of analysis error.

Risk of bias legend
(A) Bias aring from the randomization process
(B) Bias due to deviations from intended interventions
(C) Bias due to missing outcome data
(D) Bias in measurement of the outcome
(E) Bias in selection of the reportet results
(F) Overall bias

Table 2. Mobile health intervention characteristics: study aims, BCT[a] cluster, theoretical foundation, and individualization.

Study (RCT[b] and protocol) and intervention (study arm)	BCT taxonomy cluster, according to Michie et al [17] (N)	Theoretical foundation (N)	Individualization (N)	Level of individualization
Chen et al [62]				
Fitbit app and Facebook	Goals and planning, feedback and monitoring, social support, shaping knowledge, comparison of behavior, reward and threat, and associations (7)	Not mentioned (0)	Competitions with community or friends, individual goal setting, task adjustment in relation to BMI, direct biofeedback and real-time coaching, goal-specific motivational coaching, personalized advice, and guidance (6)	High
Nyström et al [61,66]				
MINISTOP app	Feedback and monitoring and associations (2)	Not mentioned (0)	Individual feedback (1)	Low
Direito et al [58]				
Zombies, Run! app (1)	Goals and planning and feedback and monitoring (2)	Self-regulatory behavior change theory [67] (1)	Audio instructions, missions and defense bases, and web-based races (3)	Low
Get Running app (2)	Goals and planning, feedback and monitoring, comparison of behavior, and reward and threat (4)	Self-regulatory behavior change theory [67] (1)	Human voice coach, training path, friend integration, low threshold approach, recovery periods, and music (6)	High
Downing et al [63,68]				
Mini-Movers SMS text messaging–based intervention	Goals and planning, feedback and monitoring, and reward and threat (3)	Social cognitive theory [69], SMART[c] goal framework [70], and CALO-RE[d] taxonomy [71] (3)	Individual goal setting; goal-specific feedback; tailored SMS text messages; and just-in-time delivery of SMS text messages based on preferred time, date, and activity (4)	High
Fassnacht et al [59]				
SMS text messaging–based feedback intervention	Goals and planning, feedback and monitoring, and associations (3)	Not mentioned (0)	Individual goal setting, task adjustment in relation to BMI, tailored feedback messages, and goal-specific motivational coaching (4)	High
Gaudet et al [57]				
FitBit app immediate intervention (1)	Goals and planning, feedback and monitoring, social support, shaping knowledge, comparison of behavior, reward and threat, and associations (7)	Not mentioned (0)	Competitions with community or friends, individual goal setting, task adjustment in relation to BMI, direct biofeedback and real-time coaching, goal-specific motivational coaching, personalized advice, and guidance (6)	High
FitBit app delayed intervention (2)	Goals and planning, feedback and monitoring, social support, shaping knowledge, comparison of behavior, reward and threat, and associations (7)	Not mentioned (0)	Competitions with community or friends, individual goal setting, task adjustment in relation to BMI, direct biofeedback and real-time coaching, goal-specific motivational coaching, personalized advice, and guidance (6)	High
Hammersley et al [64,72]				
Time2b-Healthy Facebook and on the web	Goal setting, revision of goals, feedback, and challenges (4)	Self-efficacy model [73] and SMART goals framework [70] (2)	Tailored reminder emails, a Facebook group with individual goal setting, and goal-specific motivational coaching (4)	High
Mendoza et al [60]				

Study (RCT[b] and protocol) and intervention (study arm)	BCT taxonomy cluster, according to Michie et al [17] (N)	Theoretical foundation (N)	Individualization (N)	Level of individualization
Fitbit app and Facebook	Goals and planning, feedback and monitoring, social support, shaping knowledge, comparison of behavior, reward and threat, and associations (7)	Not mentioned (0)	Individual awards in a Facebook group, competitions with community or friends, individual goal setting, task adjustment in relation to BMI, direct biofeedback and real-time coaching, goal-specific motivational coaching, personalized advice, and guidance (7)	High
Pyky et al [41,74,75]				
Clans of Oulu gamified app and web-based MOPO portal	Goals and planning, feedback and monitoring, social support, comparison of behavior, comparison of outcomes, reward and threat, associations, identity, and covert learning (9)	Transtheoretical Model of Behavior Change [76] (1)	Stage of behavior change, individual feedback on physical activity and sitting time, GPS-based tasks, competitions with community, and peer-referenced comparison (5)	High
Woudenberg et al [65,77]				
App-based social network intervention—MyMovez	Comparison of behavior, reward and threat, and identity (3)	Theory of Planned Behavior [78], Self-Determination Theory [79], and Self-Persuasion Theory [80] (3)	Content tailored to influential youths, comparing individual scores with others, individual rewards, and individual identification with health behavior (4)	High
Sirriyeh et al [56]				
Instrumental SMS text message intervention	Goals and planning, shaping knowledge, and identity (3)	Theory of Planned Behavior [78] (1)	Individual goal setting (1)	Low
Affective SMS text message intervention	Goals and planning, self-belief, and identity (3)	Theory of Planned Behavior [78] (1)	Individual goal setting (1)	Low
Combined SMS text message intervention	Goals and planning, shaping knowledge, self-belief, and identity (4)	Theory of Planned Behavior [78] (1)	Individual goal setting (1)	Low

[a]BCT: behavior change technique.

[b]RCT: randomized controlled trial.

[c]SMART: Specific, Measurable, Achievable, Relevant, and Time-Bound.

[d]CALO-RE: Coventry, Aberdeen, and London-Refined.

Among the 11 included studies, 3 (27%) had multiple study arms [56-58], resulting in a total of 15 mHealth interventions. In studies with multiple arms, each study arm represented a subintervention. Unfortunately, the subtrials of Sirriyeh et al [56] could not be integrated into the meta-analysis because of missing data. Overall, 33% (5/15) indicated a low level of individualization, and 66% (10/15) of interventions showed a high level of individualization. Individual goal setting was the most common technique used to individualize mHealth interventions. If the level of individualization in the studies was low, there was also a low use of BCTs in these interventions. The reporting of the theoretical foundation was not mentioned in 40% (6/15) of interventions and was therefore generally poor, although the interventions of Downing et al [68] and Woudenberg et al [65] were each based on 3 underlying theories. The most common theories were self-regulatory BCT [67]; Specific, Measurable, Achievable, Relevant, and Time-Bound goals framework [70]; Theory of Planned Behavior [78]; Self-Determination Theory [79]; Self-Persuasion Theory [80]; Transtheoretical Model of Behavior Change [76]; social cognitive theory [69]; and the Coventry, Aberdeen, and London-Refined taxonomy [71]. The number of behavior change elements correlated with the number of individualized elements. Of the 12 included interventions, 2 (17%) were SMS text messaging based, 5 (42%) included some form of social media (eg, Facebook), and 4 (33%) used the Fitbit app.

ROB in Studies

Across the 11 studies, 7 out of 60 ratings (5 dimensions ×12 studies) indicated high ROB, and 7 ratings showed an unclear ROB, resulting in an overall rating of 3 (27%) studies with low, 2 (18%) studies with unclear, and 6 (55%) studies with a high ROB. Potential biases frequently occurred in dimensions A (bias arising from the randomization process) and D (bias in the measurement of the outcome). More detailed ROB information for each study can be found in Multimedia Appendix 1 [41,57-65] and Multimedia Appendix 2 and is also integrated into the forest plots for the meta-analysis.

Synthesis of Results

Effects of High-Individualized and Low-Individualized mHealth Interventions on Decreasing IPA

Approximately 82% (9/11) of studies evaluated the effects of mHealth interventions on decreasing IPA levels, of which 22% (2/9) included multiple study arms [57,58]. Notably, the nonimmersive app of Direito et al [58] (arm 2) contributed to a reduction in IPA, whereas the immersive app (arm 1) increased IPA. One of the trials [56] was not included because of missing data on IPA. Splitted shared group procedure was used in studies with multiple study arms to avoid unit of analysis error [48]. As shown in Figure 2, the meta-analysis of IPA demonstrated a significant, small overall effect size (Cohen d=0.23; 95% CI 0.02-0.45; Z=2.13; P=.03). Trials with high levels of individualization (9/11, 82% of studies) significantly decreased IPA levels, with a moderate effect size (Cohen d=0.33; 95% CI 0.08-0.58; Z=2.55; P=.01). In contrast, those with low levels of individualization (2/11, 18% of studies) indicated no overall effect or even a nonsignificant increase in IPA (Cohen d=−0.06; 95% CI −0.32 to 0.20; Z=0.48; P=.63). A test for subgroup differences indicated that the described difference between interventions with high and low levels of individualization was statistically significant (χ^2_1=4.0; P=.04; I^2=75.2%). The overall heterogeneity was moderate (τ^2=0.02; χ^2_9=1.1; P=.002; I^2=64%), and several ROB dimensions indicated a high ROB. As can be seen in Figure 2, dimensions A (bias arising from the randomization process), C (bias because of missing outcome date), and D (bias in the measurement of the outcome) were most frequently represented.

Effects of High-Individualized and Low-Individualized mHealth Interventions on Decreasing SB

Overall, all 10 included studies evaluated the effects of mHealth interventions on decreasing SB time, and 2 (20%) studies included multiple study arms [57,58]. The results showed a difference in positive effect sizes between the 2 arms of the Gaudet et al [57] study, although it was a crossover trial. In contrast, the Direito et al [58] immersive app (arm 1) showed a slight reduction in SB, whereas the nonimmersive app (arm 2) showed a slight increase. In contrast to the meta-analytic outcome measure IPA, the analysis indicated neither a significant subgroup difference between interventions with low and high levels of individualization (χ^2_1=0.4; P=.54; I^2=0%) nor a general, significant effect within each subgroup (Z=1.70, P=.09; Z=.53, P=.59). Of the 15 interventions, 8 (53%) demonstrated a small increase in SB time. The heterogeneity of the included studies was overall low to moderate (τ^2=0.01; χ^2_{11}=12.7; P=.31; I^2=13%) but varied by subgroup (trials with high levels of individualization: τ^2=0.02, χ^2_9=12.5, P=.19, I^2=28%; trials with low level of individualization: τ^2=0.00, χ^2_1=0.1, P=.70, I^2=0%). As demonstrated in Figure 3, several ROB dimensions indicated an unclear or high ROB. Dimensions A (bias arising from the randomization process), C (bias because of missing outcome date), and D (bias in the outcome measurement) were the most frequently represented.

Reporting Biases

Publication bias between studies was assessed using funnel plots for the 2 outcomes of IPA and SB. Statistical tests (eg, Egger regression [81]) for publication bias were not performed because of the small number of included studies.

Visual inspection of funnel plots (Figures 4 and 5) indicated no serious publication bias in either case. The results of the study by Chen et al [62] occurred outside of the 95% CIs for both outcomes but for high-individualized trials only. Low-level individualization showed a smaller effect, and no results were outside the 95% CI. This also applies to the result of Pyky et al [41] for the IPA outcome. Therefore, it is particularly important to critically reflect on the results reported by Chen et al [62] and Pyky et al [41].

Figure 4. Funnel plot of comparison: insufficient physical activity outcomes. SMD: standardized mean difference.

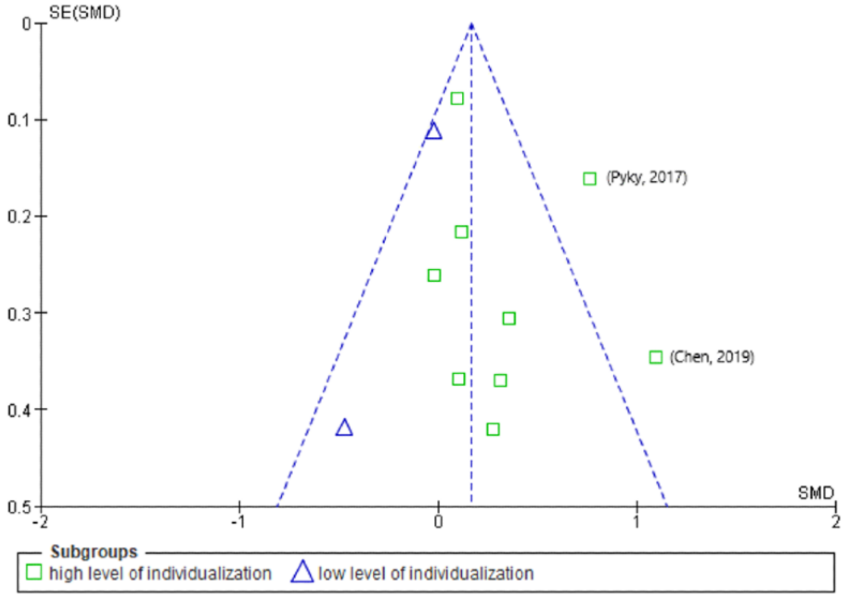
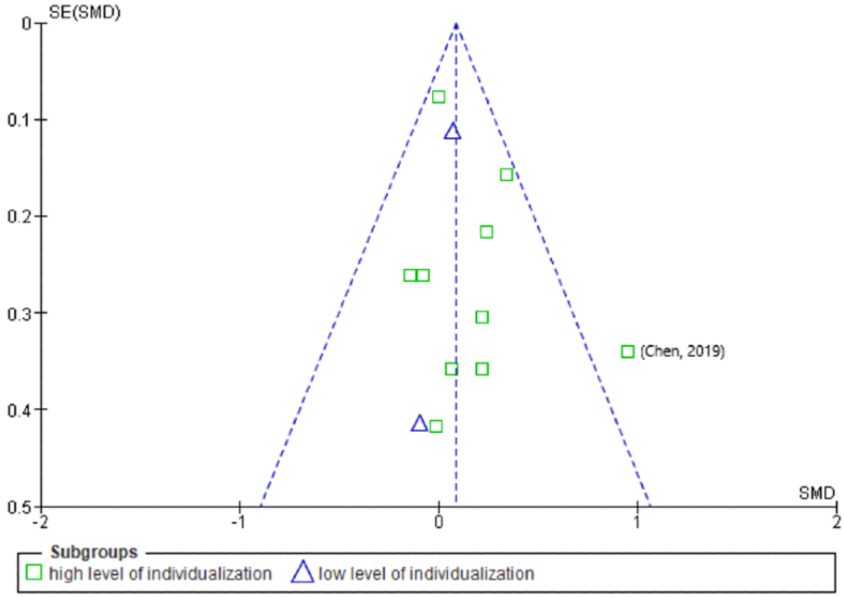


Figure 5. Funnel plot of comparison: sedentary behavior outcomes. SMD: standardized mean difference.



Certainty of Evidence

As shown in Table 3, moderate confidence was evident in the meta-analysis effect estimate for IPA. The true effect is likely to be close to the estimate; however, there is a possibility that it is substantially different. By contrast, our confidence in the estimated effect is very limited for the primary outcome of SB, and the true effect may be substantially different. This potential bias is reinforced by the studies of Chen et al [62] and Pyky et al [41], which have above-average effect sizes while being severely weighted.

Table 3. Summary of findings based on Grading of Recommendations, Assessment, Development, and Evaluations approach (N=11).

Subgroup	Studies, n (%)	Study design	Risk of bias	Inconsistency	Indirectness	Imprecision	Publication bias	Relative risk (95% CI)	Certainty
IPA[a], high level of individualization	7 (64)	RCT[b]	Not serious	Not serious	Not serious	Serious (−1)	Probably not	0.25 (0.02 to 0.47)	Moderate
IPA, low level of individualization	3 (27)	RCT	Not serious	Not serious	Not serious	Serious (−1)	Probably not	−0.05 (−0.24 to 0.15)	Moderate
SB[c], high level of individualization	8 (73)	RCT	Not serious	Not serious	Not serious	Serious (−1)	Probably yes (−1)	0.12 (−0.07 to 0.32)	Low
SB, low level of individualization	4 (36)	RCT	Not serious	Serious (−1)	Not serious	Serious (−1)	Probably yes (−1)	0.74 (−1.08 to 2.55)	Very low

[a]IPA: insufficient physical activity.

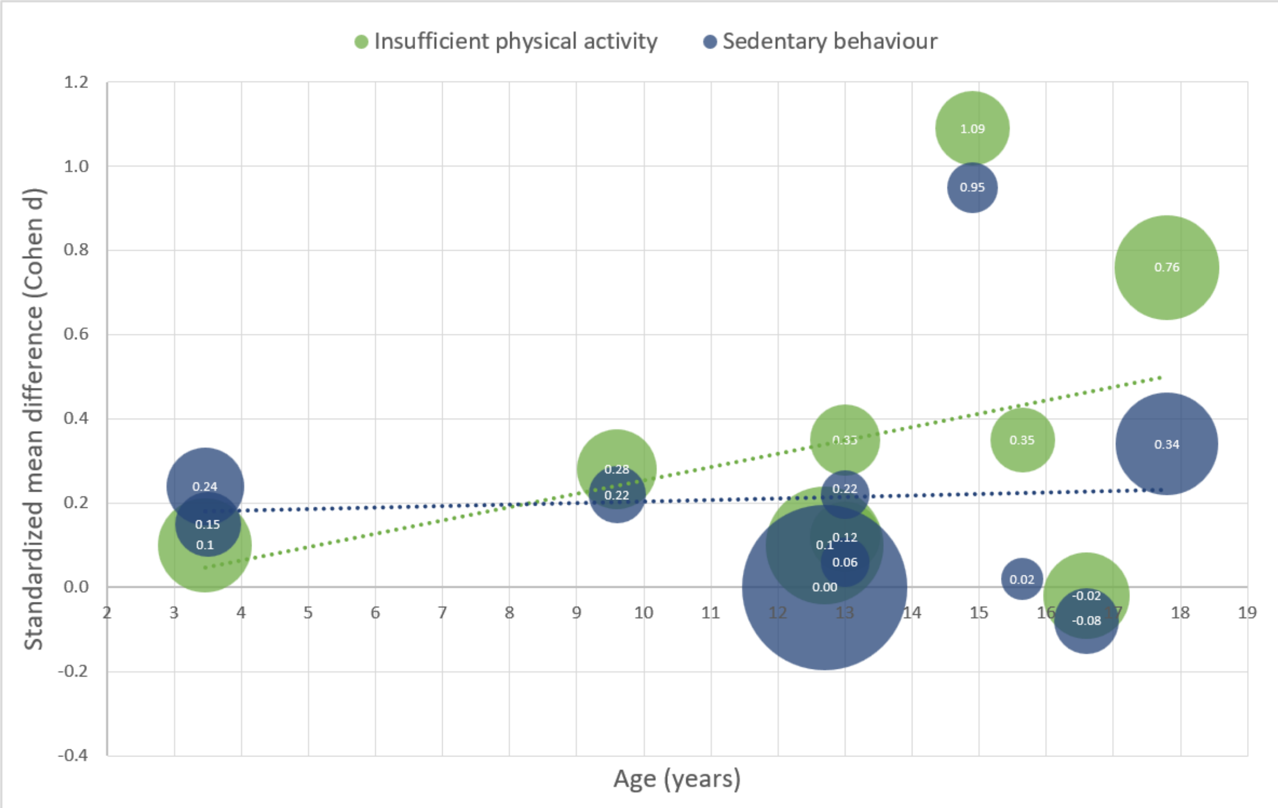
[b]RCT: randomized controlled trial.

[c]SB: sedentary behavior.

Additional Analyses

In an exploratory approach, the effect sizes obtained from the highly individualized interventions were further explored in a meta-regression analysis with age as a moderator variable to explain the moderate heterogeneity between studies and incorporate developmental psychological aspects of children and adolescents. Therefore, Figure 6 shows a weighted grouped scatter plot of the standardized mean differences (Cohen *d*) of individual interventions (including multiple study arms) and the mean age of participants. Group differentiation was based on the primary outcomes (IPA and SB). Meta-regression analysis results indicated that effect sizes were negligible for children (aged 1-14 years). There were nonsignificant differences in IPA in the adolescent age groups (14-18 years). Although the effect size (Cohen *d*) of highly individualized interventions with respect to SB remained approximately the same across age (τ^2=0.0115, SE 0.0226; τ=0.1071; I^2=21.23%; H^2=1.72; R^2=0.00%; test for residual heterogeneity: QE_{10}=11.8472, P=.30; test of moderators: QM_1=0.1451, P=.70) the effectiveness of highly individualized interventions of IPA increased slightly but not significantly across age (τ^2=0.0564, SE 0.0546; τ=0.2375; I^2=57.01%; H^2=2.33; R^2=28.47%; test for residual heterogeneity: QE_9=20.3088, P=.02; test of moderators: QM_1=2.0165, P=.16). Although the small number of included interventions allowed only descriptive conclusions to be drawn, the underlying tendency is evident in the data and needs to be examined in future studies.

Figure 6. Grouped bubble plot of weighted standardized mean differences of individual trials and mean age of participants. Group differentiation based on the primary outcome (IPA and SB). High-individualized trials included only.



Discussion

Principal Findings

This review and meta-analysis aimed to identify and characterize existing mHealth interventions for children and adolescents in the context of primary prevention of IPA and SB. In addition, this analysis aimed to provide clarity on whether and how effective mHealth interventions are in reducing IPA and SB in healthy children and adolescents. As a broad objective, we aimed to examine whether age and individualization influenced the overall effectiveness of mHealth interventions.

Summary of Evidence

Out of 828 identified studies, a total of 11 (1.3%) were included for the qualitative synthesis and 10 (1.2%) for the meta-analysis based on the inclusion criteria. Trials included 1515 participants (mean age 11.69, SD 0.788 years; 65% male and 35% female) with self-reported (3/11, 27%) or device-measured (8/11, 73%) health data on the duration of SB and IPA for an average intervention period of 9.3 (SD 5.6) weeks (excluding follow-ups). Studies with high levels of individualization decreased IPA levels significantly (Cohen d=0.33; 95% CI 0.08-0.58; Z=2.55; P=.01), whereas those with low levels of individualization (Cohen d=−0.06; 95% CI −0.32 to 0.20; Z=0.48; P=.63) or addressing SB (Cohen d=−0.11; 95% CI −0.01 to 0.23; Z=1.73; P=.08) indicated no overall significant effect. Heterogeneity was moderate to low, and a test for subgroup differences indicated significant differences between trials with high and low levels of individualization (χ^2_1=4.0; P=.04; I^2=75.2%). Age as a moderator variable showed a minor moderating effect; however, the results were not significant, which might have been because of being underpowered. This review is the first to examine the age- and individualization-dependent effectiveness of mHealth interventions to reduce IPA and SB in children and adolescents and strengthens the evidence of moderate mHealth effectiveness. This is in line with existing research on mHealth for children and adolescents [12,28].

Characteristics of Observed mHealth Interventions

One of the main qualitative results concerning the first research question is that gamified approaches tend to have a higher effect in this population, and several previous interventions have already been shown to be effective [82,83]. The 18% (2/11) of trials showing the highest effectiveness in this meta-analysis (*Fitbit and Facebook intervention* by Chen et al [62] and the *Clans of Oulu intervention* by Pyky et al [41]) used this approach. However, it should be mentioned that the intervention *Zombies, Run!* by Direito et al [58], which showed a very low effect size, was also a gamified approach; however, it is hardly individualized and uses few BCTs. Therefore, the results suggest (in line with existing research [82]) that gamified approaches can be effective for children and adolescents but only if individualization, theoretical foundation, and integration of BCTs occur simultaneously. However, the 2 most effective interventions mentioned above are united by a distinguishing feature in addition to gamification. Both involve the social component and integrate community-based systems of social participation and association with real-world PAs in the surrounding environment. Hammersley et al [72] and van Woudenberg et al [65] integrated similar approaches. This may suggest that friends, family, and surrounding environments are relevant determinants for children and adolescents in the context of mHealth and should be considered in the development of mHealth interventions to reduce inadequate PA and SB.

This review also demonstrates that mHealth interventions for children and adolescents are rarely theory based [18,24,25], although theories were occasionally mentioned, and therefore reinforce the need for enhanced theoretical substantiation in the development of mHealth interventions. The consequences of non–theory-based approaches include low effect sizes and methodological deficiencies, at least in self-developed interventions [59,61]. No negative effect of missing theoreticity could be shown when already existing and evaluated apps (eg, Fitbit app) were used [57,60]. In this respect, another striking aspect of the results is that most of the considered interventions used commercially available apps (especially Fitbit models and the corresponding app) or self-developed approaches. Models from other well-known commercial providers were not used. Data transfer software was often cited as a reason in some studies. From a scientific point of view, one of the problems may be that Fitbit does not disclose the mechanisms and underlying theories behind its development.

Regarding the quality of the integrated data, it should be mentioned that many trials addressed multiple outcomes [84] and used questionnaire data as outcome parameters [85]. A more appropriate approach would be to focus only on objective data or consider a combination of objective and subjective data, similar to the approach of Chen et al [62]. The use of only qualitative data can become a problem if an objective comparison with WHO recommendations has to be provided [86]. Therefore, we encourage researchers in the field of mHealth to use accelerometry-based measurements and more standardized outcome measures in future intervention studies.

Another key aspect of qualitative analysis is the individualization of the included mHealth interventions. It is noticeable that the type of individualization varies considerably between techniques that are frequently used (eg, *individual goal setting*) and other techniques that are unique to one of the interventions (eg, individualization based on the stage of behavior change). Similar to existing ideas in the field of behavior change mechanisms [17], a consistent taxonomy is needed and should be a part of future research.

Effectiveness of Observed mHealth Interventions

Across all interventions, it appears that mHealth interventions to reduce IPA in children and adolescents showed an overall significant moderate effectiveness, whereas interventions to reduce SB showed no overall significant effect. Accordingly, it appears easier to change IPA than SB in children and adolescents. More structural changes are probably necessary to reduce SB, which include educational policies for schools. For instance, it is harder to reduce sitting time in class, at lunch, at home while doing homework, or during transportation than it is to do another hour of sports in the evening. Potential ideas that could be implemented in the context of mHealth would be *just-in-time adaptive interventions* with reminders for small exercise breaks [20]; in the school context, the use of automated standing desks to interrupt sitting times; or the assignment of physically activating homework that encourages children and adolescents to explore their invigorated environment.

It should be further discussed that the considered mHealth interventions had no or even a small reverse effect on the reduction of SB. Although it has been shown that screen time and PA are independent constructs [33,34], it becomes evident that the use of apps leads to as much or slightly more time spent in SB, although IPA decreases. Thus, there is presumably a shift in time resources among children and adolescents through the use of mHealth intervention. A similar finding emerged for the game Pokémon Go [82]. The consequences of this finding are far-reaching and suggest that the use of mHealth in adolescence and childhood deserves careful consideration. For younger age groups, in particular, the use of an app as a family or with parental support could make sense but results in low effect sizes, as shown by 20% (3/15) of the considered interventions [61,64,68].

Moderating Effects of Individualization and Age

Looking at the average age of the target groups in the interventions used in the meta-regression, it is noteworthy that the highest effect sizes were evident in adolescent age groups. Therefore, it is reasonable to assume that participants in different age groups are differently impressionable by mHealth. There are multiple explanations for this finding. First, as children age, unhealthy behaviors may be established, and apps may need to become more individualized to be effective [21]. Second, the more the child evolves into an individual, the more important it becomes to address their individuality in health interventions. The second hypothesis is supported by one of the key findings of the meta-analysis that individualized mHealth interventions to reduce IPA differ significantly from nonindividualized interventions with the same objective. This is in line with previous research on other populations [21]. However, it is interesting to note that interventions with the most individualized elements are not the most effective [60]. Thus, more individualization does not necessarily lead to higher effectiveness; rather, the selection of particular relevant parameters in combination with the rest of the intervention characteristics seems to result in an effective intervention. For example, the development of a new intervention could be accompanied by a kind of intervention mapping [87] accompanied by a target group analysis. This would reveal the needs and requirements of the target group of an mHealth intervention. Future research should aim to deepen these partially exploratory findings and identify the underlying psychological mechanisms. We hypothesize that there is a sweet spot at which the addition of further mechanisms for individualization and behavior change no longer leads to a larger effect, which would have severe implications for the development of mHealth interventions. Furthermore, based on the results of this review, we would like to point out that the content and functions of mHealth interventions for children and adolescents should always be adapted to the age of the target group to avoid possible developmental psychological difficulties and associated low effect sizes. It should also be mentioned that the results of the meta-regression, as suggested in the Introduction section, again indicate that SB and IPA are not correlated constructs. Therefore, PA promotion does not necessarily imply SB reduction. Therefore, mHealth should be addressed separately.

Strengths and Limitations

This review is the first to differentiate between SB and IPA when considering the effects of mHealth on children and adolescents and contrast both study effects and bias. Moreover, no other review in the field to date includes a narrative analysis of individualized elements in mHealth interventions and relates them to intervention effectiveness. Another unique feature is the exploratory meta-regression. In addition to these strengths, this review has numerous limitations, both at the study and review levels.

At the study level, apart from the studies by von Pyky et al [41], van Woudenberg et al [65], and Nyström et al [61], the sample size was generally moderate to small, which may have biased the results. It should also be noted that most of the studies included multiple outcome parameters and that the primary objective of these studies was not to decrease IPA and SB. As a consequence, we assume that the observed effect sizes do not fully reflect the magnitude of the true effect. If all the included mHealth interventions were targeted at reducing IPA or SB alone, the results would certainly be more conclusive. Conspicuous among studies with small sample sizes compared with those with larger samples is the lower rating in the ROB assessment. In addition, there was a small number of included studies and partly considerable heterogeneity because of deviants, for example, the results of the study by Pyky et al [41]. This could be because of the major variability in the study design or the diverse target and age groups.

At the review level, the asymmetries observed in the funnel plot of the SB outcome indicate a publication bias. This is probably because of the study by Pyky et al [41], although the ROB assessment in this study was positive. Furthermore, it should be noted that the study results of Sirriyeh et al [56] could not be included in the meta-analysis because of a lack of reporting and as the authors did not provide any data when asked repeatedly. As the study was a 4-arm randomized controlled trial, this would certainly have been insightful for the review. In the included studies with several study arms, such as that of Direito et al [58], it was observed that the results of individual studies sometimes differed considerably. In this case, the immersive app *Zombies, Run* showed a substantially smaller effect than the nonimmersive app *Get Running*. Although other existing meta-analyses in the field of mHealth for children and adolescents similarly integrate multiple study arms (eg, He et al [29]) and we attempted to avoid potential overpowering by using the splitted shared group procedure [48], this approach should be considered controversial. Arguably, 1 author team was responsible for an excessive degree of evidence. For example, if a study shows a high ROB and includes 4 study arms, it leads to a globally insufficient certainty of evidence. As the only way to avoid this potential bias is to deliberately exclude existing evidence, further research should focus on minimizing the number of study arms and developing new statistical methods to address this issue. Another limitation of this review was that follow-up data were not extracted. As mHealth in children and adolescents is still a relatively young field of research, we did not consider there to be enough studies with follow-up measurements for a meta-analysis and therefore decided not to include follow-up measurements for reasons of evidence comparability. However, concerning mHealth in adults, it has already been shown that the effects of the interventions decrease in the long term [13]. If more mHealth trials with children and adolescents become published, we suggest replicating this review, including its follow-up effects. We assume that the long-term effects are considerably stronger in children and adolescents than in adults, as they may not yet be as well-established as for adults.

In general, the results of this review and meta-analysis should be interpreted with caution, as only moderate to low certainty of evidence is warranted based on the Grading of Recommendations, Assessment, Development, and Evaluations rating. In addition, many publications identified in the systematic literature screening were excluded as they were study protocols or small pilot studies. Therefore, this review should be updated at a later date. Furthermore, there is also limited comparability between the included studies, as the mechanisms of the considered mHealth interventions certainly move along disparate causal pathways in different age groups.

Conclusions

The findings of this review suggest that the considered mHealth interventions for healthy children and adolescents can foster low to moderate reductions in IPA but not SB. As no significant effects were shown for SB, future studies should identify how targeted SB can be reduced using mHealth. In the future, it may also be useful to test the described interventions in clinical populations (eg, children and adolescents diagnosed with obesity or metabolic syndrome), as distressing pressure may be greater here, potentially increasing adherence to use. Moreover, individualized mHealth interventions to reduce IPA are more effective for adolescents than for children. Although only a few mHealth studies have addressed inactive and sedentary young people, and their quality of evidence is moderate, these findings indicate the relevance of individualization in the period of adolescence on the one hand and the difficulties in reducing SB with mHealth interventions on the other. Future research and policy makers should aim to strengthen the evidence and systematically evaluate individualized mHealth interventions for children and adolescents. Especially in multidisciplinary collaborations among app development, science, and engineering, there is great potential for high-quality mHealth intervention development.

Acknowledgments

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Risk of bias in individual studies.
[PNG File , 125 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Risk of bias across studies.
[PNG File , 49 KB-Multimedia Appendix 2]

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Abbreviations

BCT: behavior change technique
IPA: insufficient physical activity
MET: metabolic equivalent of task
mHealth: mobile health
MVPA: moderate to vigorous physical activity
PA: physical activity
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PROSPERO: International Prospective Register of Systematic Reviews
ROB: risk of bias
SB: sedentary behavior
WHO: World Health Organization

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Article

Personality Traits, Gamification and Features to Develop an App to Reduce Physical Inactivity

Charlotte Meixner [1,*], Hannes Baumann [1] and Bettina Wollesen [2]

[1] Faculty of Psychology and Kinesiology, University of Hamburg, 22765 Hamburg, Germany; hannes.baumann@uni-hamburg.de
[2] Biopsychology and Neuroergonomics, TU Berlin, 10623 Berlin, Germany; bettina.wollesen@tu-berlin.de
* Correspondence: charlotte.meixner@uni-hamburg.de; Tel.: +49-40-42838-5331

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Abstract: Background: Health benefits from physical activity (PA) can be achieved by following the WHO recommendation for PA. To increase PA in inactive individuals, digital interventions can provide cost-effective and low-threshold access. Moreover, gamification elements can raise the motivation for PA. This study analyzed which factors (personality traits, app features, gamification) are relevant to increasing PA within this target group. Methods: N = 808 inactive participants (f = 480; m = 321; age = 48 ± 6) were integrated into the analysis of the desire for PA, the appearance of personality traits and resulting interest in app features and gamification. The statistical analysis included chi-squared tests, one-way ANOVA and regression analysis. Results: The main interests in PA were fitness (97%) and outdoor activities (75%). No significant interaction between personality traits, interest in PA goals, app features and gamification were found. The interest in gamification was determined by the PA goal. Participants' requirements for features included feedback and suggestions for activities. Monetary incentives were reported as relevant gamification aspects. Conclusion: Inactive people can be reached by outdoor activities, interventions to increase an active lifestyle, fitness and health sports. The study highlighted the interest in specific app features and gamification to increase PA in inactive people through an app.

Keywords: gamification; app features; physical activity; personality; mhealth; health app

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1. Introduction

Physical inactivity can be regarded as a major risk factor to develop chronic diseases like diabetes mellitus, high blood pressure, and cardiovascular diseases. Hence, it can be considered a global cause of death [1]. The growing incidence of cardiovascular, musculoskeletal, and mental illnesses results in medical costs amounting to billions of euros [2,3]. These negative effects have led to a global interest in reducing health risks, identifying protective factors, and promoting physical activity (PA) [1,4]. However, the main reasons for insufficient PA are complex. According to the ecological approach, the interrelation between the individual and the environment and the exchange relationship between people, values and norms of society cannot be disregarded [5,6]. If, for example, children at school observe that other children are rewarded for walking around quietly during breaks, they are likely to also walk more quietly and thereby meet the teacher's expectations (depending on the children's commitment to the school). In this way, children can learn that children who are less active enjoy a higher reputation than those with a tendency to be more active [5,6]. In addition, inactivity can be attributed, for example, to scheduling problems, unwillingness, too little awareness about the relevance of PA, s lack of access to programs and interventions and insufficient diversity [7–9]. Furthermore, other personal factors and individual motives can be prerequisites for action to increase PA. For instance, Sudeck, Lehnert and Conzelmann (2011) classified motives for health-related PA in terms of (1) fitness/health, (2) figure/appearance, (3) activation/joy, (4) distraction, (5) aesthetics, (6) contact motive and (7) competition/performance [10,11]. This means that that different aspects might determine individuals' goal setting and encourage them to increase PA in relation to motivational factors. However, these motives might not be sufficiently addressed in common interventions. Even though programs might address individual motives, the problem of reaching inactive people remains.

A contribution to the solution might be the development of individualized mhealth (mobile health) and health applications (apps) which integrate features like pedometers and other gamification elements to increase motivation and volition [12]. Reports based on common gaming apps (e.g., Pokémon Go, Ingress and Zombie run) showed positive effects on PA by, e.g., increasing the daily number of steps [13]. In particular, the Pokémon Go app developed by Niantic 2016 has millions of active users worldwide. Therefore, this app can be considered as an intervention that might help to increase PA. The mobile game connects the Pokémon world with the real world. Its goal is to capture Pokémon through an individualized avatar. The Pokémon then are used in battles against other users, who all have the common goal of reaching new levels through various tasks and by visiting different locations [13,14]. A study by Althoff (2016) shows that by using the app an increase of more than 25% is achieved in a period of 30 days, compared to the activity level before. In particular, inactive people felt motivated by the gamification elements of the app. This motivation was irrespective of personality traits [13]. In order to maintain user motivation, newer editions of the game are planned with additional sensors, thematic challenges and rewards. The Pokémon Go exemplar demonstrates the possibilities of increasing PA through digitalization, e.g., in the form of apps [15].

However knowledge of (a) the appropriate amount of PA, (b) the influence of personality traits, and (c) suitable gamification elements and app features are necessary to develop an app that appropriately promotes PA, and reaches physically inactive people.

1.1. A. Physical Activity

The positive effects of PA on health (e.g., on self-efficacy, wellbeing and quality of life) have been widely investigated over the last decades [16,17]. A certain amount of PA supports body weight control, cognition, self-efficacy, wellbeing, quality of life and mortality [16–21]. In addition, a reduction in the development of chronic diseases such as diabetes mellitus, hypertension and cardiovascular disease has been demonstrated [19,22]. The health-promoting physiological, as well as psychological, effects of PA can be achieved if the World Health Organization's (WHO) recommendations for PA (for adults: ≥30 min of moderate daily exercise and >150 min of exercise per week) are fulfilled [23]. In accordance with Krug et al. [24], who state that three quarters of men and four fifths of women are not sufficiently active according to WHO recommendations, actual results in a study within the age groups 40–50 years showed that the majority of respondents (80.2%) did not reach WHO recommendations [25]. However, with this age group, the prevalence of developing a chronic disease like diabetes mellitus or hypertension is rising. Nevertheless, 50.2% of the respondents who did not follow the WHO recommendations consider the improvement of their health to be very important and are willing to enter into the process of health promotion. Thus, 65.6% of the respondents who did not meet the WHO recommendations wanted to improve their fitness, 60.4% aspired to an improvement in mobility, 63.2% to an improvement in endurance, 40.8% to a more active lifestyle and 47% to improved performance. Another 57.5% would like to do more outdoor activities [25]. To achieve the current WHO recommendations and to establish a sustainable level of PA, a willingness to change one's behavior, increased motivation and measures to promote sport and PA are required [23,26].

1.2. B. Personality

To enable an individualized approach in an app, it is first necessary to understand the personality traits of the app users. There are different methods to classify personality traits. A conventional personality theory is the big five personality theory, which was not used in this study because the neuropsychological approach is disregarded and does not take motives and emotions into account [27].

The situation is different with the Personality System Interaction Theory (PSI), according to Kuhl [28], which takes into account both motivational and emotional components and thus allows conclusions to be drawn about the actions of personality types. Therefore, a recent study by Brand and Cheval recommends not only taking the big picture into account, but also considering the current sensations in the change of behavior and the emotions [29]. In PSI theory, the personality of an individual is divided into four dimensions [30]. According to PSI theory, there are two emotional systems and two cognitive systems. The two emotional systems are (1) the need for stimulation and (2) the need for security, the cognitive system includes (1) the need for information and (2) information processing [31]:

- The need for stimulation can be low or high. If the need for stimulation is classified as low, the person needs freedom in their life, which enables them to have strength, assertiveness and positive interactions with other people. If the need for stimulation is high, the free space is not necessarily needed, energy is drawn from the action itself.
- The need for security is also characterized by a high or low level of expression. For example, if the need for security is low, goals, structures and plans are perceived as obstructive. In addition, people quickly deviate from their goals and strategies. In contrast, structures and plans are regarded as beneficial and adhered to by individuals with a high need for security when implementing goals.
- Persons who, when difficulties arise, attribute the errors to themselves and justify them can be assigned to the specific information intake. Persons with specific information acquisition have a distinctive eye for detail in comparison to automatic information acquisition, to which a perception of the big picture and the recognition of obstacles provide the potential for action.
- Information processing can be based on objective or personal perception. A person with the personality trait of objective information processing conducts conversations on a factual level, acts with foresight and on the basis of an analytical approach. The characteristic of personal information processing is ascribed to people with a great need for harmony and high importance in communication [30].

These findings about personality theory can be used to ensure targeted communication in digital applications [31]. Moreover, the integration of these aspects in combination with health behavior change theories and gamification might increase adherence to the long-term use of applications to increase PA [32].

1.3. C. Digitalization, Appfeatures and Gamification

In addition to club sports or fitness studios, digitalization already plays an essential role in prevention and health promotion and enables new access to PA [33,34]. Digitalization through e-health or mhealth creates a low-threshold offer and cost-efficient interventions [35–38]. A common form of application is the smartphone, into which additional applications can be integrated. Possible applications include health apps, which can support a health-promoting lifestyle, improve care, promote self-help, provide information and autonomy [39,40].

According to the Motivation-Volition (MoVo) process model [41], the continuous perception of a movement intervention, in this context an app to increase PA, depends on the patient's state of health. The model depends on five psychological factors (strong goal intention, high self-accordance of the goal, realistic implementation plan, strategies of action control, and expectation of positive consequences) [41]. Furthermore, motivation should not be ignored. The self-determination theory of Deci and Ryan identifies three essential needs for intrinsic motivation: self-determination/need for autonomy, characterized by free choice (e.g., without pressure to choose an intervention that increases PA), the need for competence with optimal challenge and feedback, and social integration [42] and can be satisfied by the use of gamification [43].

For a targeted approach to the individual in a health app, an analysis of personality structures can reveal the necessary contents of individualization aspects in an app. For example, a study by Fahr and Stevanovic (2018) [44] shows that the personality traits of a person (e.g., personal information processing) are decisive in their usage behavior when it comes to apps. According to Becker (2013), the interest in an app decreases after a short time, which can result in a high drop-out rate in app usage [45,46]. The individualization of content through the targeted implementation of personality theories makes it possible to reduce the drop-out rate in app usage [38]. App developers are thus faced with the great challenge of increasing the user's motivation to commit to an app.

In addition to the individualization of an app and a targeted approach, app features can maintain the motivation to use the app through an interesting interface, technically flawless use, intuitive operation and automated customization. Furthermore, content and features such as gamification elements are recommended to increase motivation [47]: Gamification is defined as "[…] the use of game design elements in non-game contexts" [48] (p. 2) and describes the use of game content to integrate people into processes and motivate them to act, solve problems or learn [49]. A variety of game-based elements are used, such as reminders, level upgrades, avatar design, leaderboards and competitions. The positive effects on motivation and behavioral change through gamification have been shown in various studies [50–54]. In summary, gamification is used in many apps to motivate app users to change their behavior, e.g., to increase PA, and to ensure their motivation for the long-term use of the app.

The German CASPAR study (coaching app for setting oriented prevention work) examined in more detail the gamification elements that can lead to an increase in PA among users [25] and came to the conclusion that the currently available game elements of an app mainly reach those who already meet the WHO recommendations on PA. Contrary to expectations, the target group that has PA as its goal but does not meet the guidelines cannot be addressed in the same way with the existing elements [25]. Here, a lack of health literacy is to be assumed, which would enable the individual to behave in a healthy way and positively influence his or her own health [25,55]. According to the Physical Activity-Related Health Competence Model (PAHCO), the competences include movement competence, control competence and self-regulation competence [55]. These enable the implementation of motor skills, the training of specific knowledge and regular PA [55]. The study also left open the question of whether the motivational aspects that can lead to an increase in PA depend on the personality type [25]. This contribution follows up this open topic. For the development of an app to increase PA for inactive people, the most important research questions of this study are:

(1) Which PA activities are of the most interest for physically inactive participants?
(2) Are desires for PA programs dependent on personality traits?
(3) Which factors (e.g., personality aspects) determine the resulting interest in features and gamification and which elements are especially relevant for physically inactive people?

The underlying research hypothesis of this study was the assumption that PA is not determined by personality, whereas the interest in app features and gamification elements is associated to personality traits.

2. Materials and Methods

2.1. Study Design

The cross-sectional study was part of a project which aims to develop a health app and to design health promotion offers in a sustainable manner. This study design procedure was approved by the local ethics committee (file reference: AZ: 2019_270).

2.2. Sample

A German health insurance company recruited the study participants in the summer of 2019. A total number of N = 18,000 insured persons were contacted via email. Included participants had to be adults and had to be contractually capable. A number of n = 808 (80.2%) of the 1008 respondents did not comply with WHO recommendations and were integrated into the analysis of this study (Figure 1).

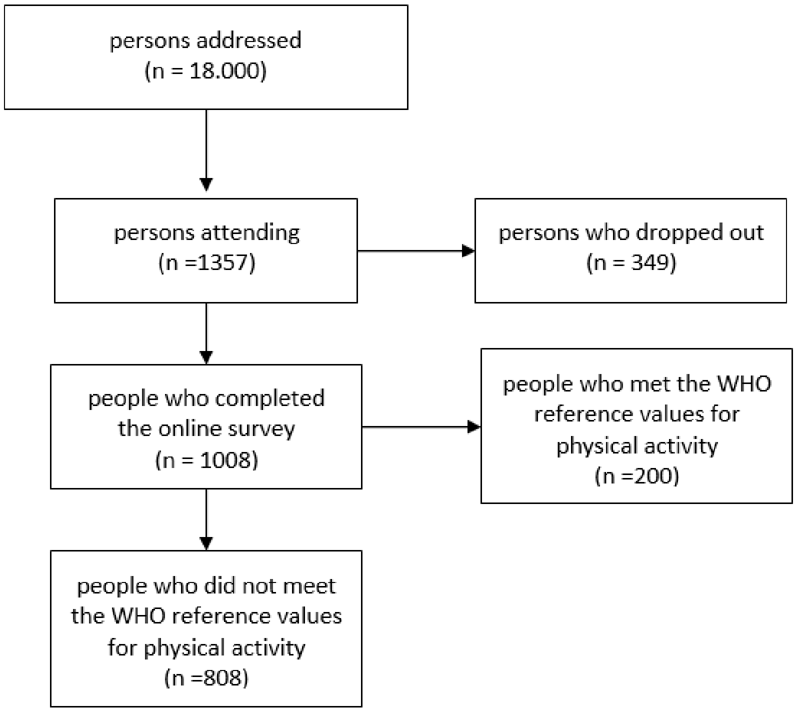

Figure 1. Study process.

2.3. Measures

The web-based questionnaire was tested, improved and validated by a research team from the University of Hamburg. The questionnaire integrates the reference values of the WHO [23] and the German Society for Nutrition [56]. Furthermore, the questions are based on the CALO-RE Taxonomy of Behaviour Change [57] and the Baecke questionnaire for the measurement of a person's habitual physical activity [58]. Moreover, relevant key aspects related to personality traits and requirements for app features and gamification were extracted from 36 qualitative interviews. Furthermore, these interviews were used to validate the determination of the personality traits by using the Visual Questionnaire (ViQ) [30]. In the last step, the online questionnaire was finalized with an expert rating by six experts of different disciplines (psychology, sports science, app development, health insurance). The resulting instrument was divided into five sets of questions (the questionnaire can be requested from the authors).

(1) Sociodemographic (4 items): The sociodemographic questions covered the number of the respondents living in the household, their age and sex.
(2) Health status and fields of action (5 items), included physical activity (6 items), nutrition (6 items) and relaxation (6 items): In the health status and fields of action thematic block, a survey was conducted on health potentials and deficits in the areas of exercise, nutrition and stress/relaxation (including compliance with WHO criteria). Further questions in the individual fields of action reflected the interest and objectives of the interviewee.
(3) Personality and motivation (4 items): The personality questions were derived from previous qualitative interviews and checked for construct validity in a validation study using the Visual Questionnaire (ViQ) [30]. The ViQ is a validated survey instrument. The results showed a high correlation between the two survey instruments. The implied personality analysis included health-specific questions, which resulted in a manifestation in the four personality dimensions (need for stimulation, need for security, information acquisition and information processing).

(4) Smartphone use (2 items): The questionnaire section on smartphone use was designed to generate information about which mobile devices the participants own and whether health apps are already in use.
(5) App feature (3 items): The questions were aimed at the wishes, ideas and needs of the respondents to design the app in a user-friendly way, adapted to their needs. These were relevant functions, such as the possibility of linking the app with other devices (trackers, smartwatches).
(6) Gamification (3 items): The question block gamification asked about the interest in gamification elements, such as the possibility of progress control or a level increase.
(7) App usage (9 items): The block on app usage enabled an assessment of the interviewee's usage time, intensity and preferences.

This study focused mainly on interests in PA, personality, app features and gameplay elements. For the evaluation of gamification elements and app features, the results of the previous evaluation were used [25]. In this evaluation, the interest in different gamification elements was retrieved. A story in an app, the creation of an avatar, rating other users, comparing rankings, sharing results and tasks and completing tasks under time pressure were of little interest (mean value < 3). For this reason, only those elements that the majority of respondents considered interesting were considered further (mean value > 3). These were:

- receiving feedback,
- immaterial rewards,
- leveling up,
- monetary incentives,
- diaries or strategy documentation,
- suggestions for activities,
- earning points,
- fulfilling weekly goals and tasks,
- information or instruction videos,
- reminders,
- knowledge about a healthy lifestyle,
- connection to their health insurance company's bonus program,
- progress,
- individualization of app content.

In addition, individuals' wishes for improvements in the field of PA were collected in the first step. For further investigation, in the second step, they were combined into four groups: fitness offers, outdoor exercise, a more active lifestyle, and health sports. In a previous publication [25], respondents who did not meet the WHO recommendations expressed a desire to improve fitness, mobility, endurance and performance. These were summarized here in the category "fitness". Further goals that were named were a more active lifestyle as well as increased outdoor activity and health sports. These three headings were adopted to the additional analysis of this article.

2.4. Procedures

The online questionnaire (created with the software Questback) was introduced with notes on participant information, anonymity, voluntariness and data protection. The participants received an invitation to complete the questionnaire via mail. Completing the questionnaire took about 30 min. Only surveys that were completely filled out were included in the data analysis.

2.5. Analyses

The evaluation was carried out using descriptive statistics and mean value comparisons. The data analysis was conducted in four steps:

1. A frequency analysis and a chi-square calculation of the desires for sports (fitness, more active lifestyle, nature activities and health sports) and the appearance of personality traits was carried out.
2. The personality traits were then examined with regard to their sport desires using the chi-squared test.
3. In a further step, a one-way ANOVA (personality trait, app feature or gamification) was performed to find out which personality traits determine the resulting interest in app features and gamification. For the evaluation, personality traits, app features and gamification elements were divided into three blocks:

   Block I: Personality traits (stimulation needs, security needs, information acquisition and information processing).

   Block II: App features (individualization of app content, coupling the app with trackers or smartwatches, diaries or strategy documentation, suggestions for activities, information or instruction videos, reminder, e.g., setting targets, knowledge about a healthy lifestyle, connection to a health insurance company's bonus program).

   Block III: Gamification elements (comparison in a ranking or ladder format, progress checks, earning points, collecting points with family, immaterial rewards, monetary incentives, connection to a health insurance company's bonus program, own avatar, tasks under time pressure (e.g., countdown), level advancement, sharing and comparing goals, history in the app, auditory, haptic or visual feedback, evaluating other family members).

4. In the final step, a logistic regression analysis was performed to check the correlation between the identified variables.

The statistical calculations were done with SPSS Statistics (IBM SPSS Statistics, Version 25.0, NY).

3. Results

The analysis of preferred sports activities showed that 97% of the participants would like to increase their fitness, 75% would like to do more outdoor activities, 54% would like to be more active in their lifestyle and 49% would like to do health sports.

The sports goals do not differ from the personality traits (Table 1). People with a high level of information processing show the most interest in sports goals (41% fitness, 45% more active lifestyle, 42% nature activities, and 44% health sports).

Table 1. Targets for an increase in physical activity depending on personality traits.

Personality Trait	Fitness	More Active Lifestyle	Nature Activities	Health Sports
need for security	23%	21%	24%	22%
information acquisition	9%	8%	9%	9%
need for stimulation	6%	5%	5%	5%
information processing	41%	45%	42%	44%
Not quoted	21%	21%	20%	20%
Chi-squared value (x^2); Significant (p); Coefficient of contingency (C)	$x^2 = 7353$ $p = 0.118$ C = 0.096	$x^2 = 7535$ $p = 0.110$ C = 0.097	$x^2 = 3200$ $p = 0.525$ C = 0.063	$x^2 = 4163$ $p = 0.384$ C = 0.072

The desire for app features and gamification elements in an app to increase PA is also independent of personality traits.

Further analysis of whether the interest in app features and gamification content can be traced back to the type of sports objective yields significant results, which can be seen in Table 2.

Table 2. Targets for an increase in physical activity and interest in app features and gamification.

App Feature	Fitness	More Active Lifestyle	Nature Activities	Health Sports
individualization of app content	F(5.818); p = **0.016** eta^2 = 0.007	F(15.888); p = **0.000** eta^2 = 0.020	F(3.921); p = **0.048** eta^2 = 0.005	F(5.411); p = **0.020** eta^2 = 0.007
diaries or strategy documentation	F(4.181); p = **0.041** eta^2 = 0.005	F(22.032); p = **0.000** eta^2 = 0.027	F(13.181); p = **0.000** eta^2 = 0.016	F(12.478); p = **0.000** eta^2 = 0.016
suggestions for activities	F(4.506); p = **0.034** eta^2 = 0.006	F(36.159); p = **0.000** eta^2 = 0.044	F(17.938); p = **0.000** eta^2 = 0.022	F(12.778); p = **0.000** eta^2 = 0.016
connect the app with tracker or smartwatch	F(2.306); p = 0.129 eta^2 = 0.003	F(9.445); p = **0.002** eta^2 = 0.012	F(2.556); p = 0.110 eta^2 = 0.003	F(3.747); p = 0.053 eta^2 = 0.005
information or instruction videos	F(4.617); p = **0.032** eta^2 = 0.006	F(24.998); p = **0.000** eta^2 = 0.030	F(19.048); p = **0.000** eta^2 = 0.023	F(12.566); p = **0.000** eta^2 = 0.016
reminders, e.g., to set targets	F(8.812); p = **0.003** eta^2 = 0.011	F(33.138); p = **0.000** eta^2= 0.040	F(18.958); p = **0.000** eta^2 = 0.023	F(18.457); p = **0.000** eta^2 = 0.023
knowledge about healthy lifestyle	F(.923); p = 0.337 eta^2 = 0.001	F(11.946); p = **0.000** eta^2 = 0.015	F(6.938); p = **0.009** eta^2 = 0.009	F(12.083); p = **0.001** eta^2 = 0.015
connection to a health insurance company's bonus program	F(2.505); p = 0.114 eta^2 = 0.003	F(13.370); p = **0.000** eta^2 = 0.016	F(3.563); p = 0.059 eta^2 = 0.004	F(14.127); p = **0.000** eta^2 = 0.017
Gamification				
receiving feedback	F(8.646); p = **0.003** eta^2 = 0.011	F(25.367); p = 0.000 eta^2 = **0.031**	F(12.652); p = **0.000** eta^2 = 0.016	F(6.289); p = **0.012** eta^2 = 0.008
immaterial rewards	F(5.032); p = **0.025** eta^2= 0.006	F(17.322); p = **0.000** eta^2 = 0.021	F(4.048); p = **0.045** eta^2 = 0.005	F(17.713); p = **0.000** eta^2 = 0.022
level up	F(5.003); p = **0.026** eta^2 = 0.006	F(14.677); p = **0.000** eta^2= 0.018	F(3.303); p = 0.070 eta^2= 0.004	F(1.778); p = **0.002** eta^2 = 0.183
monetary incentives	F(12.339); p = **0.000** eta^2 = 0.015	F(11.885); p = **0.001** eta^2= 0.015	F(4.150); p = **0.042** eta^2= 0.005	F(14.741); p = **0.000** eta^2 = 0.018
by earning points for my performance	F(3.929); p = **0.048** eta^2= 0.005	F(23.492); p = **0.000** eta^2 = 0.029	F(2.566); p = 0.110 eta^2 = 0.003	F(12.964); p = **0.000** eta^2 = 0.016
by monitoring my progress	F(9.084); p = **0.003** eta^2 = 0.011	F(21.869); p = **0.000** eta^2 = 0.027	F(0.84); p = 0.772 eta^2 = 0.000	F(7.706); p = **0.006** eta^2 = 0.010

According to statistical ANOVA calculations, the individualization of an app, a diary function, videos and reminder functions as well as suggestions for activities, turned out to be mandatory for all four target areas. For the target areas of fitness, nature activities and health sports, linking the app to a tracker or a smartwatch was not of interest. For the target area fitness, the acquisition of knowledge for a healthier lifestyle via an app was not relevant. A link to a bonus program was also not relevant for those interviewees who had the aim to increase their fitness and who pursued activities in nature. Gamification elements considered relevant were feedback, level ups, immaterial rewards, monetary incentives, point accumulation, and progress towards the goals of fitness improvement, more active lifestyles and more health sports. Level advancement, collecting points and progress were considered irrelevant to nature activities (Figure 2).

In the next step, all metrically scaled app features and gamification variables were converted into four binary logistic regression models. For the four overall models the following values were obtained: fitness (chi^2(18) = 20,267, p = 0.317, n = 705, pseudo R^2 = 0.125); active lifestyle (chi^2(18) = 56.754, p = 0.000, n = 705, pseudo R^2 = 0.103); outdoor activities (chi^2(18) = 53.53, p = 0.000, n = 705, pseudo R^2 = 0.111) and health sports (chi^2(18) = 39.524, p = 0.002, n = 705, pseudo R^2 = 0.073). Within the model for fitness goals, "monetary incentives" proved to be a significant coefficient (forest (1) = 7.301, p = 0.007, b = 0.489); for goals of a more active lifestyle, the coefficients "suggestions for activities" (forest (1) = 12.222, p = 0.000, b = 0.255) and "receiving feedback" (forest (1) = 0.124, p = 0.049, b = 0.124) were significant. For the model on nature activity objectives, the coefficients "proposals for activities" (forest (1) = 8.200, p = 0.004, b = 241) and "reminder function" (forest (1) = 6.306, p = 0.012, b = 276) were significant. The coefficient "progress" is, in contrast to this, a negative significant regression coefficient in this model (forest (1) = 11.051, p = 0.001, b = −0.310). None of the coefficients integrated in the model are significant for the target area of health sport (Figure 3).

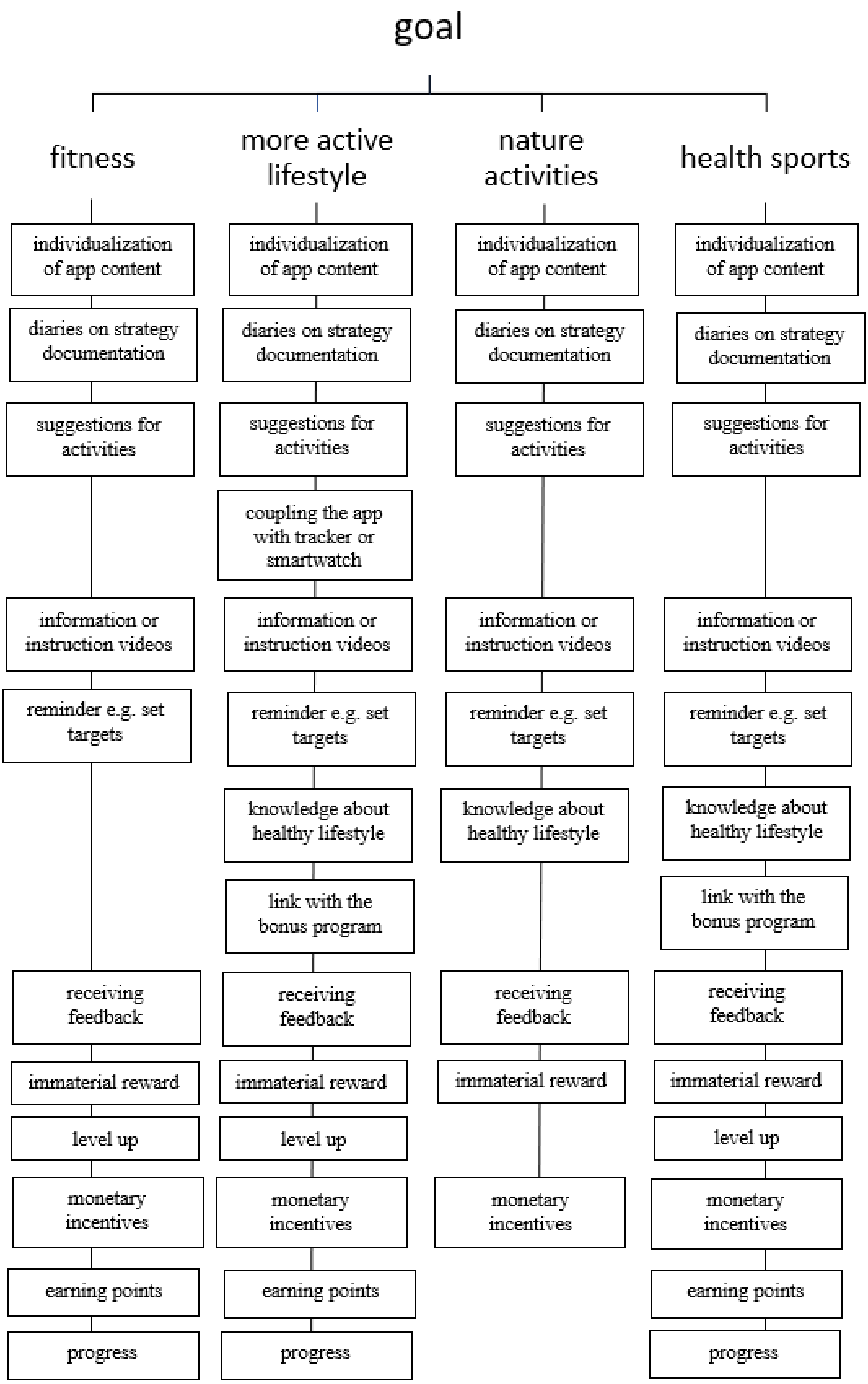

Figure 2. Interest of inactive persons in app features and gamification elements in an app to increase physical activity.

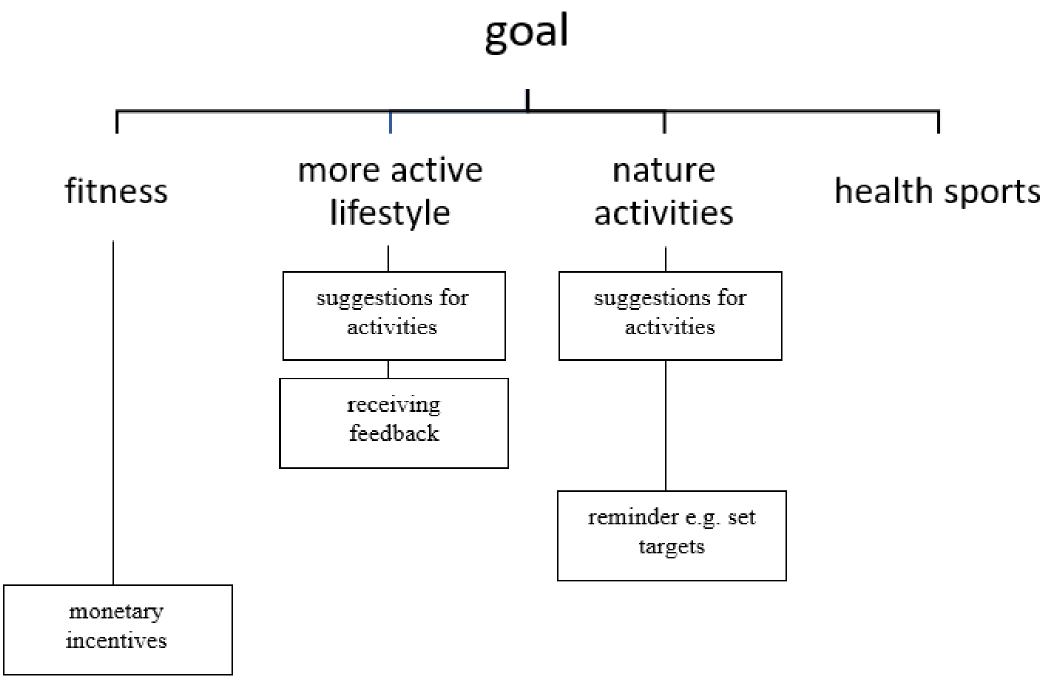

Figure 3. Interest of inactive persons in app features and gamification elements in an app to increase physical activity after conducting a regression analysis.

4. Discussion

For the development of an app to increase PA in inactive persons, the goals to increase PA that existed among the inactive persons who took part in the survey were investigated. In a further step, participants' wishes for a sports program were analyzed by taking personality traits into consideration. Furthermore, we examined whether personality traits determined participants' interest in app features and gamification elements and which features and elements are relevant for physically inactive persons to increase PA. The underlying assumption was that PA is not determined by personality and that personality traits determine the interest in app features and gamification elements.

4.1. Physical Activity Interests of the Inactive Participants

Overall, the results showed that 97% of the inactive people wanted to improve their fitness and 75% wanted to increase their PA through outdoor activities. Nearly half wanted to achieve a more active lifestyle and engage in health sports. These results fit to the contents of most apps for increasing PA and addressing fitness in the form of running and workouts or by increasing the number of steps in everyday life [15,59–61]. However, it remains unclear why the existing apps to increase PA were not used by our participants. The reasons for this observation might be complex and could be interpreted through certain aspects of the ecological approach [5,6]. However, this integrative concept was not the main focus in the area of app development and design. On the other hand, the specified requirements and needs of the individual were addressed in order to identify relevant contents for app development. Thus, a central aspect might be that the first step, the motivation and volition to increase one's own fitness with an app, is not fulfilled; however, this is only speculative. Another aspect might be the missing knowledge about relevant or suitable apps. Third, the development of apps does not always follow the concept of user integration [62], a lot of apps are not based on an analysis of user-specific requirements and the effects on PA are not always evaluated sufficiently [63]. In addition, the increase in PA through nature activities and lifestyle changes has been found to be low so far, but by moving around outdoors, e.g., in the Pokémon Go app, positive effects are shown, especially among inactive people [15].

4.2. Influence of Personality Traits on PA Goals

The statistical analysis revealed that the sports goals of the inactive participants are not dependent on personality traits. The four personality traits were equally distributed within this group of inactive participants. Therefore, goals for physical activity might not depend on these personality aspects. This leads to the assumption that individual interests and motives for behavioral changes as well as the pursuit of competence, autonomy and social integration are more important than personality traits [10,42]. Following a recent review to understand persuasion contexts in health gamification [32], an understanding of the contextual factors makes gamification successful. We hypothesized that these factors are mandatory for increasing PA as well. Moreover, other theoretical models might help to explain the motivation to be active or inactive, e.g., a behavioristic learning perspective, in which motivation is influenced by positive and negative reinforcements from the past [43]. Cognitive motivation theories also assume that motivation depends on situation-specific goals or expectations and internal processes [43]. In addition, the perspectives of interests, motives and individual preferences, which might include contextual aspects, have to be considered [11,43]. Therefore, one might conclude that, for the sports goals of these inactive participants, motivational as well as contextual aspects are more important than personality traits.

4.3. Factors Determining Interest in Features and Gamification to Increase PA

The results regarding app features and gamification elements again did not show an association to personality traits. These results are in line with findings by Rasche and colleagues, who examined different aspects on the motivation to play the Pokémon Go game, including personality traits [4]. Exergaming aspects like leveling up or doing activities with family and friends were more important than personality traits [4]. Moreover, new features and unknown technologies, as well as features linked to real life activities, can promote the motivation to use an app [4]. Furthermore, an appealing app design and the consideration of individual preferences as well as contextual factors are crucial [4,32]. In contrast to our results, previous studies found a correlation between the interest in app features or gamification elements and personality traits [64,65]. However, these studies were conducted according to the big five model and analyzed player types, not physically inactive participants [64,65]. To create a successful app, including features and gamification aspects to increase health-related behavior, Alahäivälä and Oinas-Kukkonen [32] described eight relevant aspects in the conclusion of their systematic literature review. These are:

(1) Identifying potential outside persuaders, (2) deciding and/or recognizing what change is targeted and which gamification strategy has to be used based on it, (3) understanding the area of application, and finding the right actions to apply gamification, (4) being mindful of the potential effects of user demographics, (5) deciding which technologies to use, based on contextual factors, (6) using appropriate persuasion routes, (7) using theories of health behavior change for guidance, (8) choosing gamification strategies based upon the aforementioned matters. In summary, we suggest including these aspects into the development of an app to increase PA.

Our results, after performing the one-factorial ANOVA on the elements and features that are especially relevant for physically inactive persons, highlighted that these contents need to be regarded with respect to the individual's goals for PA (fitness, nature, lifestyle or health). For example, "Pairing the app with a tracker or smartwatch", "knowledge about a healthy lifestyle," and "connection to a health insurance company's bonus program" were considered to be relevant for increasing an active lifestyle (cf. Figure 1). In contrast, to increase PA through nature activities, these features, except "knowledge about a healthy lifestyle", were irrelevant. Most apps for increasing PA include feedback, self-monitoring and goal setting as elements for behavioral change and show positive effects on PA and weight reduction [65–68]. These elements were also rated as relevant by the participants of this study. Moreover, according to Deci and Ryan's theory of self-determination, the use of features and gamification elements can satisfy needs by, for example, using the gamification element "feedback" to satisfy the need for competence, the creation of an "avatar" or the "choice of one's own paths in a story" to satisfy the feeling of autonomy and "team tasks" to fulfill the need for social inclusion [43,51,69]. The most desired gamification elements highlighted in this study could be considered as "connection to a health insurance company's bonus program", "immaterial reward" and "monetary incentives". We assume that including these elements would also increase the extrinsic motivation to increase PA in our study population. "Instructional videos", "imparting knowledge", "level ascent" and "feedback" might enable orientation to help participants choose the right amount and content of PA. Moreover, these aspects could help to can satisfy the need for competence in the form of intrinsic motivation. Finally, app features like individualization will address the need for autonomy.

Interestingly, gamification elements that address social interaction like comparing one's own results with others or competitions were not considered to be relevant by our study participants. This might be explained by different aspects. First, one might assume that people who are inactive might have a lower health literacy and are more likely to neglect WHO recommendations than those who fulfil them [25]. In turn, they might be more unfit and afraid to compare their results to highly active participants. Moreover, they might have less health competencies (movement, control and self-regulation) according to the PAHCO model [25,55]. Thus, the motivational elements in an app (such as level up) and elements that enable competence development (feedback, instruction videos) are more relevant than competitions. Overall, the use of comparative or competitive features should be avoided for inactive persons. These features might confront the participants with negative emotions about their own performance or unfavorable behavior [70]. In addition, various studies provided evidence that a fear of threats and experience can occur in a competitive environment [71]. In the interaction between different complex negative experiences, users' emotions can be negatively affected. However, the emotions of the user are related to the experience and long-term use of an app [43]. As various studies have already shown that gamification can positively influence motivation and behavioral change [26,33,51], negative emotions according to inappropriate gamification elements or app features should be avoided [43]. In addition, behavior patterns also depend on external factors [6]. Knowledge or the development of competences can be influenced by external factors, e.g., by the community, school and parental home. The extent to which the environment can be involved in the promotion of PA via an app remains undetermined.

Single-factor ANOVA considers the variables independently, explaining the number of variables that were identified as relevant. The additional regression analysis provided an indication of the main internal subjective effects. It revealed the variables that are essential and must be integrated into an appropriate app design. These are monetary incentives, suggestions for activities, receiving feedback and reminders, e.g., to set targets. However, it seems to be obvious that these variables might influence each other. This aspect resulted in less significant values in comparison to the more conservative ANOVA analysis. Interestingly, only four game elements are relevant to achieve the goals for PA: monetary incentives, suggestions for activities, receiving feedback and reminders, e.g., to set targets. Gamifying elements to encourage more PA in the form of health sports seem uninteresting for the inactive respondents. This may be due to the fact that, in Germany, health sports in particular, e.g., in the form of bonuses for health behavior from statutory health insurance, are already available [72]. However, to fulfill the criteria of individualization [12,38], the ANOVA analysis revealed additional relevant aspects that have to be taken into account for successful app development.

Overall, this study indicates that inactive persons, regardless of their personality traits, can be addressed by the appealing design of an app that includes app features like suggestions for activities, information or instruction videos, diaries and gamification elements like immaterial rewards, monetary incentives, progress and level ups in order to achieve the goal of increasing PA. Nevertheless, these elements are dependent on the PA goals. However, it remains unclear whether gamification elements and features have a different relevance in inactive persons depending on gender and age. Other features, such as calendar functions, could also be included in further studies. These aspects were not controlled within this study design. Further studies could also aim to confirm the results found here in a targeted manner, using a comprehensive battery of questionnaires. The questionnaire of this study used only contained parts of validated questionnaires (e.g., the Baecker questionnaire with a sufficiently high degree of reliability [58]) and was further developed with a team of experts and adapted to the needs and requirements of the health insurance company. The full use of the original questionnaires (e.g., the Coventry, Aberdeen, and London – Refined (CALO-RE) Taxonomy of Behaviour Change) would probably have resulted in a large number of respondents not feeling addressed by the questions. This would probably have led to a significantly smaller sample size. As an outlook for further investigations, the validation of game elements could be achieved in the form of an analytical factor reduction. Future studies should also address the extent to which gamification elements in other digital media and channels, e.g., streaming services or YouTube channels, are suitable to increase PA in inactive persons. A design of how an app for inactive persons could be designed is shown in Figure 4.

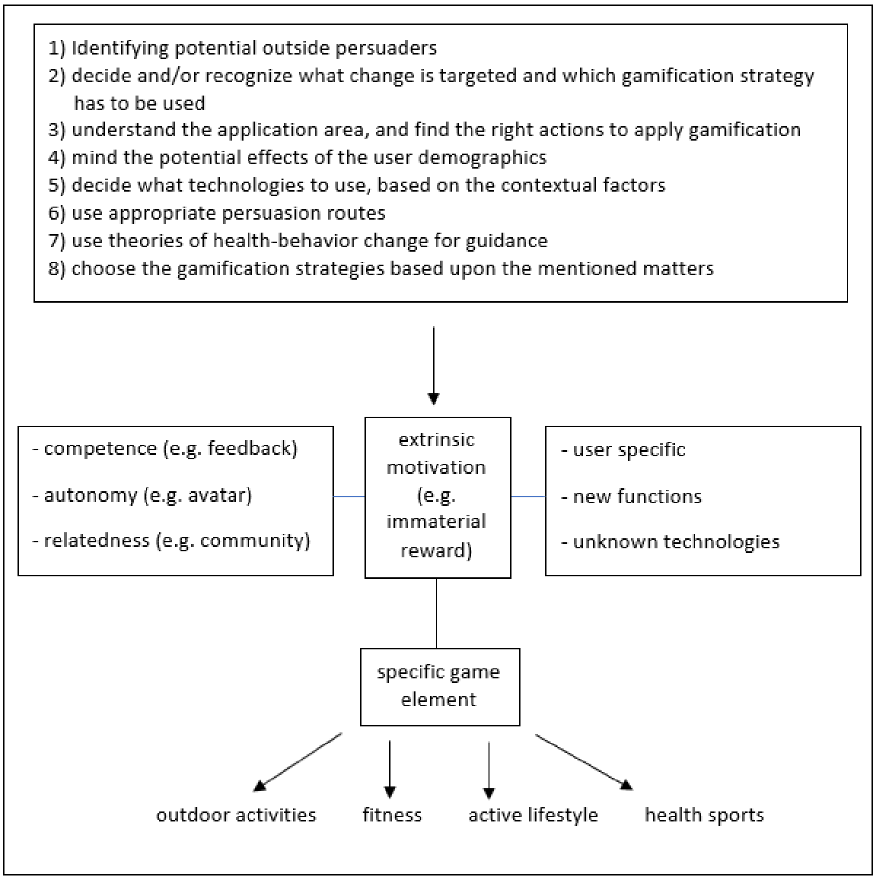

Figure 4. Design of an app to increase the physical activity (PA) of inactive persons.

In addition, further studies for sustainable app development and to support behavioral change processes should identify the competencies as well as the environmental aspects that may have an impact on inactivity and objectives.

5. Conclusions

This study determined the interest of inactive individuals in sporting goals to increase PA and whether personality traits determine interest in sporting goals, app features and gamification. The results show that interest is mainly in the area of fitness, followed by the goal of increased outdoor activities and a more active lifestyle. This study also shows that, in addition to the goals of increasing PA, interest in app features and gamification elements is not determined by personality traits. On the other hand, the perceived relevance of the elements and features are related to the goals for PA. For a demand-oriented approach, gamification elements and characteristics are highly relevant to achieving goals in the areas of fitness, outdoor activities, lifestyle and health sports. These elements and features enable the provision of feedback and competence promotion (e.g., through instructional videos) and the prospect of rewards in the form of monetary incentives or immaterial rewards. At this point, the study shows that gamification and app functions that promote competence development can provide hints and guidance and, taking into account motivational aspects (both intrinsic and extrinsic), can arouse interest in PA in inactive individuals. There is a need for further research in this area to provide sustainable evidence of gamification aspects, with the goal of developing health competences according to age and gender requirements and to enable a transfer to other digital media.

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Original Paper

App-Tailoring Requirements to Increase Stress Management Competencies Within Families: Cross-sectional Survey Study

Laura Luise Bischoff[1], MA; Hannes Baumann[1], MEd; Charlotte Meixner[1], MA; Patricia Nixon[2], MSc; Bettina Wollesen[1,3], Prof Dr

[1]Department of Movement Science, Faculty of Psychology and Human Movement, University of Hamburg, Hamburg, Germany

[2]Fitbase Institute for Online Prevention GmbH, Hamburg, Germany

[3]Biopsychology and Neuroergonomics, Technical University of Berlin, Berlin, Germany

Corresponding Author:
Laura Luise Bischoff, MA
Department of Movement Science
Faculty of Psychology and Human Movement
University of Hamburg
Mollerstraße 10
Hamburg, 20148
Germany
Phone: 49 40 42838 93
Email: laura.bischoff@uni-hamburg.de

Abstract

Background: Families experiencing high levels of psychological distress are considered a particularly vulnerable population for adverse effects on mental and physical health. Moreover, highly stressed individuals engage less in mental health promoting activities and show low stress management competencies. App-based stress interventions seem promising for the treatment and prevention of stress outcomes and might be a low-threshold solution.

Objective: The aim of this study was to identify the requirements for a tailored app to reduce stress in a cohort of highly stressed families that have low stress management skills.

Methods: Parents (n=1008; age: mean 47.7 years, SD 6.1; female: 599/1008, 59.7%) completed an extensive web-based survey and were subdivided into a target (stressed individuals with low stress competency) and nontarget group according to their reported stress level and stress management competencies. Group differences were analyzed using analysis of variance. In principal component analysis with Kaiser varimax rotation, personally defined stress management goals were grouped into components. Linear regression models were also calculated.

Results: A 3-factor solution cumulatively explained 56% of the variance in personally defined goals of interest for stress management with (1) active strategies (25.61% explained variance), (2) general competency (17.95% explained variance) and (3) passive strategies (12.45% explained variance). The groups differed in age ($F_{1,978}$=27.67, P<.001), health index ($F_{1,958}$=246.14, P<.001), personally defined general-competency goal ($F_{1,958}$=94.16 P<.001), as well as "information acquisition" ($F_{1,971}$=14.75, P<.001) and "need for stimulation" ($F_{1,981}$=54.49, P<.001) personality traits. A regression model showed that for the active strategies goals of interest, only app feature information or instructional videos had a significant effect (P=.02). The general competency factor showed none, and the passive strategies factor showed significant effects for 2 app features—suggestions for planning possible activities with the family (P=.01) and diaries for documentation and development of strategies (P=.03).

Conclusions: The results of this survey study highlight the need to develop an app to increase stress management competencies that takes into consideration perceived stress level, stress management skills, personality, and personally defined goals of the user. The content of the app should be tailored to previously detected personality traits, especially selective information acquisition and low need for stimulation. Furthermore, personally defined stress management goals seem to affect interest in some features.

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KEYWORDS

mhealth; ehealth; mobile applications; stress management; app features; gamification; family; personality traits

Introduction

Background

Stress is associated with heightened risks of adverse physical and mental health consequences, such as impaired sleep [1], gastrointestinal diseases [2], diabetes [3], coronary heart disease [4], or depression [5]. These consequences are a tremendous burden from a societal, personal, and economical perspective. Families experiencing high levels of psychological distress are considered a vulnerable population [6]. Melchior et al [7] found, for example, that participants who are simultaneously exposed to elevated levels of work stress and high family demands have heightened rates of sickness absence due to psychiatric disorders. Studies investigating work–family spillover effects show that perceived stress at work can be transferred to family members [8-10]. In accordance with the work–family spillover theory, parents play a significant role in their children's health and coping by implementing or reinforcing certain behaviors [11,12]. Family stress was, for example, predictive of less adequate child dietary intake, with one effect occurring indirectly via impaired parent–child relationship quality [13]. In general, health is subject to sociostructural and milieu-specific dependencies for which the family is an important influencing factor [14-18]. It, therefore, seems to be of the utmost importance to create effective interventions to manage high stress levels in families.

Stress Management Competencies

An increasing amount of literature suggests that interventions using different stress management techniques, such as mindfulness, lead to significant psychological health benefits in a wide range of populations [19-22]. Various stress management techniques have been applied and evaluated in diverse populations over the last decades in in-person settings or digital interventions. Active techniques, such as physical activity, can lead to a reduced perception of stress. Regular endurance and strength training, as well as yoga, have been shown to be effective in reducing stress [23-25] as well as acting as buffer against stress appraisal in times of elevated stress [25-27]. Similar results can be found for breathing exercises [28,29] and mindfulness training [30,31], with heterogeneous results for meditation exercises [32,33]. However, these active stress management techniques require regular practice. In comparison, passive but effective ways of managing stress and improving well-being are wellness and sauna [34] and spending time in nature [35,36].

In this study, we define the subjective ability to apply and perform such stress management techniques according to personal demands and stress level as *stress management competencies*. It should, however, be noted that highly stressed individuals are less likely to engage in mental health promoting activities [37-40]. Consequently, families reporting high stress levels presumably also have less stress management competencies. Thus, low-threshold options are needed (1) to support family members experiencing high levels of stress and (2) to teach stress management techniques.

Tailoring in Mobile Health Stress Reduction Interventions

In an increasingly computer-educated European population, information and communication technology might provide unique and low-threshold opportunities to engage parents and families in mobile health (mHealth)–related services and encourage behavior change, to improve health and reduce stress [41-43].

New concepts, such as the PSYCHE system [44], have emerged as technology aids in order to improve or sustain mental health or stress monitoring [45]. Such wearables include personal health records and are designed to encourage health-related behaviors. Various mobile interventions with different guidance formats (eg, self-help, adherence-focused, eCoaching) have been developed to date and have been shown to be effective in the treatment of diabetes [46], depression [42,47], or sleep disorders [48]. Moreover, web-based stress management interventions seem promising for the treatment and prevention of detrimental stress-related outcomes [49]. Nevertheless, 2 meta-analyses [42,49] show that apps incorporating cognitive behavioral therapy or aspects of mindfulness training yield heterogeneous results. In fact, one of the biggest concerns about the usage of mobile interventions for health promotion is low adherence, which can be associated with reduced effectiveness [50,51]. For this reason, research has called for the examination of suitable components that could help to overcome this challenge.

Tailoring [52] was identified as having positive effects on the health outcomes of web-based interventions. Tailoring is defined as

> *any combination of information or change strategies intended to reach one specific person, based on characteristics that are unique to that person, related to the outcome of interest, and have been derived from an individual assessment. [53]*

A meta-analysis on tailored print health behavior change interventions has demonstrated that tailored messages were superior compared to generic messages and were associated with larger effect sizes [52]. Moreover, variables such as gender or ethnicity did not moderate this effect which underlines the potential of tailored health communication to raise health-related awareness and knowledge about health for various target populations. To further capture the impact of tailoring, research has expanded to using the web as delivery mode, which again demonstrated the superiority against nontailored interventions [54,55]. Next to personalized messages, tailored web-based interventions often include gamification elements such as receiving rewards or social comparisons [56]. A comprehensive systematic review identified engagement promotion and enhancement of effectiveness as main reasons for the application of gamification [57]. Another systematic review on gamification demonstrated that, on average, only one gamification element, such as stories, themes, or display of progress was applied in web-based mental health interventions, with a maximum of 3 applied [56]. Altogether, these studies underline the vast opportunities for tailoring and the inclusion of gamification features and that users might perceive such interventions as more personally relevant and credible which again could have a significant impact on health outcomes.

Research on tailored web-based stress management interventions is scarce, yet tailoring could be an effective tool to empower users in their stress management skills and to reinforce self-determined health-related behaviors.

Personality Traits

On the other hand, studies show that certain personality traits are associated with specific coping behaviors [58,59] and app usage behaviors [60,61], as well as the response to gamification elements [62]. Individuals with personality factors such as high neuroticism, for example, show more vulnerability toward high stress values and problem coping strategies such as wishful thinking, withdrawal, and emotion-focused coping [58,59]. Notably, personality might predict coping strategies in highly stressed samples more accurately than in less stressed samples [58]. Furthermore, conventional personality theories such as the Big Five Personality theory focus on cognitive or emotional contents to explain motivation and self-regulation. The Personality System Interaction (PSI) theory, on the other hand, focuses on:

> *functional relationships among affective and cognitive macrosystems, i.e., the dynamic processes that underlie human mental functioning [63]*

and might be more suitable to detect and predict self-regulation and volitional aspects of health behavior. PSI theory distinguishes between 2 emotional—(1) the need for stimulation and (2) the need for security—and 2 cognitive systems—(1) the need for information and (2) information processing [64]. Meixner et al [65] investigated the associations between personality traits assessed via PSI theory, interest in app-based monitored physical activity goals, app features, and gamification in order to create tailored mHealth content and found no significant interaction. Furthermore, they concluded that the problem of inactive participants should, in fact, be addressed with app features and gamification elements in accordance with their prior defined goals rather than with their personality traits. Nevertheless, with respect to earlier studies suggesting personality traits being associated with higher stress vulnerability and potentially different stress management competencies, we hypothesize that the results by Meixner et al [65] might not be transferable to stress outcomes and tailored app features.

Study Objectives

To develop and implement a tailored mobile app that appropriately reaches vulnerable und highly stressed families in order to improve their stress management competencies, the following aspects should be addressed: (1) existing stress management techniques and perceived stress management competencies in families, (2) the influence of personality traits, and (3) potentially suitable features for a mobile stress management intervention such as gamification and (4) defined goals of interest in order to individually manage stress.

Previous studies have focused on evaluation of the usage and tailoring effectiveness; however, evidence on the assessment of users' needs and preferences is limited. Given the adverse impact of low adherence on treatment outcomes, understanding technological and content-related factors is crucial for the design and large-scale implementation of app-based stress reduction interventions into routine health care, and ultimately, to help users to interact in a health-promoting way. With respect to the health impairing consequences of high stress levels for each family member, it seems highly relevant to evaluate the families' needs and preferences for mHealth approaches.

Therefore, the aim of this exploratory study was to identify the requirements of an individualized app to reduce stress in a cohort of highly stressed families that have low stress management skills.

The main research questions were (1) Which characteristics can be identified that describe stressed individuals with low stress competency? (2) Which app features and gamification elements are of the most interest for highly stressed participants with low stress-management competency? (3) Which app features and gamification elements are relevant for different types of stress management goals?

Methods

Study Design

This cross-sectional study was part of a project that aims to develop a tailored mHealth intervention for family members and to design health promotion in a sustainable manner. This study was approved by the University of Hamburg ethics committee (file reference: AZ: 2019_270).

Sample

Every family insured by a small German health insurance cooperative (approximately 18,000 families) was invited by post to participate in a web-based survey. Participation in the study was voluntary, in accordance with the principles for medical research involving humans, and participation was not rewarded in any way. The questionnaire development process included several team-internal evaluation procedures and was implemented using Questback software [66], which allowed individual access via QR code. To avoid bias due to involuntary disclosure of sensitive information, there was a no disclosure option for each question. There were no mandatory questions for data protection reasons.

Measures

The questionnaire is available as Multimedia Appendix 1.

Sociodemographic and Health Variables (8 items)

Age in years (1 item) and gender (1 item) were assessed. In order to provide a holistic framework, the concept *health behavior* was based on self-assessment in the dimensions of physical activity (2 items), dietary behavior (2 items), and stress (2 items).

For dietary behavior and physical activity, in each case, 2 questions from the CALO-RE taxonomy of behavior change [67] and the Baecke questionnaire [68] for measuring habitual physical activity were used in combination with the reference values of the World Health Organization [69] and the German Society for Nutrition [70].

A health behavior index was developed based on the physical activity, dietary behavior, and stress questions. For this purpose, each question was first evaluated on a scale of not achieved (0), partially achieved (1) and achieved (2) based on the reference values mentioned above. These values were added, resulting in a score between 0 and 12—if all questions were consistent with the proposed reference values in all 3 dimensions, a person reached an overall health index of 12. This means that the higher the health index, the more health-promoting a person's behavior.

Personally Defined Goals of Interest for Stress Management (10 items)

The following items were extracted from qualitative interviews: performance of meditation exercises, performance of breathing exercises, performance of yoga exercises, performance of mindfulness exercises, performance of relaxation exercises, improvement of stress management competencies, improvement of the ability to perform stress management techniques from anywhere, improvement of personal resilience to stress, spending time in nature, benefit from wellness and sauna offers. We first conducted interviews and then developed a quantitative survey with items extracted from the interviews. A query of the interest for these items was conducted using multiple checkboxes.

Personality Variables (16 items)

The personality questions were derived from previous qualitative interviews and checked for construct validity using the Visual Questionnaire [65]. The personality analysis included health-specific questions, which resulted in a manifestation of 4 personality dimensions (need for security, information acquisition, need for stimulation, and information processing). Each dimension was described by 4 items, each rated on a 6-point Likert scale that ranged from 1 (agree) to 6 (disagree).

App Feature Variables (9 items)

These variables were integrated into the web-based survey to identify tailoring requirements in accordance with our exploratory approach. The questions focused on preferences, ideas, and needs of the respondents in order to design an app in a user-friendly way that was adapted to their needs. The items were individualization of app content, fulfilling common weekly goals and tasks, connecting the app with wearables, increasing knowledge about a healthy lifestyle, suggestions for activities with the family, diaries for documentation and development of strategies, reminders of goals, informational or instructional videos, and analog format for children. Each item was rated by participants on a 6-point scale that ranged from 1 (totally irrelevant) to 6 (totally relevant).

Gamification Feature Variables (14 items)

Questions asking which gamification elements respondents found appealing—comparison with others, in a ranking or on a high score list; controlling and checking progress; collecting points for performance; collecting shared points with other family members; receiving awards, recognition, or encouragement; monetary incentives for achieving goals; linking to the bonus program of the health insurance company; designing an avatar; completing tasks under time pressure, for example, a countdown; advancing to another level or increasing the level of difficulty; sharing and comparing my achieved goals with others; an accompanying storyline; receiving auditory, haptic, or visual feedback; and rating other family members—were rated on a 6-point scale from 1 (would not appeal to me) to 6 (would appeal to me very much). Similarly, these were integrated into the web-based survey in an exploratory manner.

Procedures

The web-based questionnaire (EFS Questback; 2019 version [66]) was preceded by participant information including instructions on anonymity, voluntariness, and data privacy. The participants received an invitation by post to complete the questionnaire. Completing the questionnaire took approximately 30 minutes. Only fully completed surveys were included in analysis.

Statistical Analysis

We used SPSS software (version 27.0; IBM Corp) for statistical analyses.

Step 1

All variables of the questionnaire that asked for personally defined goals of interest for stress management were factor-analytically reduced to 3 factors (active strategies, general competency, passive strategies) in principal component analysis with Kaiser varimax rotation. Bartlett and Kaiser-Meyer-Olkin measure of sampling adequacy tests were performed to test the suitability of variables for factor analysis.

Step 2

Perceived stress level and stress-management competency variables were dichotomized in order to identify stressed individuals with low stress competency as a target group. The characteristics of the target group and the rest of the participants were descriptively characterized. We compared groups using analysis of variance.

Step 3

In order to analyze which app and gamification characteristics are relevant for stressed individuals with low stress competency, the data set was then reduced to only those participants, and to reduce data to relevant variables, all feature and gamification variables with a mean value <3.5 in the target group, indicating irrelevant features, or that did not differ significantly between groups were excluded.

Step 4

We performed 2-way correlation analysis between app and gamification feature variables not excluded in step 3 and the 3 stress reduction target factors (active strategies, general competencies, passive strategies) from step 1.

Step 5

Three linear regression models were calculated, each with 1 of the 3 target factors for stress management strategies (active strategies, general competencies, passive strategies) as a dependent variable. As independent variables, the remaining variables from step 3 (individualization of app content, fulfilling common weekly goals and tasks, increasing knowledge about a healthy lifestyle, suggestions for activities with the family, diaries for documentation and development of strategies, reminders for objectives, informational or instructional videos, and controlling and checking progress) were included.

Power

In order to be able to demonstrate the anticipated small effect sizes (<0.05) in a multiple linear regression model with 95% power and 8 predictors, a minimum sample size of 463 was calculated (G*Power; version 3.1 [71]).

Data Exclusion

Only fully completed questionnaires were included. For bi- and multivariate analysis procedures, list-wise case exclusion was used.

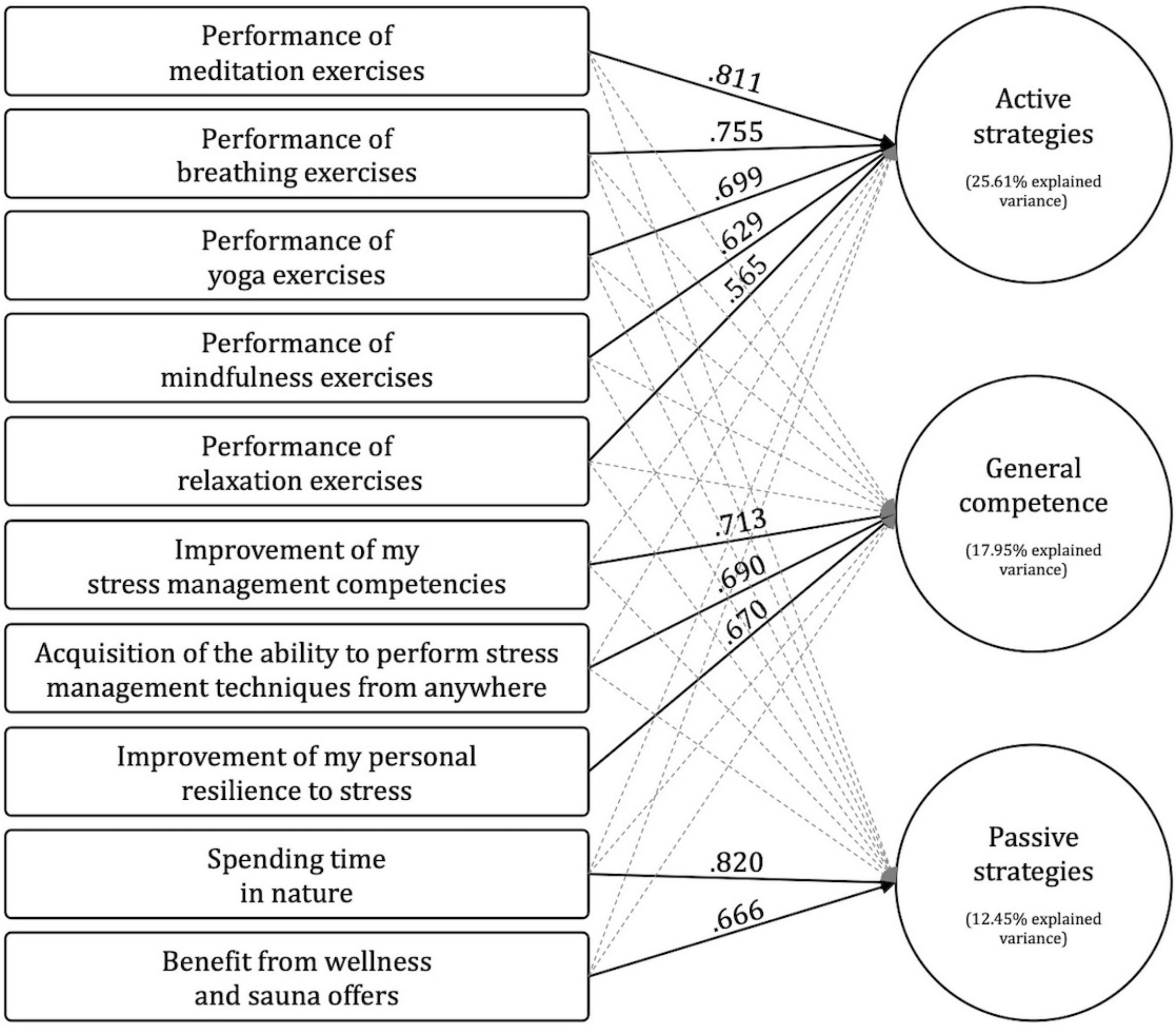
Results

Of 18,000 families invited by post to participate in the web-based survey, 1008 families completed the questionnaire (a response rate of 17.86%). The total sample consisted of 599 female, 398 male, and 7 diverse participants; 4 participants did not give any gender information. The average age of respondents was 47.79 years (SD 6.13).

Factor-Analytical Reduction of Personally Defined Goals of Interest for Stress Management

Both the Bartlett test (χ^2_{45}=2105.563, P<.001) and measure of sampling adequacy (Kaiser-Meyer-Olkin .854) revealed that 10 stress-related target variables (Figure 1) were suitable for factor analysis. Principal component analysis, with varimax rotation indicated the presence of 2 factors with eigenvalues greater than 1.0, and a 3-factor solution that cumulatively explained 56% of the variance was chosen based on the scree plot (and theoretical considerations).

Figure 1. Rotated component matrix of the 10 stress-related target variables. Significant correlations are indicated by a continuous line.



Characteristics

A comparison of participants with low perceived stress, high stress management skills, or both versus participants with high perceived stress and low stress management (Table 1) demonstrated groups differed in age ($F_{1,978}$=21.67, P<.001, ηp^2=.022), health index ($F_{1,958}$=246.14, P<.001, ηp^2=.214), active strategies ($F_{1,958}$=8.03, P=.01, ηp^2=.008), general competency ($F_{1,958}$=94.16 P<.001, ηp^2=.086), information acquisition ($F_{1,971}$=14.75, P<.001, ηp^2=.053), and need for stimulation ($F_{1,981}$=54.49, P<.001, ηp^2=.012). App feature and gamification variables that met Step 3 criteria were individualization of app content ($F_{1,977}$=8.95, P<.001, ηp^2=.009), fulfilling common weekly goals and tasks ($F_{1,994}$=7.80, P=.01, ηp^2=.008), increasing knowledge about a healthy lifestyle ($F_{1,991}$=9.06, P<.001, ηp^2=.009), suggestions for activities with the family ($F_{1,993}$=10.52, P<.001, ηp^2=.010), diaries for documentation and development of strategies ($F_{1,990}$=12.43, P<.001, ηp^2=.012), reminders for objectives ($F_{1,995}$=4.55, P=.03, ηp^2=.005), informational or instructional videos" ($F_{1,994}$=4.71, P=.03, ηp^2=.005), and controlling and checking progress ($F_{1,998}$=6.82, P=.01, ηp^2=.007).

Table 1. Comparison of sociodemographic, personality, app feature, and gamification feature variables between groups.

Variables	Nontarget group (n=548)		Target group (n=460)		Comparison		
	n	Mean (SD)	n	Mean (SD)	*F* test *(df1,df2)*	*P* value	ηp^2
Sociodemographic variables							
Age (years)	534	48.62 (6.06)	446	46.81 (6.09)	21.67 (1,978)	<.001	.022
Gender						—[a]	—
Female	294	—	305	—	—		
Male	250	—	148	—	—		
Diverse	3	—	4	—	—		
Health behavior index	525	6.64 (1.71)	435	5.06 (1.36)	246.14 (1,978)	<.001	.214
Personally defined goals for stress management							
Active strategies	548	−.08 (0.04)	460	.09 (1.01)	8.03 (1,978)	.01	.008
General competency	548	−.26 (0.04)	460	.32 (0.87)	94.16 (1,978)	<.001	.086
Passive strategies	548	−.02 (0.04)	460	.03 (1.01)	0.537 (1,978)	.46	.001
Personality variables							
Need for security	526	3.94 (0.83)	448	3.87 (0.83)	2.18 (1,972)	.14	.002
Information acquisition	525	3.66 (0.57)	448	3.52 (0.54)	14.75 (1,971)	<.001	.015
Need for stimulation	531	3.55 (0.62)	452	3.26 (0.61)	54.49 (1,971)	<.001	.053
Information processing	526	4.10 (0.59)	451	4.07 (0.58)	0.68 (1,975)	.41	.001
App feature variables							
Individualization of app content	543	4.27 (1.76)	456	4.59 (1.57)	8.95 (1,978)	<.001	.009
Fulfilling common weekly goals and tasks	541	3.78 (1.58)	455	4.05 (1.48)	7.8 (1,978)	.01	.008
Connecting the app with wearables	534	3.02 (1.74)	448	3.38 (1.81)	10.07 (1,978)	<.001	.010
Increasing knowledge about a healthy lifestyle	538	4.09 (1.62)	455	4.38 (1.44)	9.06 (1,978)	<.001	.009
Suggestions for activities with the family	541	3.61 (1.61)	454	3.94 (1.53)	10.52 (1,978)	<.001	.010
Diaries for documentation and development of strategies	540	3.45 (1.57)	452	3.80 (1.51)	12.43 (1,978)	<.001	.012
Reminders for objectives	542	4.04 (1.58)	455	4.24 (1.47)	4.55 (1,978)	.03	.005
Informational or instructional videos	540	4.08 (1.60)	456	4.30 (1.47)	4.71 (1,978)	.03	.005
Analog format for children	548	1.72 (0.45)	460	1.68 (0.47)	2.56 (1,978)	.11	.003
Gamification feature variables							
Comparison with others, in a ranking or on a high score list	544	2.26 (1.61)	454	2.26 (1.65)	0 (1,976)	.98	0
Controlling and checking my progress	546	4.25 (1.76)	454	4.53 (1.60)	6.82 (1,998)	.01	.007
Collecting points for my performance	545	3.60 (1.83)	455	3.79 (1.78)	2.66 (1,998)	.10	.003
Collecting shared points with other family members	541	3.50 (1.83)	453	3.59 (1.87)	0.61 (1,992)	.43	.001
Receiving awards, recognition, or encouragement	541	3.26 (1.77)	455	3.42 (1.76)	2.21 (1,994)	.14	.002
Providing monetary incentives for achieving goals	536	3.52 (1.88)	453	3.74 (1.81)	3.52 (1,987)	.06	.004
Linking to the bonus program of the health insurance company	541	4.16 (1.93)	456	4.40 (1.80)	3.97 (1,995)	.05	.004
Designing an avatar	541	2.46 (1.64)	454	2.72 (1.77)	5.69 (1,993)	.02	.006

Variables	Nontarget group (n=548)		Target group (n=460)		Comparison		
	n	Mean (SD)	n	Mean (SD)	*F* test (*df1,df2*)	*P* value	ηp^2
Completing tasks under time pressure (eg, a countdown)	543	2.29 (1.50)	456	2.41 (1.58)	1.59 (1,997)	.21	.002
Advancing to another level or increasing the level of difficulty	542	3.22 (1.75)	457	3.39 (1.71)	2.38 (1,997)	.12	.002
Sharing and comparing my achieved goals with others	542	2.18 (1.47)	456	2.22 (1.50)	0.22 (1,996)	.64	0
An accompanying storyline	541	2.65 (1.70)	454	2.73 (1.64)	0.52 (1,993)	.47	.001
Receiving auditory, haptic, or visual feedback	539	3.06 (1.73)	455	3.27 (1.69)	3.9 (1,992)	.05	.004
Rating other family members	539	2.43 (1.60)	454	2.46 (1.62)	0.05 (1,991)	.82	0

[a]Data not provided.

Correlations Between Personally Defined Goals of Interest for Stress Management and App Features in the Target Group

The personally defined *active strategies* factor was correlated with 5 of the 8 features (increasing knowledge about a healthy lifestyle, suggestions for activities with the family, diaries for documentation and development of strategies, reminders for objectives, and informational or instructional videos) (Table 2). The *general competency* factor was correlated with fulfilling common weekly goals and tasks, diaries for documentation and development of strategies, and reminders for objectives. The *passive strategies* factor showed the lowest correlations with the features; it was only correlated with suggestions for activities with the family and diaries for documentation and development of strategies. While some features were correlated with several target factors, others were specific to one factor.

Table 2. Correlations between personally defined goals and app features in stressed individuals with low stress competency.

Feature variables[a]	Active strategies			General competency			Passive strategies		
	r	*P* value	n	*r*	*P* value	n	*r*	*P* value	n
Individualization of app content	0.044	.35	456	0.037	.43	456	0.076	.11	456
Fulfilling common weekly goals and tasks	0.086	.07	455	0.107	.02	455	0.068	.15	455
Increasing knowledge about a healthy lifestyle	0.143	.002	455	0.066	.16	455	0.081	.08	455
Suggestions for activities with the family	0.158	.001	454	0.084	.07	454	0.152	.001	454
Diaries for documentation and development of strategies	0.136	.004	452	0.104	.03	452	0.125	.008	452
Reminders for objectives	0.145	.002	455	0.135	.004	455	0.048	.30	455
Informational or instructional videos	0.201	<.001	456	0.090	.05	456	0.061	.19	456
Controlling and checking progress	0.030	.52	454	0.034	.47	454	0.005	.92	454

[a]All significant correlations were considered to have a small effect.

Integration of the Feature Variables in Linear Regression Models

We found that the correlations were partially eliminated in multivariate models (Table 3). For the *active strategies* factor, only information or instructional videos had a significant effect (*P*=.02). The *general competency* factor showed none, and the *passive strategies* factor showed a significant effect for suggestions for planning possible activities with the family (*P*=.01) and diaries for documentation and development of strategies (*P*=.03).

Table 3. Integration of the feature variables in 3 linear regression models.

Feature variables	Active strategies		General competency		Passive strategies	
	β	*P* value	β	*P* value	β	*P* value
Individualization of app content	−.085	.21	−.042	.54	.013	.85
Fulfilling common weekly goals and tasks	.003	.97	.055	.47	.025	.74
Increasing knowledge about a healthy lifestyle	.022	.75	−.008	.91	−.026	.70
Suggestions for activities with the family	.085	.20	.005	.94	.174	.01
Diaries for documentation and development of strategies	.051	.45	.014	.84	.149	.03
Reminders for objectives	.063	.46	.152	.08	−.129	.13
Informational or instructional videos	.154	.02	.023	.73	.023	.73
Monitoring and checking progress	−.099	.11	−.086	.18	−.072	.25

Discussion

Principal Findings

The main goal of this cross-sectional study was to identify the requirements for an app that addresses stress management competencies in a cohort of highly stressed family members. We analyzed the characteristics of the target group, their individualized interests in app features and gamification aspects, their personality traits, and different types of personally defined goals.

Almost half of the study sample was identified as the high-risk population—stressed individuals with low stress competency. This underlines the importance of this study's aim. Furthermore, this group's size reflects the ever-increasing proportion of people who feel unable to effectively cope with stressors in their everyday and work–life situations, which is why the World Health Organization classified stress as the health epidemic of the 21st century and called for prevention strategies [72]. As expected, further analysis of the target group revealed a lower health index—a marker for individual health behavior based on physical activity, dietary behavior, and stress management—than that of the group with lower perceived stress levels. This finding is in line with those of prior studies, indicating that highly stressed individuals are less likely to engage in mental health promoting activities [37-40].

Notably, the target group also differed in their personally defined goals of interest for stress management. The parents who stated that they experience high stress and have low stress management competency aimed to achieve general competencies such as improvement of stress management competencies, acquisition of the ability to perform stress management techniques from anywhere, and improvement of personal resilience to stress. The nontarget group, however, aimed to achieve active strategies including performance of yoga exercises. This highlights the need to differentiate between the groups when developing and implementing mobile solutions to improve stress management competency. According to our results, the target group did not formulate specific goals but tended to have unspecific, general goals. Therefore, one might speculate that participants with subjectively higher stress levels and lower stress management competencies need more help with goal setting and more information about which strategies might reduce stress. These results further emphasize the need for tailored app features for highly stressed families. In line with Control Theory, behavior change techniques, such as goal setting, have been associated with increased intervention effects [73,74]. A study [75] evaluated a newly developed internet-based stress management intervention in a waitlist-controlled randomized trial that included principles for health behavior change such as goal setting, action planning, and coping planning for reducing stress in employees with elevated stress levels; their results showed significantly large effect differences between the intervention and waitlist control group for perceived stress at posttest. Goal-setting techniques features might thus be promising for the individual needs of stressed individuals with low stress competency.

The analysis of specific app features revealed further differences between the 2 groups regarding their app-related interests. The target participants, with low stress management competencies, indeed showed higher ratings for app features that can be used as goal-setting techniques: weekly goal and task achievements, diaries for documentation, and development of strategies and reminders for objectives. Furthermore, they had higher ratings for content individualization, connecting wearables to the app, increasing knowledge about a healthy lifestyle, suggestions for activities with the family, and informational or instructional videos. Overall, these results indicate that users identified as the high-risk population, with low stress-management competencies and high perceived stress levels, wish for features that facilitate the usage of the stress management apps. These requested features can be primarily interpreted as a need for coaching and instruction. In fact, such guided interventions have been shown to be more effective compared with unguided interventions [76]. Moreover, studies suggest guidance is conducive to the effectiveness of stress management interventions [49]. The support that might be provided in eHealth interventions can be technical or content-related, in order to ensure the correct usage [77].

A comprehensive systematic review [57] has established engagement promotion and enhancement of effectiveness as main reasons for the use of gamification in mental health promotion. In an attempt to meet this call, our study investigated the participant's interest in such elements. Nevertheless, among gamification feature variables, only controlling and checking progress met relevance criteria. This leads to the assumption that the interest in gamification elements is mostly independent of perceived stress competencies and stress levels. The greater interest of the target group in tracking features of their progress further underpins the assumed need for coaching and instruction as well as goal setting.

Interestingly, persons reporting high stress levels and low stress management skills were younger than participants with lower self-reported stress and differed significantly in 2 personality traits variables. Specifically, their personality structure indicated lower scores in information acquisition (*P*<.001) and need for stimulation (*P*<.001). According to PSI theory, stressed individuals with low stress competency thus have more selective information acquisition and lower needs for stimulation than the nontarget group members [64]. Kuhl [78] describes individuals with selective information acquisition in accordance with Jung [79] by pointing out their analytical and structured thinking and their intuitive ability to control their behavior. Unconscious perception and behavior programs may consequently support them. A low need for stimulation, in contrast, indicates less action-oriented and more introverted behavior [64]. This is frequently associated, in other studies [80,81], with the occurrence of anxiety, stress, and depression. Thus, our results suggest that these 2 personality traits are vital for the perception and management of stress. Literature repeatedly demonstrated this influence of personality traits on stress perception [82,83]. For the development of an app to improve stress management skills, individualization of the content based on personality structure will address individuals in the target group more adequately. The content should be tailored to people with selective information acquisition and a low need for stimulation. This might be achieved by a minimalistic user interface, decreasing the participants' stimulation, thereby focusing their attention on the essential contents. Ervasti et al [84] were able to show, with a study on the influence of personality on interest in stress apps that high neuroticism levels (originated in the Big Five theory, but conceptually comparable to low stimulation need in PSI theory) were positively correlated with interest in stress management apps, which is analogous to the results of this study. The predictive value of neuroticism on stress perception was also highlighted in a comprehensive meta-analysis [58].

Furthermore, it appears that interest in some features was higher, depending on specific personally defined goals of interest. While multiple correlations were found between personally defined goals and app features, correlations were partially eliminated in multivariate models. Nevertheless, our results indicate that the probability of interest in informational or instructional videos was higher when active goals had been set. Similarly, interest in suggestions for family activities and diaries was higher when personally defined goals yielded passive strategies.

Our results support the theory that creating a stress management app requires tailored content to address the differences in perceived stress levels, stress competencies, and personality traits. These findings build on those of Lustria et al [54], who pointed out that presenting general health information without considering individual needs or personal relevance may substantially limit the extent of health behavior change. Our study substantiate this call for individualized messaging based on preassessment of key individual-difference variables by reinforcing the notion that highly vulnerable families with low perceived stress competency need an individualized app content, additionally tailoring different personality types. Tailoring works by increasing the personal relevance of health messages [85] and holds promise.

Limitations and Future Research Directions

One limitation of the study is that only individual parents were surveyed. Assessing more than one family member could not be realized at this stage of the project but will be aimed for in future studies. With respect to spill-over effects of perceived stress across family members [8-10], a holistic analysis of requirements of an app that targets the entire family is needed.

A further limitation is that the identification of our target group was only based on 2 items. This was due to practical reasons and the length of the existing survey in a larger research project. The results presented and discussed in this paper can, thus, only be regarded as exploratory and should be replicated using validated scales such as the Perceived Stress Scale [86]. Nevertheless, because of the large sample size, our results underpin those from existing research, reinforcing the notion of tailoring in the development of web-based stress management interventions.

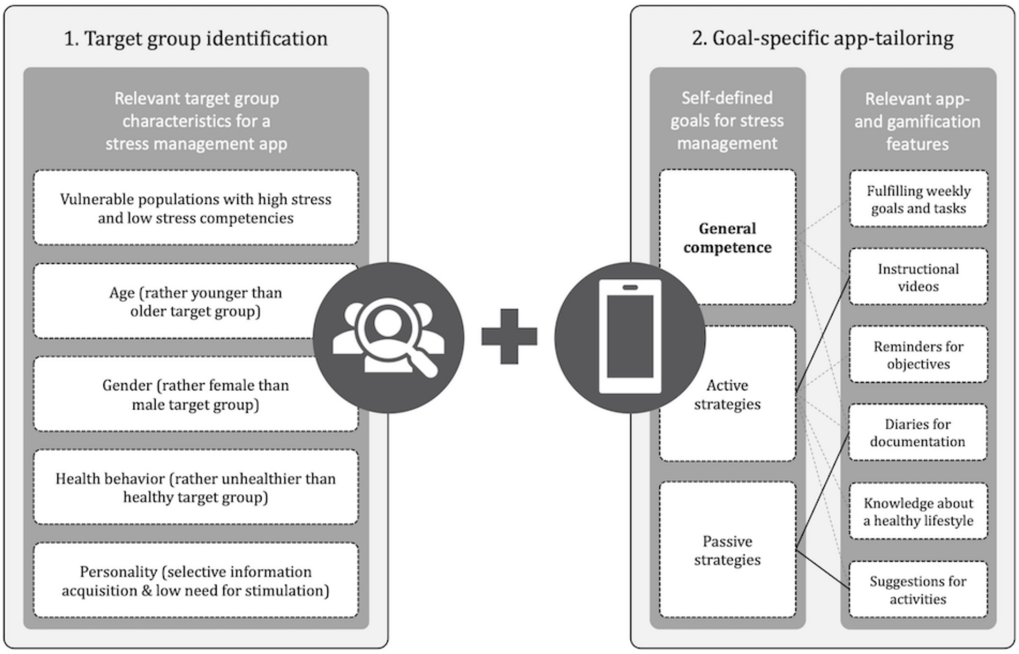
Future research should bring these preliminary data into practice and develop and evaluate an app that adequately addresses the stress level and stress competency as well as personality traits and personal goals of the user. Furthermore, there is still no evidence to support whether already existing apps are well accepted by our target group and whether these apps provide motivating factors for long-term use to build and maintain stress management skills. For this reason, further studies on the sustainable development of apps and the support of behavior change processes, in the course of stress management, should identify the situations and conditions that can have an impact on work–life stress, coping, and goals of individual family members.

There is also a need for further research in this area to provide sustainable evidence for features and gamification elements with the aim of developing age- and gender-specific stress coping skills and, if necessary, to enable transfer to other digital media.

Practical Implications

Nevertheless, there are some important practical implications. Health authorities and mHealth or app developers should take our findings into account when planning and implementing tailored app-based mental health promotion interventions for families. In a first step, target group identification is necessary. The target sample—highly stressed families with low stress competencies, in this case—can be characterized by age, gender, health behavior, and personality. The design of the app, as well as its promotion, should address the unique characteristics of the target group, for example, in this case, a minimalistic user interface that decreases stimulation. In a second step, the app should be designed in such a way that individual setting of a stress management goal is possible. These self-defined goals, defined beforehand, represent specific demands and wishes for relevant app and gamification elements (Figure 2).

Figure 2. Planned development of a tailored app to increase stress management competencies within families, based on our results. In step 2, the continuous lines depict the significant effects of the calculated linear regression models whilst the dashed lines represent significant correlations.



Conclusions

The results of this cross-sectional study show that, in order to develop an app to increase stress management competencies within families, the content should be based on preassessed of competencies, goals, and personality traits of the potential user, and thus, tailored to the user's needs. Highly stressed parents with low stress management skills want features in an app that make it easier to use and include goal setting techniques. In fact, a need for coaching and instruction was identified, which underpinned prior research showing that guided stress management interventions have more promising results.

This study delivers first results and directions to inform further research in the growing field of mobile and web-based solutions in mental health care. The relationship between integrated elements of behavior change techniques, the usage of gamification elements, and most notably, tailoring of the content of a web-based intervention and the resulting health behavior change show promise that is urgently needed with respect to increasing stress levels and its associated adverse health effects.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Web-based questionnaire on health app tailoring requirements (translated from German).
[DOCX File , 20 KB-Multimedia Appendix 1]

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Abbreviations

mHealth: mobile health
PSI: Personality System Interaction

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Gesundheitsbezogene Ziele der digitalen Prävention und Gesundheitsförderung in Familien

Health-Related Goals of Digital Prevention and Health Promotion in Families

Autorinnen/Autoren
Charlotte Meixner[1], Hannes Baumann[1, 2, 3], Bettina Wollesen[1, 2]

Institute
1 Institut für Bewegungswissenschaft, Universität Hamburg, Hamburg, Germany
2 Technische Universität Berlin, Institut für Psychologie und Arbeitswissenschaft, Berlin, Germany
3 Medical School Hamburg, Institute of Interdisciplinary Exercise Science and Sports Medicine, Hamburg, Germany

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Korrespondenzadresse
Bettina Wollesen
University of Hamburg
Human Movement Science
Mollerstr. 2
20148 Hamburg
Germany
bettina.wollesen@uni-hamburg.de

ZUSAMMENFASSUNG

Ziel der Studie Digitale Technologien gewinnen in der primären Prävention zunehmend an Bedeutung. Die Mehrheit digitaler Angebote richtet sich an das Individuum; Zielgruppen wie Familien werden selten adressiert, die Ermittlung und die Berücksichtigung des Bedarfs und der Bedürfnisse sind für eine adressatengerechte Appentwicklung bedeutend. Das Studienziel ist die Ermittlung der Grundvoraussetzungen und gesundheitsbezogenen Ziele der befragten Familien für die Handlungsfelder Bewegung, Ernährung und Entspannung sowie die Erfassung inhaltlicher Schnittmengen der Familienmitglieder in einer Gesundheits-App.

Methodik Die Online-Befragung erfolgte mit N = 1008 Elternteilen (Ø 48 Jahre, 59 % weiblich, 39,3 % männlich, 1,7 % divers) zu deren Gesundheitszustand sowie den Themen Bewegung, Ernährung und Entspannung, Smartphonenutzung, Appfeatures und Gamification. Die quantitative Datenauswertung (Häufigkeitsanalysen, Chi^2-Test, Faktorenanalyse sowie einfaktorielle Varianzanalyse) erfolgte mit IBM SPSS Analytics (25; Armonk, NewYork).

Ergebnisse Der Gesundheitszustand wurde von der Mehrheit der Befragten als positiv bewertet. Die Minderheit erfüllte die Referenzwerte der WHO in der Bewegungsaktivität und Ernährung. Weiter berichteten die Befragten über ein hohes Stresslevel und niedrige Stressmanagementkompetenzen. Als Zielbereiche zur Gesundheitsförderung ließen sich vor allem aktive Entspannungsmaßnahmen, Ernährung, Kompetenzerweiterung, körperliche Aktivität, Naturaktivitäten und Sport-Erholungsangebote identifizieren. Signifikante Unterschiede für die Akzeptanz seitens der Kinder zeigten sich mit steigendem Alter für die Bereiche aktive Entspannungsmaßnahmen [$F(2) = 3,367$; $p = ,035$] und Sport- und Erholungsangebote [$F(2) = 7,480$; $p = ,001$].

Schlussfolgerung Die Studie deckt inhaltliche Schnittpunkte der Familienmitglieder für einen Prozess der gesundheitlichen Verhaltensänderung mit digitaler Unterstützung auf. Das Interesse an einzelnen Angeboten differiert zwischen den Altersgruppen der Kinder. Weitere Forschung sollte Nutzungspräferenzen in einer familiären Gesundheits-App, die Nutzung in verschiedenen Familienkonstellationen sowie eine familiengerechte Ansprache identifizieren.

ABSTRACT

Study aim There is an increase in digital technologies to support health promotion. The majority of offerings is aimed at the individual but are less adapted to social life constellations such as families. The goal of this is study was to highlight the need and the requirements for an addressee-oriented app development. This was to be achieved by determining the initial situation and health goals of the surveyed families in the fields of exercise, nutrition and relaxation, and identifying points of intersection of the family members for a health app.

Methods The online survey was conducted with n = 1008 parents (Ø 48 years, 59 % female, 39.3 % male, 1.7 % diverse) on health status as well as exercise, nutrition and relaxation, smartphone use, app features and gamification. Quantitative data analysis (frequency analyses, Chi^2 test, factor analysis, and single-factor analysis of variance) was performed using IBM SPSS Analytics (25; Armonk, NewYork).

Results The majority of those surveyed considered their state of health to be good. The minority met the WHO reference values for physical activity and nutrition. In addition, the respondents were exposed to a high level of stress with simultaneously low coping skills. The identified target areas were active relaxation measures, nutrition, general competence, physical activity, nature activities and sports-recreation opportunities. Significant differences were found in age, in the active relaxation measures [$F(2) = 3.367$; $p = 0.035$] and sports-recreation opportunities [$F(2) = 7.480$; $p = 0.001$].

Conclusion The study reveals intersections of families' content for a behavior change process with digital support. The interest in individual offers differs between the age groups of the children surveyed. Further research should identify health app usage preferences in families and in different family constellations as well as a family-friendly approach.

Digitalisierung birgt große Chancen für neue Interventionen zur Prävention und Gesundheitsförderung. Digitale Medien, z. B. Gesundheits-Apps gelten als niedrigschwellige Angebote zum Einstieg in Prozesse der Gesunderhaltung und Gesundheitsförderung [1] und gewinnen im Zuge von Pandemien wie Covid-19 an Bedeutung. Am Markt für Gesundheits-Apps stieg 2014–2016 weltweit die Anzahl digitaler Gesundheitsangebote von 16.316 auf über 100.000 an [2, 3]. Die Mehrheit der Gesundheits-Apps richten sich geschlechtsunspezifisch an Erwachsene sowie Jugendliche. Nur wenige Apps sind für Kinder bestimmt und bedürfen, z. B. Hilfestellung eines Erwachsenen, so dass Datenschutzrichtlinien adäquat umgesetzt werden können. Dies betrifft die Datenerfassung, Einwilligung und das Löschen personenbezogener Daten. Zudem sind viele Gesundheits-Apps nicht passfähig für spezifische Lebenssituationen und Zielgruppen. Aus diesem Grund bieten sich insbesondere bei Kindern und Jugendlichen Potenziale. Hier lässt sich speziell in der familienbasierten Anwendung eine hohe Nutzer-Akzeptanz erwarten [3, 4].

Prävention und Gesundheitsförderung erfordern auch im Familienkontext individuelle Verhaltensveränderungen. Die Motivationsbildung bedarf hierbei positive Ergebniserwartungen, Kontrollüberzeugungen und Gesundheitskompetenz [5, 6]. Letztere erwerben Kinder bestenfalls im primären Sozialisationsort [7] sowie im sozialstrukturellen und milieuspezifischen Umfeld der Familie [8, 9]. Insbesondere die emotionale Bindung zu einer Bezugsperson gilt als wichtige Voraussetzung für eine gesundheitsförderliche Entwicklung des Kindes [10, 11]. Eltern besitzen hier eine Vorbildfunktion (z. B. sich mit Freude zu bewegen) und können das häusliche Umfeld anregend gestalten (z. B. Möglichkeiten zur Bewegungsförderung schaffen). Andererseits wirkt sich z. B. eine geringe familiäre Förderung des Gesundheitsverhaltens ungünstig auf das zukünftige Bewegungsverhalten der Kinder und Jugendlichen aus [8, 9]. Dies führt dazu, dass Bewegungsempfehlungen der Weltgesundheitsorganisation (WHO) [12] (Erwachsene 150–300 Minuten Bewegung pro Woche, in mäßiger Intensität oder 75–150 Minuten bei intensiver aerober Betätigung; Kinder und Jugendliche zwischen fünf und 17 Jahren: tägliche Bewegungszeit von ≥ 60 Minuten in moderater bis hoher Intensität) nicht umgesetzt werden. Somit bleiben gesundheitsförderliche Potenziale von Bewegung ungenutzt [12–14].

Analog zu ihrem Einfluss auf die Bewegung nehmen Eltern eine richtungsweisende Rolle für das Ernährungsverhalten ihrer Kinder ein (z. B. durch die Verstärkung bestimmter Verhaltensweisen) [14–16]. Aktuell erreichen nur 15 % der Frauen und 7 % der Männer die von der Deutschen Gesellschaft für Ernährung (DGE) empfohlenen fünf Portionen Obst und Gemüse pro Tag [17]. Zudem ist die Förderung einer ausgewogenen Ernährung unerlässlich. Bereits die Frühstücksmahlzeit ist bei Kindern und Jugendlichen von hoher Bedeutung, da regelmäßiges Frühstücken mit einem positiven Ernährungsverhalten assoziiert ist und zur positiven kognitiven und physischen Entwicklung beiträgt [18, 19]. Aktuelle Studienergebnisse (N = 4347 Kinder und Jugendlichen im Alter von 11–15 Jahren) belegen jedoch, dass 51 % der Mädchen und 59 % der Jungen das tägliche Frühstück auslassen [20]. Als Resultat einer ungesunden und unregelmäßigen Ernährung erhöht sich das Risiko für Übergewicht und Adipositas, insbesondere bei jungen Menschen und sozial benachteiligten Familien [8, 11, 14–17, 21, 22].

Ferner zeigen aktuelle Studien [23, 24], dass mehr als die Hälfte der deutschen Bevölkerung Stress empfindet, u. a. durch die Situation am Arbeitsplatz, Termine und Verpflichtungen, die Pflege von Angehörigen und die finanzielle Situation. Aber auch fehlende soziale Unterstützung oder die Familie, die einerseits eine soziale Ressource darstellt, wird aufgrund zugehöriger Verpflichtungen als Stressor angesehen (z. B. Work-Privacy Konflikte) [25]. Viele Alltagsanforderungen führen schon bei Kindern zu Stressbelastungen (z. B. Trennung der Eltern; schulischer Leistungsdruck) [13]. Somit ist es bereits im Kindes– und Jugendalter relevant, geeignete Bewältigungsstrategien zu erlernen [26].

All diese Aspekte können in digitalen Technologien zur Prävention und Gesundheitsförderung adressiert werden [27]. Da über 80 % der Kinder bereits mit 10 Jahren ein eigenes Smartphone besitzen, ermöglichen Gesundheits-Apps einen Einstieg in die Gesundheitsförderung [28]. Für die Handlungsfelder Bewegung, Ernährung und Entspannung sind die Potenziale für digitale Interventionen für Familien nicht ausgeschöpft [1]. Bislang liegen nur wenige Studien zur Nutzung von Gesundheits-Apps bei Heranwachsenden vor. Erste Untersuchungen kamen jedoch zu dem Ergebnis, dass Themen wie Sport/Fitness und Ernährung als gemeinsames Interesse bei Kindern und Jugendlichen sowie den Eltern vorliegen [29]. Nach welchen Kriterien gesundheitsbezogene Apps dabei gewählt werden, und welchen Nutzen und welche Wirkung diese Apps speziell bei Heranwachsenden erzeugen, ist noch unerforscht [30]. Im Gegensatz dazu ist der positive Nutzen von Gesundheits-Apps bei Erwachsenen belegt: Vorteile sind u. a. die sofortige Verfügbarkeit von Interventionen, Gesundheitsmonitoring und Reminderfunktionen [2]. Zudem erhöhen Gesundheits-Apps die Eigenmotivation und eignen sich u. a. zur Steigerung der körperlichen Aktivität, zur Ernährungsaufklärung, zum Erlernen von Entspannungsübungen und unterstützen somit Maßnahmen in der Primärprävention [31–33]. Die Nutzungsdauer einer Gesundheits-App ist für die Umsetzung der eigenen Gesundheitsförderung entscheidend, um nachhaltig eine Veränderung z. B. im Lebensstil zu erzielen. Weiterführend werden motivierende Aspekte z. B. unter Einbezug von Gamification diskutiert [30, 32, 34].

Zur Entwicklung nachhaltiger Präventions- und Gesundheitsförderungsangebote ist es ein Ziel, die Beteiligten während des gesamten Prozesses aktiv einzubinden [33]. Für die digitalen Zugangswege der Prävention und Gesundheitsförderung für Familien bedarf es daher einer Ermittlung der Grundvoraussetzungen, gesundheitsbezogenen Ziele und Schnittpunkte für alle drei Handlungsfelder sowie spezielle Anforderungen an eine App. Daher adressiert diese Studie folgende Fragen:

- Wie stellt sich der IST-Zustand gesundheitsrelevanter Merkmale (Stress, Bewegung und Ernährung) in Familien dar?
- Welche gesundheitsbezogenen Ziele in den Bereichen Bewegung, Entspannung und Ernährung sind für Familien von Interesse?
- Welche Schnittpunkte ergeben sich bei Kindern und Erwachsenen für App-Inhalte zur gemeinsamen Prävention und Gesundheitsförderung?

Handlungsleitend für die Analyse war die Annahme, dass die Befragten ein großes Interesse an einer digitalen Maßnahme zur Prävention und Gesundheitsförderung aufweisen, das sich in den Zielen einer Erhöhung der Bewegung, gesünderer Ernährung und in der Zunahme der Entspannungsfähigkeit als App-Inhalt widerspiegelt.

Methodik

Studiendesign

Die Querschnittsstudie diente der Bedarfsanalyse zur Entwicklung einer Gesundheits-App für Familien mittels einer quantitativen Onlinebefragung. Die Teilnahme an der Studie war freiwillig, entsprach den ethischen Grundsätzen für medizinische Forschung am Menschen (Deklaration von Helsiniki). Die Datenerhebung erfolgte anonym. Das Online-Survey (01.05.2019–31.05.2019) nahm ca. 30 Minuten Zeit in Anspruch und erfolgte über die Software Questback.

Stichprobe

Zur Teilnahme an der Befragung lud eine Krankenkasse 18.000 Versicherte mit dem Einschlusskriterium „Kinder im Alter von 8–16 Jahren“ postalisch ein. Den Fragebogen beantworteten N = 1.357 Versicherte, stellvertretend für die ganze Familie, wovon n = 1.008 Befragte diesen beendeten (Ausfüllquote von 74 %; 59 % weiblich, 39 % männlich, 2 % divers; Durchschnittsalter 48 Jahre), 349 TeilnehmerInnen brachen diesen vorzeitig ab. N = 619 der 1008 befragten Familien hatten mindestens ein Kind im Alter von 8–14 Jahren und wurden in dieser Studie inkludiert. Die verbleibenden 389 Familien hatten ausschließlich ältere Kinder (mindestens ein Kind zwischen 14 und 16 Jahren), weshalb eine Exkludierung dieser Teilnehmenden erfolgte. 39 % der n = 619 inkludierten Familien hatten Kinder im Alter von 8–10 Jahren, 32 % Kinder im Alter von 11–12 Jahren und 29 % Kinder im Alter von 13–14 Jahren (62 % weiblich, 37 % männlich, 1 % divers). Die Studienteilnahme erfolgte freiwillig. Ein positives Votum der Ethikkomission lag vor (Aktenzeichen: AZ: 2019_270).

Fragebogen

Der validierte Fragebogen erfasste soziodemografische Daten, nach der Anzahl der im Haushalt lebenden Personen, Alter in Jahren (1 Item) und Geschlecht (1 Item). Die Angaben basierten auf Selbsteinschätzung eines erwachsenen Familienmitgliedes für die ganze Familie. Somit zielten die Fragen in den Handlungsfeldern körperliche Aktivität (7 Items), Ernährung (6 Items) und Stress (5 Items) auf die Einschätzung des Befragten sowie auch auf andere Familienmitglieder (PartnerIn und Kinder) ab [35–37]. In den drei Dimensionen wurden Gesundheitspotentiale und -defizite (inkl. Einhaltung der WHO-Kriterien) sowie Fragen zur Zielsetzung der Familienmitglieder für die drei einzelnen Handlungsfelder (10 Ziele pro Handlungsfeld) erfasst (weitere Informationen siehe ergänzendes Material). Die präsentierte Auswahl der 30 Ziele resultierte aus vorher geführten qualitativen Interviews mit Eltern und Fokusgruppeninterviews mit Kindern verschiedener Altersstufen (N = 40). Handlungsleitend hierbei waren Aktivitäten, die sich eine Familie gemeinsam vorstellen könnten.

Um Verzerrungen durch die unfreiwillige Offenlegung sensibler Informationen zu vermeiden, gab es für jede Frage die Option „keine Offenlegung“ und es wurde auf Pflichtfragen verzichtet.

Der vollständige Fragebogen kann über die korrespondierende Autorin bezogen werden.

Datenanalyse und Statistik

Die quantitative Datenanalyse umfasste vier Schritte:

1. Der erste Schritt beinhaltete eine Häufigkeitsanalyse zur Erfüllung der WHO-Empfehlungen für Bewegung, welche alle 1008 Befragten inkludierte [12] (Erwachsene 150–300 Minuten Bewegung pro Woche, in mäßiger Intensität oder 75–150 Minuten bei intensiver aerober Betätigung; Kinder und Jugendliche zwischen fünf und 17 Jahren: tägliche Bewegungszeit von ≥ 60 Minuten in moderater bis hoher Intensität), Ernährung und Entspannung sowie Ziele in den Handlungsfeldern.
2. Anschließend wurden die Angaben der Befragten und deren Familienmitglieder (n = 619) zu den 30 möglichen Gesundheitszielen mit Chi^2-Tests auf den Zusammenhang mit erfüllten bzw. nicht erfüllten Empfehlungen in die Bereiche Bewegung, Ernährung und Entspannung hin untersucht. Das Ziel bestand darin, Ziele von Personen zu identifizieren, die die Empfehlungen nicht erreichen.
   I. Gesundheitsziele Bewegung: Verbesserung der Fitness, Verbesserung der Ausdauer, Steigerung von Beweglichkeit, Akti-

vität im Freien, Steigerung der Leistungsfähigkeit, Aufbau von Muskelmasse, Aktiverer Lebensstil, Teilnahme an Sport- und Gesundheitskursen, Durchführung von Eltern-Kind-Workouts, Mitgliedschaft im Sportverein.

II. Gesundheitsziele Ernährung: Gesündere Ernährung, Ausprobieren neuer Rezepte, Einkaufen von saisonalen, lokalen oder Bioprodukten, Gewichtszu- oder abnahme, Ernährungsumstellung, Erhöhung der Flüssigkeitszufuhr, Verbesserung des Überblicks über zugeführte Nährstoffe, Selber Kochen, Vegetarische Ernährungsweise, Vegane Ernährungsweise.

III. Gesundheitsziele Entspannung: Zeit in der Natur verbringen, Umsetzung von gezielten Entspannungsmethoden, Erhöhung der Widerstandsfähigkeit, Wahrnehmung von Wellness- und Saunaangeboten, Aneignen von Übungen für unterwegs, Durchführung von Achtsamkeitsübungen, Durchführung von Meditationsübungen, Atemübungen, Yogaübungen, Verbesserung der Stressbewältigung.

3. In einem weiteren Schritt wurden von den 30 Gesundheitszielen alle 22 signifikanten Gesundheitsziele in einer Hauptkomponentenanalyse mit Varimax-Kaiser-Rotation faktorenanalytisch auf N = 6 Faktoren reduziert.
4. Für die sich aus Stufe 3 ergebenden Faktoren erfolgte eine Überprüfung von Unterschieden hinsichtlich der Gesundheitsziele als Familie, mit Kindern und Jugendlichen im Alter von 8–10, 11–12 und 13–14 Jahren mittels einfaktorieller Varianzanalyse (ANOVA). Die statistische Auswertung erfolgte mit IBM SPSS 25.0 (IBM Statistics für Windows, Version 25; Armonk, NY: IBM Corp).

Ergebnisse

Bewegung

Die WHO-Empfehlungen im Handlungsfeld Bewegung erfüllten 20 % der Gesamtbefragten (N = 1008) (Selbsteinschätzung). Nach Einschätzung der Befragten wurden die Empfehlungen, bei 20 % der PartnerInnen sowie bei 21 % der Kinder erfüllt. Die Bewegung der eigenen Kinder bewerteten die Befragten überwiegend als „gut“, auch wenn die Kriterien der WHO nicht erreicht wurden.

Ernährung

Im Handlungsfeld Ernährung erfüllten etwa 11 % der Befragten die Empfehlungen zu regelmäßigen Mahlzeiten, inkl. eines Frühstücks. Die Angaben beruhen auf Selbsteinschätzung der befragten Personen. Insgesamt beurteilten 62 % der Befragten ihren Ernährungsstil selbst als „gut“, erreichten jedoch nicht die Empfehlungen zu den regelmäßigen Mahlzeiten.

Stress

Eine Dichotomisierung der Studiengruppe, in den Kategorien eher hoch, hoch; teils teils, eher gering und gering, ergab eine Stichprobe von n = 460 (46 %) mit hoher Stressbelastung und geringer Stressmanagementkompetenz. Zudem beurteilten 61 % der Befragten das Stresslevel bei deren PartnerIn und 25 % bei den Kindern als eher hoch/hoch und schätzten die Stressbewältigungsfähigkeit niedrig ein.

Gesundheitliche Ziele der Befragten

Die Datenauswertung der Gesundheitsziele für potenzielle Handlungsfelder der Familien ergab, dass 84 % der Befragten angaben, Ernährungsziele mit der Familie umsetzen zu wollen, gefolgt von 77 %, die für Bewegungs- und 69 % Entspannungsziele stimmten. Bei einer Spezifizierung, welche Ziele konkret mit einer App unterstützt werden sollte, nannten 45 % der Befragten das Feld Bewegung, 27 % den Bereich Ernährung und 28 % das Segment Entspannung.

Ziele innerhalb der drei Handlungsfelder

▶ **Tab. 1** zeigt das spezifische Interesse an Gesundheitszielen in den Bereichen (1) Bewegung, (2) Ernährung und (3) Entspannung der Familien mit Kindern im Alter von 8–14 Jahren.

Insgesamt ergaben sich somit 22 Gesundheitsziele: Bewegung (6), Ernährung (6), Entspannung (10). Mittels Faktorenanalyse ließen sich diese 22 Gesundheitsziele auf sechs Faktoren reduzieren (▶ **Abb. 1**): Aktive Entspannungsmaßnahmen, Ernährung, Allgemeine Kompetenz, Körperliche Aktivität, Naturaktivitäten, Sport- und Erholungsangebote.

Der ▶ **Abb. 1** lässt sich entnehmen, dass als Beispiel, einer dieser sechs Faktoren, hier: *Naturaktivitäten,* die Variablen „Zeit in der Natur“ und „Aktivität im Freien“ zusammenfasst. Eine Person, die sich Zeit mit der Familie in der Natur vorstellen kann, könnte sich zu einer sehr hohen Wahrscheinlichkeit auch Aktivitäten im Freien als Familienziel vorstellen. Befragte, die Meditationsübungen als familiäre gesundheitliche Zielvorstellung haben, würden sich mit sehr hoher Wahrscheinlichkeit auch für Atemübungen, Yogaübungen, Achtsamkeits- und Entspannungsübungen begeistern.

Differenzierung der Gesundheitsziele zwischen der Altersgruppe der Kinder und Jugendlichen

Nach Einschätzung der Befragten indizierten die Ergebnisse, dass sowohl für die Familien mit Kindern in der Altersgruppe 8–10 Jahre als auch 11–12 Jahre und 13–14 Jahre in den Bereichen *Ernährung*, *Allgemeine Kompetenz, Körperliche Aktivität* und *Naturaktivitäten* gleichermaßen Interesse besteht. Ein signifikanter Unterschied zeigte sich zwischen den Altersgruppen 8–12 Jahre und 13–14 Jahre im Bereich *Aktive Entspannungsmaßnahmen* [$F(2) = 3{,}367$; $p = {,}035$] mit den Zielen der Durchführung von Meditationsübungen, Atemübungen, Yogaübungen, Achtsamkeits- und Entspannungsübungen (s. ▶ **Tab.2**).

Darüber hinaus stellte sich heraus, dass sich nach Einschätzung der Befragten Ziele im Bereich *Sport- und Erholungsangebote* [$F(2) = 7{,}480$; $p = {,}001$] als Familie für die Altersgruppen 8–10 Jahre und 11–12 Jahre signifikant besser eignen als für die Altersgruppe 13–14 Jahre. In den älteren Altersgruppen sinkt im Vergleich zu jüngeren Altersgruppen die Akzeptanz für einige gesundheitliche Zielsetzungen, die gemeinsam mit der Familie absolviert werden.

Diskussion

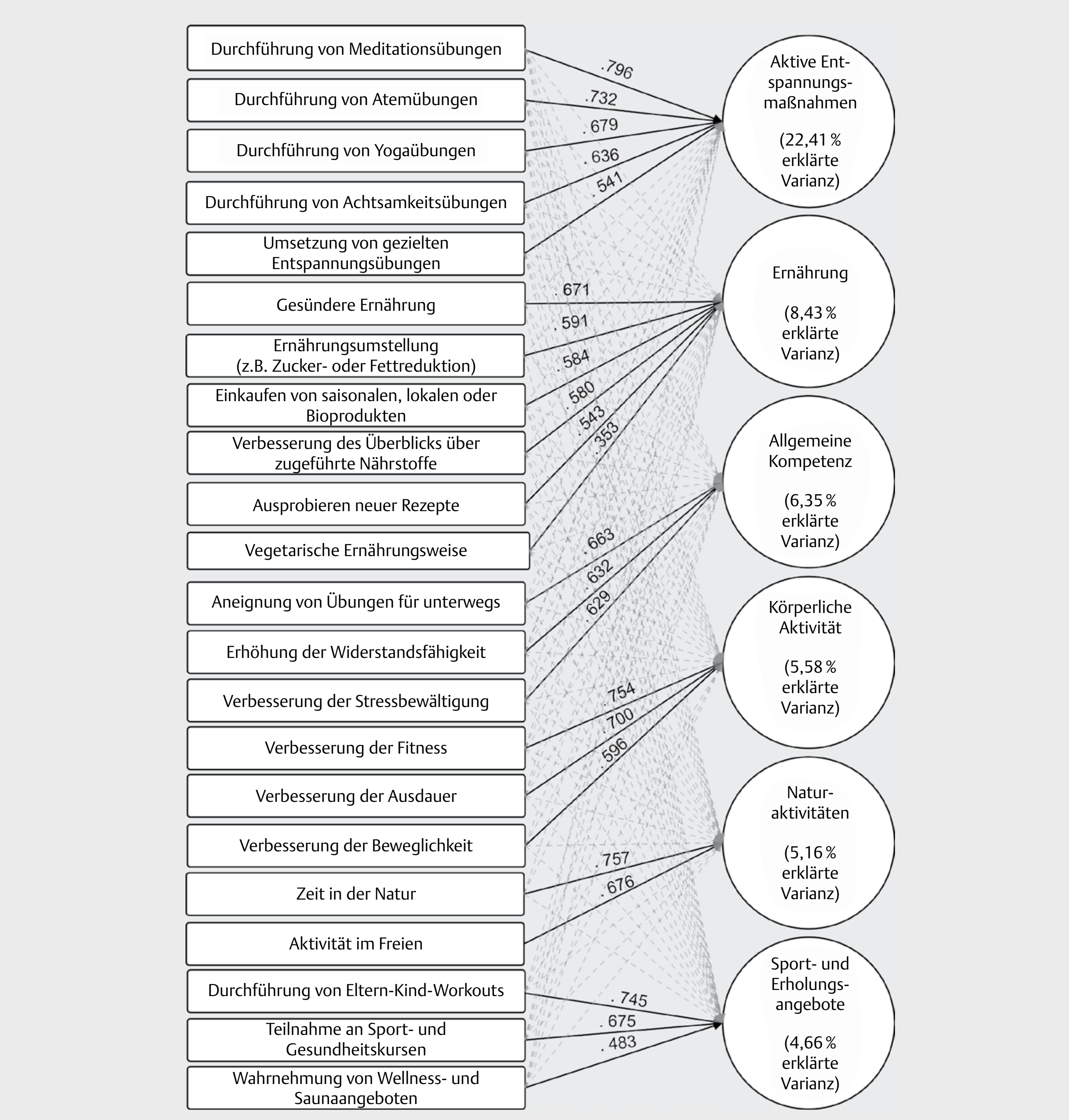
Das Studienziel bestand darin, inhaltliche Schnittmengen für die Entwicklung einer familiären Gesundheits-App zu ermitteln. Daneben wurden Gesundheitspotenziale, Ziele für Maßnahmen in den drei adressierten Handlungsfeldern für die Gestaltung der App zwischen den Eltern und Kindern identifiziert.

▶ **Tab. 1** Gesundheitsziele der Familien, in den Bereichen Bewegung, Ernährung und Entspannung.

	Interesse an Gesundheitsziel vorhanden [Angaben in Prozent]			**Familienziele positiv bewertet [Chi^2, p-Wert, C]**
	Befragte/r N = 1008	**Partner/in N = 789**	**Kinder N = 619**	
(1) Bewegungsziele				
Verbesserung der Fitness	77,8	63,5	49,7	Chi^2 = 7,992 **p = .005** C = .089
Verbesserung der Ausdauer	76,5	56,4	50,2	Chi^2 = 9,718 **p = .002** C = .098
Steigerung von Beweglichkeit	73,7	58,9	39,4	Chi^2 = 4,276 **p = .039** C = .065
Aktivität im Freien	69,9	56,6	58,4	Chi^2 = 15,663 **p = .000** C = .124
Steigerung der Leistungsfähigkeit	56,7	42,4	34,5	ns
Aufbau von Muskelmasse	53,8	30,3	35,9	ns
Aktiverer Lebensstil	46,8	42,4	33,5	ns
Sport- und Gesundheitskurse	42,8	32,8	23	Chi^2 = 9,510 **p = .002** C = .097
Eltern-Kind Workouts	23,0	15,2	20,3	Chi^2 = 69,437 **p = .000** C = .254
Mitgliedschaft im Sportverein	21,5	18,5	31,6	ns
(2) Ernährungsziele				
Gesündere Ernährung	56,9	52,4	56,5	Chi^2 = 13,930 **p = .000** C = .117
Ausprobieren neuer Rezepte	56,3	37,8	38,2	Chi^2 = 11,485 **p = .001** C = .106
Einkaufen von saisonalen, lokalen oder Bioprodukten	55,2	45,2	33	Chi^2 = 5,512 **p = .019** C = .074
Gewichtszu- oder abnahme	55,1	43	15,4	ns
Ernährungsumstellung	55,1	42,1	41,4	Chi^2 = 20,016 **p = .000** C = .140
Erhöhung der Flüssigkeitszufuhr	46,1	31,7	41	ns
Verbesserung des Überblicks über zugeführte Nährstoffe	41,5	31,2	30,1	Chi^2 = 11,793 **p = .001** C = .108
Selber Kochen	36,1	28,2	34,9	ns
Vegetarische Ernährungsweise	28,1	21,6	22,4	Chi^2 = 4,161 **p = .041** C = .064
Vegane Ernährungsweise	13,1	7,7	8,7	Ns
	Interesse an Gesundheitsziel vorhanden [Angaben in Prozent]			Familienziele positiv bewertet [Chi^2, p-Wert, C]
	Befragte/r N = 1008	Partner/in N = 789	Kinder N = 617	
(3) Entspannungsziele				
Zeit in der Natur verbringen	79,6	67,2	64,6	Chi^2 = 12,747 **p = .000** C = .112
Umsetzung von gezielten Entspannungsmethoden	68,4	48	37,5	Chi^2 = 57,386 **p = .000** C = .232
Erhöhung der Widerstandsfähigkeit	63,8	52,6	43,4	Chi^2 = 16,409 **p = .000** C = .127
Wahrnehmung von Wellness- und Saunaangeboten	58,3	46,1	21,4	Chi^2 = 19,289 **p = .000**C = .137
Aneignen von Übungen für unterwegs	57,4	36,9	40,6	Chi^2 = 32,018 **p = .000** C = .175
Achtsamkeitsübungen	57,1	39,6	32,7	Chi^2 = 26,135 **p = .000** C = .159
Meditationsübungen	54,8	34,9	24,8	Chi^2 = 22,681 **p = .000** C = .148
Verbesserung der Stressbewältigung	53,3	46,9	37,3	Chi^2 = 43,424 **p = .000** C = .203
Atemübungen	53,1	34,6	28,8	Chi^2 = 40,542 **p = .000** C = .197
Yogaübungen	49,8	34,4	28,1	Chi^2 = 27,561 **p = .000** C = .163

Gesundheit in Bewegung, Ernährung und Entspannung

Analog zu einer früheren Studie von Krug et al. (2013) [38] zeigte auch die hier befragte Kohorte, dass 80 % der Teilnehmenden die WHO-Empfehlungen für Bewegung nicht erfüllte. Im Handlungsfeld Ernährung verfehlen in dieser Stichprobe 89 % relevante Empfehlungen zur Einnahme regelmäßiger Mahlzeiten inkl. eines Frühstücks. Auch wurde das Stressniveau sowohl bei den Befragten als auch den Familienmitgliedern als hoch eingestuft, bei zeitgleich geringen Stressbewältigungsfähigkeiten [26, 39]. Somit weist ein Großteil der Befragten Handlungsbedarf in allen drei adressierten Handlungsfeldern auf. Im Hinblick auf die gesundheitsbeeinträchtigenden Folgen mangelnder Bewegung [40], ungesunder Ernährung [8, 14, 15] und eines hohen Stressniveaus [41–44] ist es relevant, gemeinsam umsetzbare familiäre Gesundheitsziele zu iden-



▶ **Abb. 1** Die Hauptkomponentenanalyse mit Varimax-Rotation ergab eine 6 Faktoren-Lösung, die kumulativ 52,59 % der Varianz erklärte. Eine hohe Faktorladung ist hierbei durch eine durchgezogene Linie gekennzeichnet, wohingegen eine gestrichelte Linie eine partitale Faktorladung indiziert.

tifizieren und einfache Zugänge zur familiären Prävention und Gesundheitsförderung, z. B. über Apps, zu gestalten.

Inhaltliche Schnittpunkte der App

Laut Quellen des GKV Spitzenverbandes (2018) [33] werden derzeit im Handlungsfeld Bewegung die meisten Präventionsangebote wahrgenommen (68 %), gefolgt von Ernährung und Entspannung [45]. Deckungsgleich stellte die Auswertung der vorliegenden Studie die Bewegung als zentrales Element zur Umsetzung von Gesundheitszielen in der Familie über eine entsprechende App heraus.

Interessanterweise identifizierte der erste Analyseschritt dieser Studie, dass die Befragten alle zur Auswahl stehenden Ziele der Entspannung als signifikant relevant einstuften. Dies lässt sich vermutlich auf das hohe Stressniveau der hier befragten Familienmitglieder zurückführen und unterstreicht den Bedarf an Copingstrategien und Entspannungsmaßnahmen. Die Evidenz bezüglich verschiedener Techniken, z. B. für mehr Achtsamkeit in der Familie

▶ **Tab. 2** Ergebnisse der deskriptiven Statistik und einfaktoriellen ANOVA der Familien mit Kindern und Jugendlichen im Altersvergleich.

	Deskriptive Statistik						ANOVA
	8–10 Jahre n = 244		11–12 Jahre n = 196		13–14 Jahre n = 179		Gruppenunterschiede
	MW	SA	MW	SA	MW	SA	[F-Wert, p-Wert, eta^2]
Aktive Strategien	,13	1,05	1,4	1,06	-,10	1,03	F (2) = 3,367, **p = ,035**, eta^2 = ,011
Ernährung	-,04	1,02	− 1,8	,92	− ,04	,98	F (2) = 1,349, p = ,260, eta^2 = ,004
Allgemeine Kompetenz	-,03	,92	− ,03	1,04	,00	,97	F (2) = ,062 p = ,940, eta^2 = ,000
Körperliche Aktivität	-,13	,96	− ,05	1,04	,03	,99	F (2) = 1,337, p = ,263, eta^2 = ,004
Naturaktivitäten	,11	,95	1,8	1,02	,15	,99	F (2) = ,286, p = ,751, eta^2 = ,001
Sport- und Erholungsangebote	,29	1,1	,055	1,08	− ,10	1,1	F (2) = 7,480, **p = ,001**, eta^2 = ,024

zeigt, dass diese einen positiven Einfluss auf das Familienleben und das Stressempfinden haben können [46, 47]. Jedoch bedarf es der Berücksichtigung der unterschiedlichen Anforderungen, Stressoren sowie Bedürfnisse einzelner Familienmitglieder [48].

Differenzierung nach Altersgruppe

Den Mehrwert dieser Studie zu bisherigen Erkenntnissen bietet die Identifikation der Appinhalte, in Abhängigkeit des Alters der Kinder. Die Ergebnisse dieser Studie zeigen, dass mit zunehmendem Alter der Kinder Aktive Entspannungsmaßnahmen (wie z. B. Meditation, Atemübungen) als gemeinsames Familienziel an Interesse verlieren. Ebenso lässt sich annehmen, dass sich die Bedeutung an der Durchführung von Eltern-Kind-Workouts, Sport- und Gesundheitskursen sowie Wellness- und Saunaangeboten als gemeinsames Programm, ab der Altersstufe der 13–14 Jährigen reduziert. Diese Ergebnisse sind vermutlich auf den Beginn der Pubertät zurückzuführen, einhergehend mit der Abkehr von den Eltern und der Veränderung des eigenen Körperbildes. Bei der Entwicklung einer Gesundheits-App für Familien ist eine Individualisierung und gezielte Ansprache [1, 49] sowie eine entsprechende Differenzierung der Appinhalte nach Alter ratsam.

Maßnahmen zur Steigerung der Allgemeinen Kompetenz, welche hier eine Steigerung der Widerstandsfähigkeit und Verbesserung der Stressbewältigung inkludiert, werden hingegen als Familienziel, unabhängig des Alters, gewertet.

Im Ernährungssegment sehen die Befragten ebenfalls eine Möglichkeit des Setzens von Gesundheitszielen (z. B. neue Rezepte auszuprobieren). Die Umstellung auf eine vegane Kost, eine Gewichtszu- oder -abnahme, die Erhöhung der Flüssigkeitszufuhr und selber kochen wurden nicht als gemeinsames Familienziel benannt und sind somit gemäß den Gesundheitszielen der Familien in der App nicht ausschlaggebend.

Maßnahmen der Bewegung und Naturaktivitäten wurden für alle Familienmitglieder, unabhängig der Altersgruppe, positiv eingestuft, sodass die Kombination eine Basis für eine familienorientierte Prävention und Gesundheitsförderung über eine Gesundheits-App darstellt. So lassen sich die Ziele mehr Zeit in der Natur zu verbringen mit Aktivitäten in der Natur, in Form von Bewegung, als ein Anknüpfungspunkt umsetzen, der zum einen Bewegung als auch die Zeit in der Natur, als passive Strategie der Stressbewältigung vereint [50, 51].

Zusammenfassend wird deutlich, dass alle drei Handlungsfelder von Relevanz und als ganzheitliche Angebote sicherzustellen sind. Die Hypothese, dass die Befragten ein großes Interesse an digitalen Maßnahmen zur Prävention und Gesundheitsförderung aufweisen, kann angenommen werden. Da die Entwicklungs- und Altersstufe der Kinder und Jugendlichen von entscheidender Bedeutung ist, sollte eine Individualisierung und eine gezielte Ansprache der unterschiedlichen Familienmitglieder bei der Appentwicklung Berücksichtigung finden. Erfolgt ein Einstieg in die Appnutzung als Familie mit Kindern im Alter von 10 Jahren, so ist das Vorliegen eines gemeinsamen Interesses wahrscheinlicher, welches bei Kindern im Alter von 13 Jahren nachlässt. Für die Mediennutzungsdauer spricht die BZgA Empfehlungen von täglich maximal 60 Minuten für Kinder im Alter von 6–10 Jahren aus, die in der App-Entwicklung Berücksichtigung finden sollte [52]. Weiter ist die Bereitstellung von Angeboten, die Heranwachsenden Orientierung, verständliche Informationen zum Thema Datenschutz sowie Schutz vor unseriösen Anbietern bieten, von Bedeutung, um die Chancen der Gesundheits-Apps und die Risiken und damit verbundene Hürden, zu reduzieren [53].

Zu den größten Stärken dieser Studie gehört die bundesweite Anzahl der Befragten verschiedener Familien. Nach unserem Wissen handelt es sich um die erste Studie, welche neben dem gesundheitlichen Ist-Zustand, die Gesundheitsziele identifiziert und die Schnittmenge zwischen den Familienmitgliedern untersucht.

Da in dieser Studie nur Versicherte einer deutschen Krankenkasse einbezogen wurden, war eine zufallsorientierte Stichprobenziehung limitiert. Antwortverzerrungen durch den Einfluss sozialer Erwünschtheit sind in dieser Studie nicht auszuschließen. Zudem wird durch die Freiwilligkeit an der Befragung ein Selektionsbias nicht ausgeschlossen. Soziodemographische Merkmale, wie z. B. der Bildungsstand fanden in der Untersuchung keine Berücksichtigung. Weiter erfolgte kein Rückschluss auf familiäre Strukturen in Deutschland. Da die Bearbeitung des Fragebogens durch eine Person der Familie erfolgte, ist davon auszugehen, dass Einschätzungen des Gesundheitszustandes und der Ziele der Familienmitglieder durch die subjektive Wahrnehmung der ausfüllenden Person beeinflusst wurde. Ferner ist es möglich, dass es zu Mehrfachnennungen in der Altersgruppe der Kinder kam, die aus dem Vorhandensein mehrerer Kinder in der Familie resultiert und somit kein direkter Bezug hergestellt werden konnte. Die Ausfüllquote ist auf die Instruktionen zu Beginn der Befragung zurückzuführen. 349 Personen unterbrachen an dieser Stelle die Studie.

Eine weitere Limitation dieser Arbeit ist der fehlende Diskurs zur altersgerechten Nutzung von digitalen Medien. So sollten auch bestehende Empfehlungen zum Umgang mit Medien in einer familienbasierten Gesundheits-App Berücksichtigung finden.

Schlussfolgerung

Die durch diese Studie gewonnenen Erkenntnisse verdeutlichen die Potenziale für digitale Maßnahmen der Prävention und Gesundheitsförderung in Familien und decken inhaltliche Schnittpunkte der Familienmitglieder auf. Es ist davon auszugehen, dass sich digitale Angebote für Familien insbesondere mit Kindern unter 13 Jahren eignen. Es empfiehlt sich die Altersgruppen der Kinder zu berücksichtigen. Weitere Forschung sollte Nutzungspräferenzen in einer familiären Gesundheits-App sowie die Nutzung in verschiedenen Familienkonstellationen sowie eine familiengerechte Ansprache identifizieren.

Interessenkonflikt

Die Autorinnen/Autoren geben an, dass kein Interessenkonflikt besteht.

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Hinweis

Dieser Artikel wurde gemäß des Erratums vom 20.01.2023 geändert.

Erratum

Im oben genannten Artikel wurden die Institutszuordnungen der Autoren korrigiert:
Richtig lauten sie wie folgt:

Autorinnen/Autoren

Charlotte Meixner[1], Hannes Baumann[1,2,3], Bettina Wollesen[1,2]

1 Institut für Bewegungswissenschaft, Universität Hamburg, Hamburg, Germany
2 Technische Universität Berlin, Institut für Psychologie und Arbeitswissenschaft, Berlin, Germany
3 Medical School Hamburg, Institute of Interdisciplinary Exercise Science and Sports Medicine, Hamburg, Germany

ORIGINALIA › PEER REVIEW

Voraussetzungen zur Vermittlung digitaler Gesundheitskompetenzen durch Sportlehrkräfte im Zuge der SARS-CoV-2-Pandemie

Eine explorative Mixed-Methods-Studie im Schulkontext

Hannes Baumann, Charlotte Meixner, Bettina Wollesen

korrespondierender Autor
Hannes Baumann
Universität Hamburg
Institut für Bewegungswissenschaft
hannes.baumann@uni-hamburg.de
Medical School Hamburg
Institute of Interdisciplinary Exercise Science and Sports Medicine
Technische Universität Berlin
Institut für Psychologie und Arbeitswissenschaft

Charlotte Meixner
Universität Hamburg
Institut für Bewegungswissenschaft

Prof. Dr. Bettina Wollesen
Universität Hamburg
Institut für Bewegungswissenschaft

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ZUSAMMENFASSUNG

Das aus der SARS-CoV-2-Pandemie resultierende Homeschooling bedarf der Entwicklung neuer digitaler Lehr-Lernkonzepte bei gleichzeitig mangelnder digitaler Infrastruktur und fehlenden digitalen Kompetenzen der Lehrenden und Lernenden. Auch für den Sportunterricht stellte die Umsetzung digitaler Innovationen und Methodik eine Herausforderung dar. Neben der Entwicklung von motorischen Kompetenzen, kommt dem Sportunterricht im Zuge des Setting-Ansatzes auch eine Bedeutung in der Gesundheitsförderung zu. Die Pandemiesituation offenbarte somit z.B. auch Defizite in den digitalen Gesundheitskompetenzen von Lehrkräften und Schüler:innen. Sportlehrkräfte, deren Unterricht primär auf eine face-to-face Kommunikation ausgerichtet ist, stehen somit vor der Aufgabe sowohl inhaltlich als auch medial Umstellungen in ihren Lehr-Lern-Konzepten vorzunehmen.
Um geeignete Lehr-Lern-Konzepte zur Förderung digitaler Gesundheitskompetenzen (zunächst bei Lehrenden und erst im Folgeschritt bei Lernenden) zu entwickeln, werden in diesem Beitrag Konsequenzen aus dem Distanzunterricht bei Lehrenden sowie Lernenden untersucht. Zudem erfasst die Studie Unterschiede der digitalen Gesundheitskompetenz bei den Lehrenden in Abhängigkeit des Unterrichtsfaches. Der explorativ sequenzielle Mixed-Methods-Ansatz integrierte einen Onlinesurvey mit n=118 Lehrenden der Fächer Gesundheit, Biologie und Sport sowie sechs Fokusgruppeninterviews über die Plattform Zoom mit Lehrenden und Lernenden (n=34). Die Befragung umfasste Fragen zur Ausstattung und Nutzung digitaler Medien, zur digitalen Gesundheitskompetenz und zu Hürden bei der Vermittlung digitaler Gesundheitskompetenzen. Die Auswertung beinhaltet Häufigkeits- und Unterschiedsanalysen. Die qualitative Analyse erfolgte durch Inhaltsanalyse nach Mayring mit MAXQDA 2020.
Beide Befragungen ermittelten sowohl fehlende digitale Kenntnisse als auch eine fehlende mediale Infrastruktur. Die Zielgruppen zeigten hohes Interesse und Bedarf für den Ausbau digitaler Gesundheitskompetenz. Sportlehrkräfte wiesen im Vergleich zu Lehrenden der Unterrichtsfächer Biologie und Gesundheit eine geringere digitale Gesundheitskompetenz und ein geringeres Interesse daran auf ($F[2,99]=4{,}07$; $p=,020$; η^2partiell=,107). Die Ergebnisse weisen die Erfordernis einer verbesserten Infrastruktur (z.B. Zugang zu WLAN) nach und ermitteln einen hohen Bedarf zur Förderung der digitalen Gesundheitskompetenz im Setting Schule. Aus der Analyse beider Untersuchungen lassen sich für eine erfolgreiche Umsetzung der Vermittlung digitaler Gesundheitskompetenzen vier Felder übergeordneter Handlungsempfehlungen ableiten: (1) Zur benötigten infrastrukturellen Grundvoraussetzungen, (2) zu Inhalten zur Vermittlung digitaler Gesundheitskompetenzen im Sportunterricht, (3) zur methodischen Umsetzung und (4) zur Weiterbildung von Sportlehrenden.

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Abstract: The homeschooling resulting from the SARS-CoV-2-pandemic requires the development of new digital teaching-learning concepts in the face of a simultaneous lack of digital infrastructure and digital skills among teachers and students. The implementation of digital innovations also became a particular challenge for physical education. In addition to the development of motor skills, physical education also plays an important role in health promotion as part of the setting approach. The pandemic situation thus also requires, for example, the developments of digital health competencies in physical education. Physical education teachers, whose lessons are primarily oriented towards face-to-face communication, are confronted with both content-related and media-related changes in their teaching-learning concepts.

In order to develop suitable teaching-learning concepts for the promotion of digital health competencies (first for teachers and only in a subsequent step for students), this article examines the consequences of distance learning for teachers and students. In addition, the study captures differences in digital health literacy among teachers depending on the subject taught. The exploratory sequential mixed-methods approach integrated an online survey with *n*=118 teachers of health, biology, and physical education, and six focus group interviews via the Zoom platform including teachers and students (*n*=34). The survey included questions about digital media infrastructure in schools, digital health literacy and potential barriers of health literacy promotion in schools. The analysis included frequency analysis and ANOVA. Qualitative analysis was conducted through Mayring content analysis using MAXQDA 2020.

Both studies identified a lack of digital literacy as well as a lack of media infrastructure. The target groups showed high interest for digital health literacy development. Physical education teachers demonstrated lower digital health literacy compared to biology and health teachers ($F[2,99]=4.07$; $p=.020$; η^2 partial=.107). The results demonstrate the need for improved infrastructure (e.g., access to WLAN) and identify a high need to promote digital health literacy in the school setting. From the analysis of both studies, four fields of overarching recommendations for action can be derived for a successful implementation of the teaching of digital health literacy: (1) On the basic infrastructural requirements needed, (2) on content for teaching digital health literacy in physical education, (3) on methodological implementation and (4) on further training of physical education teachers.

1 EINLEITUNG

Thematische Hinführung

Im lebensweltbezogenen Settingansatz (vgl. Rosenbrock, 2015), der sich auch auf das Setting Schule übertragen lässt, werden Kinder und Jugendliche altersgerecht an Maßnahmen der Gesundheits- und Bewegungsförderung beteiligt. Hierbei steht die Förderung der sportlichen Aktivität im Vordergrund (Hanssen-Doose et al., 2018). Zudem ist die Vermittlung von Gesundheitskompetenzen (von Sørensen et al. (2012) definiert als die Fähigkeiten, Gesundheitsinformationen zu finden, zu verstehen, zu bewerten und für gesundheitsbezogene Entscheidungen anzuwenden) in den Bildungsplänen einzelner Bundesländer verortet (primär in den Unterrichtsfächern Sport, Biologie und Gesundheit) (Töpfer & Sygusch, 2014). Die Pandemiebedingungen resultierten in Herausforderungen der Gesundheitsförderung (z.B. fehlende Sport- und Beratungsangebote), die mit digitalen Gesundheitskompetenzen (z.B. zielgerichtete Beschaffung evidenzbasierter Gesundheitsinformationen, digitale Bewegungsförderung, Nutzung digitaler Anwendungen zur Infektionsnachverfolgung) gezielter bewältigt werden könn(t)en (Dadaczynski et al., 2021). Bisher fehlt jedoch in den meisten Bundesländern die curriculare Anbindung digitaler Gesundheitskompetenzen, welche seit Beginn der SARS-CoV-2-Pandemie bedingten bundesweiten Lockdowns rapide an Bedeutung gewannen (Crawford & Serhal, 2020). Weiterhin führten Kontaktbeschränkungen zur Reduktion sozialer Interaktionen. Für die Vermittlungsprozesse im Schulalltag erforderte dies u.a. kurzfristig digitale Lösungen. Der bisher auf Präsenz ausgerichtete Unterricht wurde in ein Homeschooling überführt – eine Situation, die viele Lehrer:innen, Eltern und die Schüler:innen überforderte (OECD, 2020). Daraus resultierende sozio-affektive Komplikationen und unzureichende körperliche Aktivität wurden insbesondere bei sozioökonomisch benachteiligten Kindern beobachtet (López-Bueno et al., 2021).

Zentrale Veränderungen für Lehrende umfassten den bedarfsgerechten Einsatz digitaler Lehr-Lern-Plattformen (z.B. Iserv und Commsy), digitaler Konferenztools (z.B. Zoom) oder anderen Interaktionsformen mit kurzer Vorbereitungszeit, um das Unterrichtsmaterial an digitale Formate anzupassen.

Die Schüler:innen erleben z.B. das Fehlen bekannter Tagesstrukturen des Schulalltags als Überforderung (Magson et al., 2021). Homeschooling erfordert mehr Selbstmanagementkompetenzen (u.a. Fähigkeit zur Eigenmotivation, Festlegen von Arbeitsstrukturen, Erstellung von Tagesplänen) oder Unterstützungsbedarf durch die Erziehungsberechtigten. Darüber hinaus mangelt es an Zugängen zu digitalen Endgeräten und dem Internet. Erziehungsberechtigte, Lehrer:innen sowie Schüler:innen sind somit mit der Situationen konfrontiert, Lehr-Lern-Prozesse gemeinsam neu zu gestalten.

Gleichzeitig wirken sich die eingeschränkten Bewegungs- und Interaktionsmöglichkeiten auf das physische und psychische Wohlbefinden aus, weswegen digitaler Gesundheitsförderung in Zeiten der Isolation mehr Bedeutung zukommt. Unklar ist, wie vor allem im Sportunterricht eine Förderung digitaler Gesundheitskompetenzen in Distanzunterrichtssituationen möglich ist. Das Fach Sport kann dabei als Bezugspunkt für primärpräventive Inhalte dienen und hat im Vergleich zu anderen Fächern den Vorteil, dass die Wirksamkeit zahlreicher digitaler Gesundheitsangebote in den Bereichen Bewegung und Ernährung bereits belegt ist (Anshari et al. 2017). So zeigt sich beispielsweise in einer Metaanalyse von Baumann et al. (2022), dass mHealth bei der Verringerung von Inaktivitätszeiten von Kindern und Jugendlichen erste positive Effekte aufweist, sofern entsprechende Verhaltensänderungsmechanismen in der App enthalten sind. Daher widmet sich dieser Beitrag der Fragestellung, mit welchen Voraussetzungen Lehrende für das Fach Sport in der Praxis konfrontiert sind und wie die Vermittlung von Unterrichtsinhalten zur Förderung von digitaler Gesundheitskompetenz gelingen kann.

Theoretischer Rahmen

Digitale Gesundheitskompetenz umfasst eine Verknüpfung von Gesundheits- und Medienkompetenzen und integriert Aspekte aus e- und mhealth Konzepten (Bittlingmeyer, et al., 2020). Grundlage dafür bildet die individuelle Medienkompetenz nach Blömeke (2001), welche definiert ist als die Fähigkeit und Fertigkeit einer Person, ein mediales Verhalten kompetent, funktional und selbstbestimmt auszuführen (Six und Gimmler, 2018). Lehrer:innen sollten fähig sein, digitale Medien und deren Inhalte selbst angemessen zu nutzen und zu gestalten. Für das universitäre Setting zeigten Dadaczynski et al. (2021) eine enge Verbindung von Medien- und Gesundheitskompe-

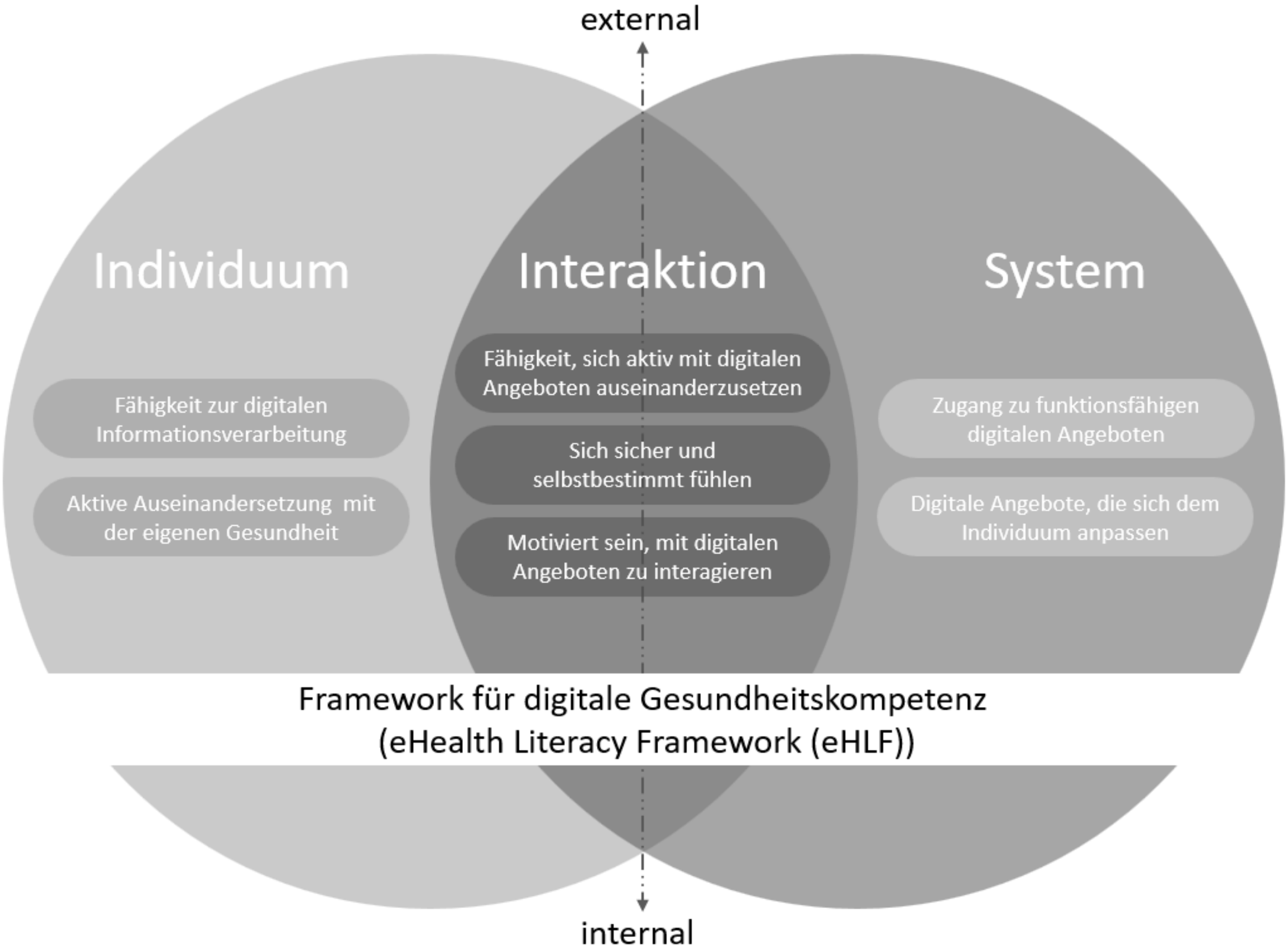

Abb.1 *Framework für digitale Gesundheitskompetenz (eHLF) adaptiert nach Norgaard et al (2015)*

tenzen. Für die Autoren ist digitale Gesundheitskompetenz demnach die gesundheitsbezogene Selbstfürsorge, die im digitalen Raum durch gute Medienkompetenz wirksam wird. Digitale Gesundheitskompetenz umfasst somit das Zusammenspiel personaler und sozialer Faktoren bei der Nutzung digitaler Technologien im Suchen, Aneignen, Erfassen, Verstehen, Bewerten, Kommunizieren und Anwenden von Gesundheitsinformationen in allen Kontexten der Gesundheitsversorgung mit dem Ziel, die Lebensqualität über die gesamte Lebensdauer hinweg zu erhalten oder zu verbessern (Bautista, 2015).

Auch bei Schüler:innen besteht Handlungsbedarf zum Aufbau digitaler Kompetenzen. Ein Drittel der 7.-8. Klässler:innen zeigt z.B. Schwierigkeiten im Suchen und Bewerten digitaler Gesundheitsinformationen (jeweils 42%; Endberg & Lorenz 2017). Auch Jugendliche äußern Probleme digitale Gesundheitsinformationen zu finden und deren Bewertung in Bezug auf Zuverlässigkeit und Relevanz vorzunehmen (Dadaczynski et al., 2021).

Zum grundlegenden Verständnis des Konstruktes Gesundheitskompetenz und dessen Determinanten über die Lebensspanne können etablierte Modelle wie das integrativ konzeptionelle Modell von Sørensen und Kollegen herangezogen werden (2012). Es beinhaltet vier erforderliche Kompetenzdimensionen: Gesundheitsinformationen finden, verstehen, beurteilen und anwenden. Für den speziellen Fall digitaler Gesundheitskompetenz, reicht dieses Modell jedoch nicht aus. Norgaard und Kollegen (2015) entwickelten deshalb das konzeptionelle eHealth Literacy Framework (eHLF), welches den Fokus auf digitale Gesundheitsanwendungen richtet. Es beinhaltet sieben Dimensionen (siehe Abbildung 1), verteilt auf drei Ebenen in Verbindung mit internalen und externalen Faktoren.

Das eHLF grenzt sich in der Interaktion zwischen der Ebene des Individuums und des Systems von anderen Modellen ab: Wie eine Person mit Informationen im Kontext eines Systems umgeht (Dimension 3) ist nicht nur durch technische Fähigkeiten determiniert. Das Erleben von Sicherheit und Kontrolle (Dimension 4), Nutzen und Komfort und die richtige Einstellung im Umgang mit der Technologie (Dimension 5) sind ebenso relevant wie Wissen um das Innenleben der Systeme und die Fähigkeiten, sie zu navigieren (Norgaard et al., 2015; Kayser et al., 2018). Lorenz et al. (2017) konnten zeigen, dass Sportlehrkräfte einen sicheren Zugang zur Informationsbeschaffung mittels digitaler Medien (siehe Dimension 4) als relevant ansehen und hier gesteigertes Lerninteresse der Schüler:innen vermuten (Lorenz et al., 2017).

Das zentrale Hindernis bei der Gestaltung digitaler Unterrichtssequenzen stellt jedoch die technische Ausstattung an Schulen dar. Im europäischen Vergleich ist die IT-Ausstattung in Deutschland unterdurchschnittlich (Bitcom, 2015). Auch, wenn die grundsätzlichen Voraussetzungen für digitalen Unterricht technisch und organisatorisch erfüllt wären, ergäben sich Probleme in der direkten Umsetzung. Dies führen Schulze et al. (2018) und Petko et al. (2018) auf die kritische Einstellung einiger Lehrkräfte gegenüber Mediennutzung und fehlende Kompetenzen im Umgang mit Medien zurück. Eine Mehrheit der Lehrenden spricht sich z.B. gegen die Nutzung des eigenen Smartphones der Schüler:innen im Unterricht, u.a. für Recherchetätigkeiten, aus

(Wößmann et al., 2017). Gleichzeitig beurteilen Lehrer:innen den Nutzen und Einsatz digitaler Medien positiver, wenn ihre eigenen Kompetenzen höher ausgeprägt sind (Bos et al., 2015; Kreijns 2013, Sadaf et al., 2016, Scherer et al., 2015). Als Vorteile digitaler Methoden nennen Lehrer:innen:

» erhöhte Kommunikationsmöglichkeiten (Wößmann et al., 2017)
» flexiblere Arbeitszeitgestaltung (Wößmann et al., 2017)
» verbesserter Zugang zu Materialien (Schuhknecht, 2020)
» webbasierte Trainings- und Lernsysteme, die den Lernerfolg dokumentieren und die Methode an den Lernstil der Adressat:innen anpassen (Schuhknecht, 2020)
» Open Online Kurse (Taraghi, 2013; Anhalt, 2020)

Ableitung von Forschungsfragen

Unklar ist, welches Fachwissen und welche Kompetenzen Lehrkräfte im Einsatz digitaler Medien besitzen und ob sich fehlende Kompetenzen auf die Qualität des digitalen Unterrichts auswirken. Zudem führen Situationen wie der Lockdown zu fehlendem Ausgleich zwischen Anforderungen des Lehrens und Lernens und notwendiger Erholung z.B. durch Bewegung im Freien oder im Sportverein. Regelmäßige Bewegung ist jedoch eine wichtige Grundvoraussetzung für die körperliche und psychische Entwicklung von Kindern und Jugendlichen (RKI, 2018). Die Nutzung digitaler Medien im Sportunterricht, um Bewegungsaktivität in die Freizeit zu transferieren, könnte ein Ansatzpunkt für die Ausbildung digitaler Gesundheitskompetenzen sein. Im Sinne der Definitionen von Gesundheitskompetenz als Fähigkeit die Gesundheit aufrecht zu erhalten, zu fördern und zu gestalten (Bittlingmeyer, et al., 2020), könnten digitale Methoden im Sport dazu beitragen, geeignete Informationen und Angebote zu finden (z.B. YouTube Videos mit Bewegungsanleitungen), Kriterien zur Qualitätsbeurteilung entsprechender Angebote zu lernen und Angebote zu nutzen, wenn eine andere Art von Bewegungsaktivität pandemiebedingt nicht möglich ist. Derartige Ansätze müssten in der Aus- und Weiterbildung von Sportlehrkräften adressiert werden. Die Relevanz digitaler Gesundheitskompetenzen von Lehrenden und Lernenden rückte die Pandemie besonders in den Fokus, jedoch wird dieser Aspekt über die Pandemiebedingungen hinaus für die adoleszente Lebenswelt im Zeitalter der Digitalisierung vermutlich zunehmend an Bedeutung gewinnen. Zusammenfassend verdeutlicht die Analyse der aktuellen Situation, dass nicht nur digitale Kompetenzen der Lehrenden und Lernenden bedeutsam sind, sondern dass auch eine Überführung dieser Kompetenzen in digitale Lehr-Lern-Prozesse zur Erhöhung von digitalen Gesundheitskompetenzen von zentralem Interesse ist. Die folgende explorative Studie widmet sich daher folgenden Fragestellungen:

» Welche erforderlichen infrastrukturellen Grundvoraussetzungen für digitalen Unterricht sind an den Schulen vorhanden und wie werden diese genutzt? (quantitativ)
» Unterscheidet sich die digitale Gesundheitskompetenz der Lehrenden (Fachkompetenz) in Abhängigkeit der Unterrichtsfächer Sport, Biologie und Gesundheit? (quantitativ)
» Welche Vermittlungsmethoden und potentiellen Hürden zur Umsetzung digitaler Gesundheitskompetenz im Sportunterricht lassen sich ermitteln? (quantitativ)
» Welche Veränderungen der Lehr-Lern-Prozesse nahmen Lernende und Lehrende während des SARS-CoV-2-Pandemie bedingten Digitalunterrichts wahr? (qualitativ)
» Welche fachlichen Kompetenzen und Grundvoraussetzungen für die Durchführung digitalen Unterrichts ergeben sich aus den SARS-CoV-2-Pandemie bedingten Veränderungen der Lehr-Lern-Prozesse? (qualitativ)

Ein besonderer Fokus liegt bei der Beantwortung der Forschungsfragen auf der Betrachtung der Sportlehrenden. Ziel ist es, aus den Ergebnissen Lösungen und Handlungsempfehlungen zur praktischen Umsetzung geeigneter Lehr-Lern-Konzepte zur Erhöhung digitaler Gesundheitskompetenz im Fach Sport, auch unter Pandemiebedingungen, zu entwickeln.

Resultierendes Forschungsdesign

Um Handlungsempfehlungen für die Sportlehrkräfteausbildung abzuleiten, adressiert das Studiendesign alle Phasen des Lehrberufs (universitäre Ausbildung, Vorbereitungsdienst, Schuldienst). Zur Beantwortung der Fragestellungen integriert diese Querschnittsstudie ein explorativ-sequenzielles Mixed-Methods-Forschungsdesign (Ethikantragnummer der lokalen Ethikkommission der Fakultät PB der Universität Hamburg: 2020_296). Dies kombinierte ein quantitatives Onlinesurvey mit einer darauf aufbauenden Fokusgruppenbefragung.

2 QUANTITATIVE TEILERHEBUNG

Methodik

Die Rekrutierung Lehrender für die quantitative Teilbefragung (Onlinesurvey, April bis Juni 2020, Software Limesurvey) erfolgte nach dem Schneeballverfahren (Häder, 2019) im Raum Hamburg. Als Multiplikatoren dienten bekannte (angehende) Lehrpersonen (Studierende sowie Freunde und Familie), welche den Surveylink an weitere Personen der Zielgruppe leiteten. Die Einschlusskriterien umfassten: (1) >1 Jahr Berufserfahrung (bei Studierenden sollte das einjährige Schulpraktikum absolviert worden sein) und (2) Unterrichtserfahrung in mindestens einem der Fächer Sport, Biologie oder Gesundheit. Insgesamt nahmen n=118 Personen (w=74, m=42, d=2) vollständig an der Umfrage teil (31±10 Jahre alt; 4,8±7,2 Jahre Berufserfahrung). 45% der Proband:innen befanden sich zum Zeitpunkt der Befragung im Studium, 11% im Vorbereitungsdienst, 23% in Verbeamtung und 21% im Angestelltenverhältnis. Insgesamt unterrichteten n=52 befragte Personen primär das Fach Sport (31,4±10,5 Jahre alt; m=24 w=27 d=1), n=25 das Fach Biologie (29,6±9,1 Jahre alt; m=20 w=5 d=0) und n=25 das Fach Gesundheit (31,7±9,7 Jahre alt; m=20 w=4 d=1); n=16 befragte Personen gaben keine Fachzugehörigkeit an. n=28 Personen unterrichteten an einer Berufsschule, n=28 an einem Gymnasium, n=25 Personen unterrichteten derzeit an keiner Schule, n=11 an einer Gesamtschule, n=9 an einer Realschule, n=8 an einer Hauptschule, und n=6 an einer Stadtteilschule.
Inhalte des Onlinesurveys:

» Infrastrukturelle Grundvoraussetzungen für digitalen Unterricht an den Schulen: Die Antwortmöglichkeit integrierte Ankreuzoptionen (Mehrfachnennung möglich): Laptops, Tablets, Smartphone-Apps, Smartboards, e-Learning, Beamer, Dokumentenkameras, Wearables, Podcasts und Hörspiele, Lehrvideos, eBooks & digitale Literatur, Computerräume, WLAN.
» Digitale Gesundheitsförderung: Operationalisiert wurde dies durch eine selbstkonstruierte fünfstufige Likertskala von 1=sehr niedrig bis 5=sehr hoch in den Bereichen „Persönliches Interesse an Umsetzung von Inhalten zu digitaler Gesundheitskompetenz“, „Interesse von Lernenden an der Umsetzung von Inhalten zu digitaler Gesundheitskompetenz“, „Ausprägung digitaler

Gesundheitskompetenzen bei Lernenden", „Bedarf an Förderung von digitaler Gesundheitskompetenzen bei Lernenden" und „Umsetzbarkeit von Maßnahmen zur Förderung digitaler Gesundheitskompetenz in Schulen".

» Digitale Gesundheitskompetenz: Die deutsche Übersetzung eHLQ-G umfasst 35 fünfstufige Likert Skalen von „trifft völlig zu" bis „trifft überhaupt nicht zu". Diese Skalen werden einerseits zu einem Gesamtscore und andererseits zu den sieben Dimension des eHLF zusammengefasst (Details zum methodischen Vorgehen siehe Kayser et al., 2018). Die oben genutzte Definition digitaler Gesundheitskompetenz wurde als zusätzliche Erläuterung bereitgestellt.

» Methoden und Hürden bei der Vermittlung digitaler Gesundheitskompetenz: Die Antwortmöglichkeit integrierte folgende Ankreuzoptionen (Mehrfachnennung möglich): (1) Methoden: Projektorientiertes Lernen, kooperatives Lernen, forschendes Lernen, dialogisches Lernen, Referate und Schüler:innenbeiträge, spielerisches Lernen, mehrdimensionales Lernen; (2) Hürden: Eigene Kenntnisse, Handyverbot, Exklusion, Schulbehörde.

Die Ausfüllzeit des Fragebogens betrug 25±10 Minuten. Die Datenaufbereitung erfolgte in SPSS Statistics (IBM, 2020). Zuerst erfolgte die Kalkulation von multivariat konstruierten Variablen wie dem eHLQ Score. Dem folgten deskriptiver Statistiken zur Aufbereitung genannter Vermittlungsmethoden und potentiellen Hürden zur Umsetzung digitaler Gesundheitskompetenz im Sportunterricht. Einfaktorielle Varianzanalysen (ANOVAs) ermittelten Unterschiede in der digitalen Gesundheitskompetenz der Lehrenden in Abhängigkeit der Unterrichtsfächer.

Ergebnisse

Infrastrukturelle Grundvoraussetzungen für digitalen Unterricht an den Schulen

Die Häufigkeitsanalyse zur vorhandenen Infrastruktur digitaler Medien und deren Nutzung durch die Lehrkräfte zeigte, dass das Nutzungsverhalten der Lehrpersonen von der Verfügbarkeit der Medien abwich. Dies manifestierte sich besonders bei den Strukturen Computerräumen und Smartboards. So gaben von den 118 befragten Lehrkräften 101 (94%) an, einen Computerraum an der Schule zur Verfügung zu haben, wobei nur 59 von 101 (58%) Lehrkräften diesen auch aktiv nutzten. Verfügbarkeit von Smartboards gaben 71 (60%) der Lehrkräfte an, wobei hier nur 49 von 71 (69%) diese auch nutzten (Zusatzmaterial 2).

Ausprägung und Interesse an digitaler Gesundheitskompetenz bei Lehrenden

Die Auswertung ergab ein ausgeprägtes Interesse an der Vermittlung digitaler Gesundheitskompetenzen bei Lehrenden und einen hohen Bedarf für digitale Gesundheitskompetenz bei Lernenden. Sportlehrende zeigten zudem im Vergleich zu Lehrkräften der anderen Fächer ein geringeres Interesse an einer Förderung digitaler Gesundheitskompetenzen und schätzten das Interesse und die Ausprägung digitaler Gesundheitskompetenzen bei den Lernenden niedriger ein (siehe Tabelle 2). Sportlehrkräfte wiesen im Gesamtscore (2,85±0,25) eine geringere digitale Gesundheitskompetenz als ihre Kolleg:innen in den Fächern Biologie (2,61±0,29) und Gesundheit (2,71±0,32) auf (F[2,99]=5,48; p=,006; η^2partiell=,101). Im Bereich der eigenen digitalen Gesundheitskompetenz erzielten die Befragten den höchsten Score in der Dimension „Kenntnis der grundlegenden physiologischen Funktionen, des eigenen Gesundheitszustands und der Risikofaktoren und der Möglichkeiten, sie zu vermeiden". Ebenfalls unterschieden sich Sportlehrende von ihren Kolleg:innen in der zweiten Dimension des eHLQ-Fragebogens („Kenntnis der grundlegenden physiologischen Funktionen, des eigenen Gesundheitszustands und der Risikofaktoren und der Möglichkeiten, sie zu vermeiden") (F[2,99]=7,30; p=,001; η^2partiell=,177).

Methoden und Hürden zur Vermittlung digitaler Gesundheitskompetenz

Die Lehrkräfte gaben in absteigender Reihenfolge an, projektorientiertes Lernen (88%), kooperatives Lernen (85%), forschendes Lernen (80%), dialogisches Lernen (84%), Referate (74%), spielerisches Lernen (75%) und mehrdimensionales Lernen (52%) als gewinnbringende Methoden zur schulischen Vermittlung digitaler Gesundheitskompetenzen zu erachten (siehe Zusatzmaterial 3). Als größte Hürden bei der schulischen Vermittlung digitaler Gesundheitskompetenzen bewerteten die Lehrenden in absteigender Reihenfolge die fehlenden eigene Kenntnisse (71%), das Smartphoneverbot an Schulen (65%), Exklusion durch ungleiche digitale Ausstattung (47%) und datenschutzrechtliche Bedenken der Schulbehörde (25%).

» Dimension 7 eHLQ: Zugang zu digitalen Diensten haben, die den spezifischen Bedürfnissen und Präferenzen der Nutzer entsprechen.	2,33	0,50	2,37

3 QUALITATIVE TEILERHEBUNG

Methodik

Sowohl Lernende als auch Lehrende nahmen nach dem ersten SARS-CoV-2-Pandemie Lockdown (22.03.2020 – 04.05.2020) via Zoom an sechs Fokusgruppeninterviews (Erhebungszeitraum 01.09.2020 bis 13.09.2020) teil (n=36 Teilnehmende, n=18 Lernende und n=18 Lehrende). Die Akquise erfolgte über persönliche Kontakte (bekannte Lehrkräfte und ehemalige Studierende) aus dem Raum Hamburg. Die Lernenden unterteilten sich in drei Fokusgruppen à 6 Personen (7-8. Klasse (m=3, w=3, Alter=13,5±0,5 Jahre), 9-10. Klasse (m=2, w=4, Alter=15,4±0,48 Jahre) und 11-12. Klasse (m=4, w=2, Alter=17,5±,5 Jahre), welche auf Gruppenebene jeweils zu gleichen Teilen Landschulen, Stadtschulen und Schulen in sozial benachteiligten Stadtteilen abbildeten. Analog dazu unterteilten sich die Lehrenden ebenfalls in drei Fokusgruppen à 6 Personen. Diese wurden zwischen den Gruppen nach Erfahrung unterteilt (Lehrer:innen (m=2, w=4, Alter=30,6±2,28 Jahre), Lehrkräfte im Vorbereitungsdienst (m=3, w=3, Alter=27,8±1,34 Jahre) und Lehramtsstudierende mit mindestens einjähriger Praktikumserfahrung (m=1, w=5, Alter=26,7±2,21 Jahre) und innerhalb der Gruppen zusätzlich nach Hauptfachrichtung (Gesundheit, Sport oder Biologie) in homogene Gruppen differenziert. Aufgrund von technischen Problemen kam es zu zwei Dropouts bei den 7.-8. Klässler:innen, einem Dropout bei den 9.-10.-Klässler:innen und einem Dropout bei den Lehrkräften im Vorbereitungsdienst. Final nahmen somit n=32 Personen teil. Bei den teilnehmenden Schüler:innen hielten sich in drei Fällen die Eltern mit im Raum auf. Der Interviewleitfaden sollte die Vergleichbarkeit der verschiedenen Gruppen sicherstellen und wurde daher zur Qualitätssicherung mehrfach innerhalb des Forschungsteams und mit bekannten Lehrpersonen und deren schulpflichtigen Kindern aus dem privaten Umfeld pilotiert. Die finalen Fragen des Interviewleitfadens sind dem Zusatzmaterial 1 zu entnehmen. Die Fokusgruppeninterviews moderierten jeweils ein in qualitativer Forschung erfahrener und in der Sportwissenschaft promovierender Mitarbeiter (29, männlich)

Tab. 1: Vergleich der Ausprägung und der Interessen an digitaler Gesundheitskompetenz bei Lehrenden der Fächer Sport, Biologie und Gesundheit (*n*= 118)

	Sport [*n*=52]		Biologie [*n*=25]		Gesundheit [*n*=25]		*F* [2,99]	*p*	partielles Eta-Quadrat
	M	*SD*	*M*	*SD*	*M*	*SD*			
Digitale Gesundheitsförderung									
» Persönliches Interesse an Umsetzung von Inhalten zu digitaler Gesundheitskompetenz	4,21	0,96	4,36	0,81	4,84	0,89	**4,07**	**,020**	**,107**
» Interesse von Lernenden an Umsetzung von Inhalten zu digitaler Gesundheitskompetenz	3,27	1,04	3,79	1,14	3,96	1,17	**3,91**	**,023**	**,094**
» Ausprägung digitaler Gesundheitskompetenzen bei Lernenden	2,92	0,92	2,96	0,89	3,57	1,04	**3,96**	**,022**	**,084**
» Bedarf an Förderung von digitaler Gesundheitskompetenzen bei Lernenden	4,40	0,91	4,04	1,17	4,74	1,03	2,86	,062	,067
» Umsetzbarkeit von Maßnahmen zur Förderung digitaler Gesundheitskompetenz in Schulen	3,67	1,13	3,41	1,01	4,05	0,99	2,15	,122	,068
Digitale Gesundheitskompetenz									
» eHLQ-Gesamtscore	2,48	0,25	2,61	0,29	2,71	0,32	**5,48**	**,006**	**,101**
» Dimension 1 eHLQ: In der Lage sein, zu lesen, zu schreiben und sich zu erinnern, grundlegende numerische Konzepte anzuwenden und kontextspezifische Sprache zu verstehen.	2,49	0,44	2,54	0,42	2,67	0,51	1,09	,399	,093
» Dimension 2 eHLQ: Kenntnis der grundlegenden physiologischen Funktionen, des eigenen Gesundheitszustands und der Risikofaktoren und der Möglichkeiten, sie zu vermeiden.	2,94	0,47	3,20	0,40	3,32	0,40	**7,30**	**,001**	**,177**
» Dimension 3 eHLQ: Vertrautheit mit digitalen Diensten zur Handhabung von Informationen.	2,87	0,61	2,97	0,59	3,09	0,52	1,26	,287	,153
» Dimension 4 eHLQ: Das Gefühl haben, dass Sie der Eigentümer der in den Systemen gespeicherten persönlichen Daten sind und dass die Daten sicher sind.	2,31	0,52	2,38	0,61	2,52	2,31	1,29	,278	,124
» Dimension 5 eHLQ: Das Bewusstsein, dass die Nutzung digitaler Dienste für sie beim Umgang mit ihrer Gesundheit von Nutzen sein wird.	2,45	0,54	2,34	0,62	2,57	2,45	1,02	,364	,144
» Dimension 6 eHLQ: Zugang zu digitalen Diensten haben, bei denen die Nutzer darauf vertrauen, dass sie funktionieren, wenn sie sie brauchen und wie sie erwarten, dass sie funktionieren.	2,20	0,46	2,27	0,39	2,39	2,20	1,66	,195	,206

und eine wissenschaftliche Hilfskraft aus dem Studiengang Gesundheitswissenschaft (23, weiblich), wobei keine der teilnehmenden Personen den Interviewenden bekannt war. Die durchschnittliche Dauer der Interviews betrug 50±10,3 Minuten. Die Teilnahme an der Studie erfolgte freiwillig. Es wurde von allen Proband:innen eine Einverständniserklärung eingeholt (Bei Schüler:innen eine Einverständniserklärung der Eltern). Die simultanen Bild- und Tonaufnahmen stellten die Basis für die anschließende qualitative Inhaltsanalyse (Mayring & Fenzl 2019) mit MAXQDA 2020 (VERBI Software, 2019) dar. Nach dem Import in MAXQDA codierten eine Autorin und ein Autor unabhängig voneinander das transkribierte Interview-Material. Das zugrundeliegende Codesystem umfasste die zunächst deduktiv gebildeten Subcodes: Organisation, Technik, Kommunikation, Unterrichtsinhalt, Motivation und (digitale) Kompetenzen. Diese wurden nach den Interviews induktiv erweitert.

Ergebnisse

Veränderungen von Lehr-Lern-Prozesse während des Digitalunterrichts

Durch den digitalen Unterricht erhöhte sich nach Angaben der Fokusgruppenteilnehmenden die Bildschirmzeit sowohl bei den Schüler:innen als auch bei den Lehrenden. Zudem berichteten insbesondere jüngere Schüler:innen sowie Berufseinsteigende zu Beginn des digitalen Unterrichts von einer situativen Überforderungen und einer Notwendigkeit von gesteigerten Selbstorganisationsfähigkeiten. Die Analyse zeigte neben Herausforderungen (1) auch mögliche Chancen (2) für neue Lehr-Lern-Prozesse. Diese sind, unterteilt nach Organisation, Technik, Kommunikation, Unterrichtsinhalt, Motivation und (digitale) Kompetenzen, in Tabelle 2 gegenübergestellt.

Kompetenzen und Grundvoraussetzungen zur Durchführung digitalen Unterrichts unter SARS-CoV-2-Pandemie bedingt veränderten Lehr-Lern-Prozessen

Schüler:innen kritisierten die fehlende Kommunikation, sowie fehlende Absprache über Inhalte und Dichte von Lernaufgaben mit den Lehrenden. Zudem betonten Schüler:innen die heterogene Motivation der Lehrkräfte und befürworteten eine Förderung der digitalen Kompetenzen von Lehrkräften.

Der Vergleich der Unterrichtsfächer ergab, dass der Unterricht im Fach Sport häufiger entfiel oder sich nach draußen verlagerte. Sportunterrichtsspezifisch wurde hier die technische Ausstattung bemängelt und auf fehlende digitale Ausstattung in der Sporthalle, wie z.B. Smartwatches mit Accelerometrie-Funktionen, WLAN, etc. hingewiesen.

Sportlehrende präferierten eine Projektwoche mit den Inhalten Entspannung und Bewegung, wohingegen Lehrkräfte der Fächer Biologie und Gesundheit Lehrinhalte zu Natur und Ernährung bevorzugten. Als geeignete Örtlichkeit für eine Projektwoche nannten die Sportlehrkräfte Aula, Pausenhof und Informatikraum. Die Lehrkräfte anderer Fächer führten zudem außerschulische Bereiche, Aktivitäten im Freien, den Sportplatz und die Küche auf. Als Möglichkeit, die eigenen Kompetenzen für den Bereich digitaler Gesundheitskompetenzen zu stärken, schlugen die Lehrkräfte Schulentwicklungstage, Fortbildungen oder Informationsveranstaltungen vor. Ergänzend nannten die Lehrer:innen zeitliche und finanzielle Ressourcen, sowie eine verbesserte Kommunikation im Kollegium und einheitliche Strukturen genutzter digitaler Angebote. Zudem führten die Befragten die Erhöhung der Motivation für die Nutzung neuer Technologien insbesondere bei älteren Lehrkräften als bedeutsam an, um eine Basis für die Vermittlung der Inhalte an die Schüler:innen zu schaffen.

4 DISKUSSION

Sowohl Lehrende als auch Lernende sehen sich seit Pandemiebeginn vermehrt mit Veränderungen im Lehr-Lern-Prozess konfrontiert, die digitale Kompetenzen sowie digitale Gesundheitskompetenzen erfordern. Das übergeordnete Ziel der Studie bestand darin, Lösungen und Handlungsempfehlungen zur praktischen Umsetzung geeigneter Lehr-Lern- Konzepte zu entwickeln. Der Hintergrund besteht darin, dass Lehrende damit zunächst ihre eigene digitale Gesundheitskompetenzen verbessern, um in der Folge als Multiplikator:innen für digitale Gesundheitskompetenz von Lernenden zu agieren. Diese Veränderung hätte sowohl positive Implikationen für erneute Distanzunterrichtssituationen als auch für übergreifende methodisch didaktische Herangehensweisen im Sportunterricht. Zudem wurden infrastrukturelle Voraussetzungen und erforderliche Kompetenzen für den digitalen Unterricht in Abhängigkeit der Unterrichtsfächer (Sport, Biologie, Gesundheit) identifiziert, sowie die Meinungen von Akteur:innen aus multiplen Schulformen in den Fokusgruppen abgebildet. Zudem erfasste die Studie die besondere Situation der Sportlehrkräfte, um in der Folge Handlungsempfehlungen für die Umsetzung von digitalen Lehr-Lernprojekten und die zukünftige Ausbildung von Sportlehrkräften zu geben.

Infrastrukturelle Grundvoraussetzungen

Es fehlt an mobilen Endgeräten, mit denen innovative, digitale Lehr-Lernprojekte zur Förderung digitaler Gesundheitskompetenzen umsetzbar wären. Analog zu früheren Studienergebnissen, ergab sich eine Differenz zwischen der Existenz digitaler Medien und deren aktiver Nutzung für die Unterrichtsgestaltung (Drossel et al., 2019). Dies könnte an veralteter medialer Ausstattung oder den fehlenden digitalen Kompetenzen seitens der Lehrenden liegen (Baumgartner et al., 2016). Ein Lösungsansatz zur Beschaffung fehlender mobiler Endgeräte bestünde darin, einen Förderantrag beim Digitalpakt Schule zu stellen (BMBF, 2019). Die Verwendung privater Endgeräte hingegen könnte den ohnehin bestehenden „Digital Divide“ (Castells, 2021) weiter befeuern.

Es bestehen Optionen auch im Homeschooling eine Verknüpfung von Bewegung und Vermittlung von Gesundheitskompetenz zu erreichen. Beispielsweise kann über die App „Teamfit“ die Klasse eine Schritt-Challenge gegen die Lehrkraft durchführen. Die sorgfältige Auswahl digitaler Anwendungen zur Förderung digitaler Gesundheitskompetenzen ist bei dieser Unterrichtsintegration essenziell (Stassen et al., 2020). Zudem bedarf es einer pädagogischen Einsatzstrategie mobiler Endgeräte für das Fach Sport, da durch den hohen Bewegungsanteil andere Voraussetzungen gegeben sind als in anderen Fächern. Fortbildungen könnten Handlungsoptionen dafür gezielt aufzeigen.

Ausprägung und Interesse an digitaler Gesundheitskompetenz bei Lehrenden

Analog zu Umfragen bei Studierenden unterschätzen die Lehrkräfte eigene Kompetenzen leicht (Dadaczynski et al., 2021). Die beschriebenen Studienbefunde deuten ein Fachkompetenz-Ungleichgewicht zwischen Biologie/Gesundheits- und Sportlehrkräften in Bezug auf ihre digitale Gesundheitskompetenz an, besonders in der eHLQ Dimension „Kenntnis der grundlegenden physiologischen Funktionen, des eigenen Gesundheitszustands und der Risikofaktoren und der Möglichkeiten, sie zu vermeiden“. Dies ist verwunderlich, da grundsätzlich davon auszugehen ist, dass das Sportstudium physiologische Grundlagen zur Prävention unterschiedlichster Krankheitsbilder beinhaltete. Auch ist der Bezug zu den Inhalten digitaler Gesundheitskompetenz für Lehrende der drei Fachbereiche laut Bildungsplänen prinzipiell gegeben. Möglicherweise bestehen bei Sportlehrenden die größten Hürden für diese Form von Lehr-Lern-Konzepten. Es ist unklar, ob dies an dem Selbst- oder Rollenverständnis der Lehrenden im Fach Sport liegt. Abzuwägen ist, inwiefern die funktionale Umsetzbarkeit digitaler Inhalte im Sportunterricht vor allem für Primar- und Sekundarstufe I gegeben ist, da Sporthallen als Unterrichtsort im Vergleich zu anderen Fachräumen weniger mediale Möglichkeiten aufweisen. Zudem würde ein Fokus auf digitaler Gesundheitskompetenz im praktischen Sportunterricht zunächst die Bewegungszeit und -intensität reduzieren. Daher scheint es zunächst so, als ob im analogen Sportunterricht für digitale Gesundheitskompetenz kein Platz ist. Erst wenn der Sportunterricht (wie in der qualitativen Befragung dieser Studie gezeigt) pandemiebedingt ausfallen muss, entsteht ein zeitlicher Rahmen zur Entwicklung bewegungsbezogener Lehr-Lernkonzepte zur Förderung digitaler Gesundheitskompetenz. Bestehende innovative Konzepte dazu umfassen u.a. die Integration von Virtual-Reality-Inhalten und 360° Videos (Fischer und Paul, 2020). Die Tatsache, dass digitale Inhalte erst durch pandemiebedingte Zwänge ihre Daseinsberechtigung im Sportunterricht erhalten, offenbart jedoch weit zurückreichende strukturelle methodisch-didaktische Defizite des Sportunterrichts. Das übergeordnete Ziel sollte deshalb auch nach der Pandemie darin bestehen, beim Thema Digitalisierung Anschluss an andere Fachkulturen zu finden, die Sportstätten digital auszustatten und methodisch didaktische Ansätze zu entwickeln, um digitale Tools zur Förderung von Bewegungszeit zu nutzen.

Tab. 2: Wahrgenommene Herausforderungen und Chancen im Lehr-Lern-Prozess im Zuge des 1. Lockdowns, unterteilt nach Lehrer:innen sowie Schüler:innen

Bereich		Lehrer:innen	Schüler:innen
Organisation	Herausforderungen	» Erschwerte Organisation der Lerninhalte und Vermittlung, insbesondere bei Berufseinsteiger:innen » Veränderung in der didaktisch-pädagogischen Vermittlung/Herangehensweise	» Eigenständige Lernweise » Schwierigkeiten bei neuen und komplexen Lerninhalten » Selbstaneignung von Inhalten nahm mehr Lernzeit in Anspruch als im Präsenzunterricht » Fehlende Ruhe und Konzentrationsprobleme in großen Familien
	Chancen	» Mischformen des digitalen Unterrichts » Zoom, Lernvideos, Aufgaben werden als positiv empfunden	» Kleinere Lerngruppen und mehr Ruhe zum Arbeiten » Wahrgenommene Flexibilität durch: selbständige Zeiteinteilung, verbesserte Konzentration, Zusätzliche gewonnene Freizeit
Technik	Herausforderungen	» Abhängigkeit der Technik » Kamera war bei den Schüler:innen, z.B. bei der Nutzung von Zoom, teilweise nicht vorhanden oder bewusst ausgestellt. Fehlende Kontrolle seitens der Lehrenden. » Fehlende Ausstattung an Schulen (WLAN, Geräte)	» Abhängigkeit der Technik (Internetzugang auf dem Land gering vorhanden) » Digitale Endgeräte bei jüngeren Schüler:innen sowie sozial benachteiligten Familien teils nicht vorhanden
	Chancen	» Plattformen und Kommunikationskanäle existieren (hier bedarf es nur einer einheitlichen Nutzung/Struktur sowie Einführung)	» Plattformen und Kommunikationskanäle existieren (hier bedarf es nur einer einheitlichen Nutzung/Struktur sowie Einführung) » Unterstützung durch digitale Endgeräte (z.B. Im Umgang Laptops), digitale Medien (z.B. YouTube)
Kommunikation	Herausforderungen	» Fehlende Erreichbarkeit, insbesondere jüngerer Schüler:innen » Digitale Betreuung war beschränkt möglich anzubieten » Fehlende Nutzung eines einheitlichen Programms » Fehlende Absprachen, welche Regeln es zu beachten gilt » Fehlende Kanäle zur Kontaktaufnahme zu Kollegen » Fehlende Teambuildingmaßnahmen	» Fehlende Erreichbarkeit der Lehrkräfte (teils nur per Mail) » Digitale Betreuung war bedingt sichergestellt (Kontaktzeiten und Kommunikation verlief je nach Lehrer:in problematisch/unproblematisch » Fehlende Absprache und Menge der Inhalte » Fehlender Austausch untereinander » Kommunikation mit Lehrenden je nach Medium unterschiedlich
Kommunikation	Chancen	» Kurze Meetings können schneller und gezielter stattfinden	» Neue Medien bzw. verstärkter Einsatz (WhatsApp)
Unterrichtsinhalt	Herausforderungen	» Inhaltliche Dichte in der Vermittlung » Teils Ausfall von Sportunterricht	» Inhaltliche Dichte der Lerninhalte » Teils Ausfall von Sportunterricht
	Chancen	» Sportunterricht im Freien	» Sportunterricht im Freien
Motivation	Herausforderungen	» Motivation gering-mittelmäßig	» Motivation bei jüngeren Schüler:innen gering, gesteigerte Natur-Fokussierung und Bewegung in der Natur
	Chancen	» Bereitschaft zur digitalen Vermittlung vorhanden	» Teils gesteigerte Motivation bei Oberstufe und Studierenden
(Digitale) Kompetenzen	Herausforderungen	» Geringe Kompetenz im Umgang mit digitalen Plattformen » Abhängigkeit der Motivation und des Alters der Lehrkräfte	» Kompetenzen gerade bei jüngeren sowie sozial benachteiligten Schüler:innen kaum bis gar nicht vorhanden
	Chancen	» Zeit- und Selbstmanagement vorhanden, aber ausbaufähig » Einarbeitung war möglich	» Erlernen von Zeit- und Selbstmanagementkompetenzen » Umgang mit digitalen Plattformen schnell erlernt » Bei älteren Schüler:innen höher ausgeprägt

Methoden und Hürden bei der Vermittlung digitaler Gesundheitskompetenz im Sportunterricht

Auffällig ist bei den präferierten Methoden, dass es sich ausschließlich um kooperative und selbstständigkeitsfördernde Lernformen handelt (Dornbusch et al., 2009; Ruppert et al., 2010). Die Lehrenden wählten basierend auf ihrer pädagogischen Erfahrung somit eine Methodik, die bewusst auf die Übernahme von Verantwortung der Schüler:innen abzielt sowie deren Selbst- und Zeitmanagement fördert. Die Idee besteht darin, die Themen digitaler Gesundheitskompetenzförderung auf kooperative und selbstständigkeitsfördernde Lernformen im Sportunterricht zu übertragen. Dies kann bei den Sportlehrenden zu einer verbesserten Handlungsfähigkeit in Verknüpfung der Handlungsfelder Sport und Gesundheit führen und somit möglicherweise bei den Lernenden zu einem gesundheitsbewussteren Lebensstil beitragen.

Das Smartphoneverbot an Schulen stellt nach Meinung der Befragten eine weitere Hürde zur Umsetzung von Lehr-Lern-Projekten zur Vermittlung digitaler Gesundheitskompetenzen dar. Auch wenn durch Smartphones zwar die zwischenmenschliche Kommunikation leidet, eine Ablenkung vom Unterricht erfolgt und Cybermobbing unterstützt wird (Olin-Scheller et al., 2020), bedarf es vielmehr der gezielten und umfangreichen Förderung von Kompetenzen für eine verantwortungsvolle Technologienutzung. Smartphones können im Sportunterricht einen Mehrwert für den Unterricht darstellen (Kadry & Roufayel, 2017), eine motivierende Wirkung haben, Lernzeit erhöhen und den kritischen Umgang von Jugendlichen mit Medien fördern. Es bietet sich zudem an, im Schulalltag die Vor- und Nachteile der Smartphone-Nutzung zu thematisieren und dessen positiven Aspekte für eine konstruktive Mediennutzung hervorzuheben. Um Störungen bei der Nutzung von Smartphones im Unterricht zu vermeiden, helfen verbindliche Regeln für die Nutzung im Unterricht (Anshari et al., 2017). Im Kontext des Sportunterrichts wird das Handy aufgrund hoher Bewegungsanteile weniger genutzt, doch bestehen hier Potenziale wie bspw. smartphonebasierte Bewegungsanalysen. Hierzu sollten jedoch Smartphones von Seiten der Schule zur Verfügung gestellt werden. Schüler:innen haben so die Möglichkeit, eigene Bewegungsvideos zu erstellen und mit einer entsprechenden Anleitung der Lehrenden relevante Bewegungsphasen (z.B. beim Werfen oder Schwimmen) zu identifizieren und direktes visuelles Feedback zu erhalten (Mödinger et al., 2020).

Kompetenzen und Grundvoraussetzungen für die Durchführung digitalen Unterrichts unter SARS-CoV-2-Pandemie bedingt veränderten Lehr-Lern-Prozessen

Organisation: Die zeitintensive Organisation digitalen Unterrichts stellt ein zentrales Problem dar. Lehrpersonen stehen vor organisatorischen Hürden, da sie für die technische Organisation zuständig und gleichzeitig Ansprechpartner für digitale Probleme der Lernenden sind. Diese Doppelaufgabe reduziert aktive Lernzeit und könnte z.B. dadurch aufgegriffen werden, dass den Schulen on demand Technik-Support-Teams zur Verfügung gestellt werden. Zusätzlich dazu sind die Unterrichtseinheiten und Lernblöcke anders zu gestalten, da die Schüler:innen durch lange Bildschirmzeiten, häusliche Situationen oder auch fehlenden Selbstmanagementkompetenzen über Konzentrationsprobleme berichten (Depping, 2021). Bewegungsspiele und Konzentrationsübungen sind potentielle digitale Gesundheitsanwendungen an der Schnittstelle zum Sportunterricht. So können über Apps bspw. kollektive Bewegungsaufgaben in der Natur als aktive Bewegungspausen genutzt und auditiv geführte Meditationsübungen langfristig dazu beitragen, dass sich Lernende besser auf den Unterricht konzentrieren können. Im Hinblick auf die Zeitplanung bei synchronem Unterricht sollten Lehrende mehr Zeit für Pausen einplanen und dafür nachbereitende Aufgaben bereitstellen.

Technik: Es fehlen einheitliche Strukturen, Absprachen und digitale Kompetenzen einzelner Personen. Als Kommunikationsmedium sowie zur Verteilung der Arbeitsaufträge erwiesen sich die Plattformen, wie IServ, Commsy, Zoom für die Ausführung des digitalen Unterrichts nach Meinung der Befragten als geeignet. Schüler:innen der jüngeren Jahrgänge hingegen fehlten am meisten die sozialen Aspekte (Kontakt vor Ort) sowie zum Teil die Verfügbarkeit digitaler Medien (insbesondere innerhalb der Zielgruppe mit schlechteren sozioökonomischen Voraussetzungen) (Crawford & Serhal, 2020).

Kommunikation: Die digitale Kommunikation wurde in den Fokusgruppen kontrovers diskutiert. Sowohl Lernende als auch Lehrende sehen in der rein digitalen Kommunikation das größte Problem digitalen Unterrichts, durch fehlende nonverbaler Kommunikation, ausgeschaltete Kameras und einem schwindenden Zugehörigkeitsgefühl (Naidoo, 2021). Interessanterweise gaben die befragten Schüler:innen an, dass eine funktionierende Kommunikation abhängig von den Lehrkräften, den vorher festgelegten Regeln, den Kompetenzen der Lehrkräfte und dem Kommunikationsmedium sei, während Lehrende die Schüler:innen nur schwer erreichen konnten. Somit erfordert Kommunikation im digitalem Unterricht eine geeignete Plattform, funktionierende Endgeräte, digitale Kompetenzen und definierte Kommunikationsregeln.

Unterrichtsmethoden und Motivation: Um die jüngeren Jahrgänge für die Teilnahme an digitalen Unterrichtseinheiten auch nach der SARS-CoV-2-Pandemie zu motivieren und besser vorzubereiten, könnten eine Stärkung des eigenständigen Arbeitens bei jüngeren Klassenstufen, die generelle Verbesserung des Selbst- und Zeitmanagements bei Lernenden oder ein Mentoring-Programm mit älteren Schüler:innen mögliche Lösungsansätze darstellen. Die Wirksamkeit von Mentoring-Programmen ist im schulischen sowie im akademischen Kontext nachgewiesen (Stöger et al., 2012). In der Übertragung von digitalen Gamificationansätzen (z.B. Challenges) auf den Sportunterricht bestünde eine weitere Möglichkeit der Motivationssteigerung (Hofmann et al., 2014). Ergänzend zu bereits bestehenden medienpädagogische Anwendungsszenarien für digitalen Sportunterricht (Thumpel et al., 2020) könnte z.B. das Zeitmanagement oder die digitale Kommunikation verbessert werden, um Belastungssituationen im Homeschooling zu reduzieren (Schiefner-Rohs, 2017). Gerade bei jüngeren Schüler:innen ist die didaktisch wohlüberlegte Integration der positiven Möglichkeiten von mobilen Endgeräten in den Sportunterricht eine komplexe Aufgabe, welche die Integration von fachlichen und medienpädagogischen Inhalten erfordert (Greve et al, 2020).

Digitale Kompetenz: Während die Umstellung auf digitalen Unterricht bei Schüler:innen der Oberstufe sowie Studierenden keine Probleme erzeugte, berichteten Lehrkräfte im Vorbereitungsdienst über große Überforderung. Lehrer:innen waren je nach Ausprägung der eigenen digitalen Kompetenzen mit zusätzlichen Anforderungen belastet. Erfahrene und technikaffinere Lehrkräfte berichteten hingegen analog zu den Ergebnissen der quantitativen Befragung, dass der Einsatz verschiedener Methoden in ihrem digitalen Unterricht, in Form von z.B. digitalem Unterricht, Präsenzunterricht, Erklärvideos, Lernapplikation, Monotonie entgegenwirke und somit die Motivation der Schüler:innen steigern kann. Die Effektivität von Mischformen aus Präsenz und E-Learning-Inhalten ist wissenschaftlich belegt („Blended learning“; Mahmud et al., 2020; Vo et al., 2017). Methodische Fortbildungen in diesem Bereich (z.B. ein digitaler Methodenkoffer) bieten sich als Fördermöglichkeit für Lehrende an, um Medienkompetenzen und didaktisch-pädagogische Vermittlungskompetenzen für den digitalen Bereich aufzubauen. Zur kurzfristigen Deckung des Weiterbildungsbedarfs schlugen die Befragten Schulentwicklungstage, Fachkonferenzen, Webinare und Leitfäden vor. Ein weiterer Lösungsansatz liegt einer langfristigen Ausbildung digitaler Unterrichtskompetenz im Rahmen des Studiums, um eine Überforderung zum Berufseinstieg zu vermeiden. So kann auch eine erhöhte Akzeptanz für den digitalen Unterricht geschaffen werden, die folglich auch einen positiven Einfluss auf die Entwicklung und Kompetenz der Schüler:innen haben kann (KMK, 2017; Schulze et al., 2018; Petko et al., 2018; Schaumburg & Prasse, 2019). Dabei ist zu beachten, dass Sportlehrende (anders als andere Lehrkräfte) besonderen Ausbildungsbedarf zur Kombination von Bewegung und Digitalisierung benötigen (Wendeborn et al., 2019).

Konsequenzen für das Ausbildungsprogramm im Rahmen der Sportlehrkräftebildung

Die Studienergebnisse verdeutlichen den dringenden Bedarf Sportlehrkräfte im digitalen Unterricht zu fördern. Dieser Bedarf manifestiert sich u.a. darin, dass befragte Sportlehrkräfte im Vergleich zu Fachkollegen den niedrigsten Wert bei der digitalen Gesundheitskompetenz aufweisen. Da die Ausbildung von Gesundheitskompetenzen bereits in den Bildungsplänen einzelner Bundesländer verortet ist, sollte sowohl im Vorbereitungsdienst als auch im Studium in allen praxisbezogenen Modulen ein Lerninhaltstranfer auf den Distanzunterricht erfolgen. Dies könnte mit spezifischen Ausbildungsmodulen zu (1) technischen Möglichkeiten von Smartphones und Tablets zu Unterstützung von Bewegung, Bewegungsanalyse und Bewegungslernen, (2) e- und mHealth Möglichkeiten oder (3) Integration von altersgruppenspezifischen Aspekten der digitaler Gesundheitskompetenz, z.B. in der Auseinandersetzung mit geeigneten Bewegungsprogrammen beim Ausfall von Schul- und Vereinssport, umgesetzt werden. Dabei sei erwähnt, dass die Kompetenz zur Durchführung digital unterstützter Lehrveranstaltungen im Bereich Sport, sowie der gezielte Einsatz von Methoden zur digitalen Vermittlung von Bewegung und ggf. Bewegungskompetenz ein Folgeprodukt von digitaler Gesundheitskompetenz der Lehrkräfte darstellt, die digitale Gesundheitskompetenz jedoch nur einen Teilaspekt des gelingenden Digitalunterrichts beinhaltet.

Limitationen

Die digitale Gesundheitskompetenz von Schüler:innen wurde in dieser Studie aufgrund fehlender standardisierter Instrumente für diese Zielgruppe nicht erfragt und sollte in Folgestudien aufgegriffen werden. Zudem erfolgten die quantitative und qualitative Erhebung nicht durch eine Zufallsstichprobenziehung und die Verteilung von Biologie und Sport und Gesundheitslehrkräften innerhalb der Gruppen war ungleich, weswegen die Generalisierbarkeit der Studienergebnisse stark eingeschränkt ist. Auch subsumierte diese Studie unter "Lehrenden" sowohl Lehramtsstudierende mit Lehrerfahrung als auch Lehrkräfte im Vorbereitungsdienst und examinierte Lehrer:innen, die alle ein sehr geringes Durchschnittsalter aufweisen. Dadurch entsteht zwar der Vorteil, dass verschiedene Sichtweisen Betrachtung finden, gleichzeitig hätte eine Stichprobe nur mit examinierten und vorallem älteren Lehrkräften möglicherweise detaillierte Antworten über die Situation im Schulalltag geben können. Die Aussagekraft der Studie ist zudem dadurch limitiert, dass zwar alle teilnehmenden Studierenden eine mindestens einjährige Praktikumserfahrung aufweisen, aber nicht alle während des ersten Lockdowns unterrichtet haben. Weiterhin ist zu bemerken, dass dominante Personen deutlich mehr Redeanteile in den Fokusgruppeninterviews aufwiesen. Dies zeigte sich erst bei der Auswertung. Zukünftig sollten Moderator:innen von Fokusgruppen hier gezielt Steuerungselemente für Redebeiträge in den Prozess integrieren. Der explorative Charakters der Studie führte zum Einsatz nicht standardisierter Messinstrumente mit evtl. selektiver Item- Auswahl. Folgestudien sollten die verwendeten Instrumente zunächst validieren oder im Sinne der Vergleichbarkeit von Studienergebnissen ausschließlich validierte Erhebungsinstrumente einsetzen.

Fazit und Handlungsempfehlungen

Zusammenfassend zeigt sich, dass der pandemiebedingte Lockdown zu Problemen in der digitalen Umsetzung von Unterricht führte und vor allem Entwicklungspotentiale in den infrastrukturellen Voraussetzungen der Schulen und den Kompetenzen der Lehrenden und Lernenden bestehen. Durch die Pandemiesituation wurde deutlich, dass es an digitalen Gesundheitskompetenzen bei Lehrenden und Lernenden fehlt. Daraus folgt eine zwingend notwendige Anpassungen in der langfristig digitalen Orientierung des Sportunterrichts. Es entwickelten sich in kurzer Zeit viele neue Herangehensweisen, die bisher lediglich praxiserprobt, nicht aber theoriebasiert sind und eine grundständige digitale Gesundheitskompetenz voraussetzen. Konzepte für die Vermittlung von digitalen Gesundheitskompetenzen fehlen. Durch die gezielte Förderung dieser Inhalte in Vorbereitungsdienst und Studium könnten besonders Sportlehrkräfte profitieren und somit erneute Distanzunterrichtsituationen besser bewältigen, sowie das methodisch-didaktisch Repertoire auch darüber hinaus erweitern.

Aus der integrativen Analyse beider Untersuchungen (quantitativ und qualitativ) lassen sich für eine erfolgreiche Vermittlung digitaler Gesundheitskompetenzen im Sportunterricht vier Bereiche von Handlungsempfehlungen synthetisieren:

Tab. 3: Handlungsempfehlungen zur Vermittlung digitaler Gesundheitkompetenzen

Bereich	Handlungsempfehlung
» Handlungsempfehlungen zu benötigten infrastrukturellen Grundvoraussetzungen	» Integration von Laptops, Smartphones, Apps, sowie E-Learning im Sportunterricht
	» Kostenlose und stabile WLAN-Zugänge in den Klassenräumen und Sporthallen
	» Anschaffung von digitalen Endgeräten durch Fördermittel des Digitalpaktes
» Mögliche Inhalte zur Vermittlung digitaler Gesundheitkompetenzen im Sportunterricht	» Schrittzähl-Challenges und Gemeine Hindernisläufe mit Geotags
	» Bewegungsanalyse mit direktem zeitlich versetztem Feedback
	» Virtuell Reality Inhalte und 360 Grad Videos zum Bewegungslernen
» Handlungsempfehlungen zur methodischen Umsetzung	» Projektarbeit, kooperatives und forschendes Lernen gekoppelt mit Sportpraxis
	» Methodenvielfalt/-Wechsel, um Motivation der Schüler:innen zu erhalten
	» Förderung eigenständigen Arbeitens in Primarstufe, Mentoring in Sekundarstufe
» Handlungsempfehlungen zur Weiterbildung von Sportlehrenden	» Aktuelle, flexible und wiederkehrende Fortbildungsangebote schaffen
	» Fachkonferenzen organisieren, z.B. mit Instituten für Lehr*innenbildung
	» Hilfestellungen für die Antragstellung auf den Ausbau digitaler Infrastrukturen

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Trials

STUDY PROTOCOL

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mHealth interventions to reduce stress in healthcare workers (fitcor): study protocol for a randomized controlled trial

Hannes Baumann[1,2,3*], Luis Heuel[1], Laura L. Bischoff[2] and Bettina Wollesen[2]

Abstract

Background Causes and consequences of chronic stress levels in the context of healthcare work are well examined. Nevertheless, the implementation and evaluation of high-quality interventions to reduce stress of healthcare workers is still missing. Internet and app-based interventions are a promising venue for providing interventions for stress reduction to a population that is otherwise difficult to reach due to shift work and time constraints in general. To do so, we developed the internet and app-based intervention (fitcor), a digital coaching of individual stress coping for health care workers.

Methods We applied the SPIRIT (Standard Protocol Items: Recommendations for Interventional Trials) statement as a guideline for the present protocol. A randomized controlled trial will be conducted. There are five different intervention groups and one waiting control group. To achieve the sample sizes required by power analysis (G*Power) (β-error 80%; effect size 0.25), the sample sizes of the respective scenarios will be at best as follows: 336 care workers from hospitals, 192 administrative health personnel, 145 care workers from stationary elderly care homes, and 145 care workers from ambulatory care providers in Germany. Participants will randomly be assigned to one of five different intervention groups. A crossover design with a waiting control group is planned. Interventions will be accompanied by three measurement points, first a baseline measure, second a post-intervention measure directly after completion of the intervention, and a follow-up measure 6 weeks after completion of the intervention. At all three measurement points, perceived team conflict, work-related experience patterns, personality, satisfaction with internet-based training, and back pain will be assessed using questionnaires, as well as heart rate variability, sleep quality, and daily movement will be recorded using an advanced sensor.

Discussion Workers in the health care sector increasingly face high job demands and stress levels. Traditional health interventions fail to reach the respective population due to organizational constraints. Implementation of digital health interventions has been found to improve stress coping behavior; however, the evidence in health care settings has not been established. To the best of our knowledge, fitcor is the first internet and app-based intervention to reduce stress among nursing and administrative health care personnel.

Trial registration The trial was registered at DRKS.de on 12 July 2021, registration number: DRKS00024605.

Keywords Healthcare, Care work, Stress, Stress coping, Digital health technologies, Health intervention, App-based intervention, Digital intervention, eHealth, mHealth

*Correspondence:
Hannes Baumann
hannes.baumann@uni-hamburg.de
Full list of author information is available at the end of the article

Introduction

Background and rationale

Occupational psychosocial stress can increase the risk to develop psychological, musculoskeletal, or cardiovascular disease [1, 2]. Especially health personnel around the globe experience exceptionally high levels of occupational stress [3] leading to serious individual, organizational, and societal problems [4]. Additionally, healthcare institutions in various European countries indicate staff shortages, and often fail to retain long-term personnel, exposing health personnel to a vicious cycle of stress and extra work [5]. This is in line with findings in Germany that report job demands in the health sector to be considerably higher compared to other professions [6]. Similarly, within the European Union, it is well known that more than one in four nurses are overburdened [7]. Recurring stressors in health organizations include high work demands, leadership style, few participation opportunities for work structuring, emotional burdens, lack of appreciation, and work-family conflicts [8, 9]. In turn, these stressors may influence recreational activities of affected persons. For instance, sleep and physical activity have been found to be poor in stressed individuals [10, 11]. Additionally, individuals with lower heart rate variability (HRV) were more likely to report poorer sleep quality in the context of chronic stressor exposure than individuals with higher HRV [12]. Frequent or chronic occupational stress is linked to serious health consequences. If work-related demands outweigh individual, social, and organizational resources [13], affected persons may incur psychological and physiological consequences such as sleep disorders, gastrointestinal complaints, burnout, diabetes, and coronary heart disease [14–17]. In severe cases, inability to work can lead to long-term sickness absenteeism [18].

In general, psychosocial stressful stimuli activate neuronal, neuroendocrine, and endocrine pathways. A physiological response to stress occurs thus, among others, at the neurological level, through receptors of the sympathetic nervous system that stimulate the sympatico-adrenomedullary axis. The hormones adrenaline and noradrenaline are released in the adrenocortical medulla, leading to an increase in heart rate and a decrease in heart rate variability (HRV) under physical or psychological stress [19]. Such biological responses to stressful stimuli may be adaptative. However, extreme, frequent, or chronic activations of stress axes may be detrimental to health and may be assessable via heart rate variability [20, 21]. Chronically low HRV is associated with impaired regulatory and homeostatic functions of the autonomic nervous system, which reduce the body's ability to cope with internal and external stressors. Thus, HRV measurement is a noninvasive method that can be used to measure the autonomic nervous system in a variety of settings [22]. Studies show that for example in response to stress-inducing tasks, such as the Trier Social Stress Test, test participants show low parasympathetic activity, characterized by a decrease in High-Frequency Power (HF) and an increase in Low-Frequency Power (LF) HRV values [23–25]. The Standard Deviation of Normal-to-Normal heart beats (SDNN value) represents an index of physiological resilience to stress. When HRV is elevated and irregular, SDNN increases. On the other hand, especially when chronically stressed (e.g., at work), the SDNN value decreases [22, 26]. A low Root Mean Square of Successive Differences (RMSSD) value can also be an indicator of stress. Here, again, studies show that especially in chronic stress, values are lower than in non-stressed individuals [19, 25, 27]. However, it should be noted when evaluating HRV data that—beyond psychological stress—certain influencing variables must be considered. Age has a major influence on HRV. It increases initially, is highest in young adults, and decreases with increasing age [28, 29]. In addition, BMI correlates positively with sympathetic activity [30] and thus negatively with HRV [31, 32], whereas regular physical activity is associated with an increase in HRV [33, 34].

Interventions to reduce stress

While health complaints are frequently observed, there are personal and organizational resources which can improve resilience towards occupational stress [35–37]. Personal resources with stress-protecting qualities include social support, coping style, self-efficacy, and optimism [38–41]. Pertaining to organizational resources, a recent systematic review identified supervisor support, job autonomy, and provision of work equipment to minimize stress [42].

Stress may differentially affect professions within the health sector [43]. For instance, nurses exhibit less health behaviors (e.g., physical activity) than physicians, pharmacists, and administrative health personnel [44]. According to Gerber & Pühse [45], physical activity may exert a stress-buffering effect and thus protect against physical and psychological illness. Also, within the nursing workforce, stressors vary between settings. For example, stressors in an outpatient care include long driving times and high emotional involvement with patients while this is less problematic in hospital settings [46].

Although a variety of stressors exist in the healthcare setting, evidence suggests that perceived stress can be reduced through participation in stress management interventions. For instance, mindfulness programs improve quality of life, anxiety, stress perception, and sleep quality [47, 48]. Physical activity-based studies showed improvements in autonomous nervous system function [49], accelerometric factors such as steps per day [50], BMI, sedentary behavior, MET, and physical activity levels [51]. More recently, mHealth interventions yield the potential to address stress in a low-cost, easy-to-implement fashion [52] with existing evidence for stress-reducing effects in different occupational settings [53].

Within the health care sector, efficacious stress reduction programs include Yoga and qigong [54], cognitive-behavioral interventions such as resilience training [55], mindfulness-based stress reduction (MBSR) [56], or multimodal combinations of aforementioned intervention types [57].

Despite the plethora of studies confirming the efficacy of stress reduction interventions, the evidence for health personnel is generally weak. Study rigor issues, for instance low total intervention time, small sample sizes, and failure to assess behavioral change undermine intervention quality [58]. Further, high risk of bias due to lack of both appropriate study designs and follow-up measurement points are common [54, 59].

The poor evidence base in the field of study is due to organizational, social, and individual reasons. According to Zhang et al. [60], participation in health promotion campaigns in health care facilities is often aggravated by various barriers. Specifically, amiss communication between management and staff, colleague peer pressure, insufficient staffing, top-down decision-making, and budget constraints can impede participation rates. Additionally, healthcare personnel are difficult to reach due to low motivation to change, low self-efficacy, and high psychological and physiological demands [61].

Moreover, due to differences in individual and organizational resources, stress management interventions should be tailored to the specific needs of participants. One possibility is to categorize subjects in terms of coping style when facing difficult work situations [60]. Further, there are individual preferences that need to be considered. For instance, health and other nonhealth-related outcomes (e.g., the value of a healthy future self and time costs, respectively) have differential impacts on the decision to engage in stress management [61]. Thus, one-size-fits-all interventions [62] should not be adapted for vulnerable populations as intervention success is limited [63].

In sum, to counteract stress effects in health personnel, low-cost, easy-to-implement, setting-specific, and need-tailored health promotion interventions are necessary. One way to address these issues is digital (mHealth) interventions.

Digital Interventions for health promotion

Recent developments and studies highlight the opportunities of digital interventions to address the described concerns for implementing and evaluating interventions in the health care sector and the current stage of change readiness. Interestingly, internet-based interventions have been rarely implemented in the healthcare sector so far [64]. Digital health promotion programs can come in different forms: Web-based trainings (WBT) are presented on a secured online platform and assessed through an internet browser either on a smartphone or on a computer/laptop [65, 66], whereas app-based interventions come with a smartphone application only [67, 68]. However, there are also hybrid forms such as web apps.

Digital Interventions can be a low-threshold opportunity for health promotion and are a promising possibility to achieve prevention goals [69, 70], even though eHealth literacy is sometimes missing [65]. The free allocation of time and flexibility of availability were evaluated on a positive note. Combining such apps with so-called "wearables", such as smartwatches or fitness trackers, could allow us to continuously record health data and thus constitutes various opportunities in the context of prevention work (Gamification, Just-in-time-adaptive interventions). By implementing "wearables" into digital health applications (apps), health-related data (e.g., sleep patterns, eating patterns, and exercise) could be recorded and interventions that meet individual needs could be derived based on this data [66]. Previous studies already found positive effects of stress apps on wellbeing. Harrer et al. [67] for example found that app-based stress management interventions improved stress, anxiety, and depression in college students. Another example stems from research by Economides et al. [68] who found that a mindfulness app intervention reduced stress and irritability, while it also increased positive affect. A systematic review and meta-analysis on web- and computer-based interventions for stress reduction illustrates international research efforts. Included studies have been carried out in Western countries (Austria, Switzerland, Germany, Great Britain, the Netherlands, Norway, Sweden, and the USA) and Japan with studies predominantly having been conducted in the USA. The meta-analysis further underlines that digital interventions have shown positive effects on stress outcomes in different samples in the countries mentioned [71].

At the same time, expectations towards health apps are high, 70% of health app users believe that these can strengthen self-motivation and 56% think that app use can improve health education [72].

In order to establish long-term health behavior change, a high level of adherence motivation during the intervention implementation is necessary, and therefore individually tailored approaches may be beneficial. Often, the adherence for digital health promotion programs is rather low which reduces their effectiveness [73]. Individual tailoring [74] or gamification could be approaches to address this problem. In one meta-analysis, researchers found that web-based tailored interventions clearly outplayed generic interventions with respect to health behavior change [75]. In particular, non-tailored interventions were found to decrease user satisfaction [76].

However, the definition of a tailored health app is unclear due to the lack of a framework for individualized app elements. In one of the few reviews that adequately addresses this issue, the authors enumerate the Individualized Elements in the app and grade whether it is a tailored or non-tailored mHealth intervention [77]. The evidence of this review is clear, however, that there is a wide range of potential approaches for individualization and that these are often accompanied by established behavior change mechanisms, yet the effectiveness of individual elements must first be investigated in stand-alone interventions, as tailored mHealth interventions are often multicomponent in nature.

One approach to design individually tailored digital solutions could be a focus on users' personalities. A smartphone app that focuses on stress reduction thus firstly needs to focus on personality characteristics as studies showed that personality characteristics are associated with specific coping behavior [78], app usage behavior, and receptivity to gamification elements [79]. Focusing on personality characteristics also allows for app-tailoring. Additionally, it needs to address users on their current state of readiness for behavioral change App modules that focus on conflict solving skills and communication techniques could work to address those issues. To the best of our knowledge, to date there are no studies investigating the effect of tailored mHealth interventions to reduce stress in the healthcare sector.

In summary, for the development of a digital health intervention, the specific combination of different contents has to be considered. These are (1) evidence-based feasible interventions, (2) tailoring and individualization, and (3) additional elements to gain adherence and long-term usage. Therefore, the present study aims to compare both web-based vs. app-based and tailored vs. non-tailored stress management interventions. All included types of interventions were previously found to improve users' wellbeing in different facets. While generalized web-based interventions that are designed for a broad user population require less technical effort than those containing individualization, a lack of individual tailoring appears to be a central issue when it comes to user motivation and willingness for behavior change. Individual-tailored app-based interventions on the other hand could address this need but require high technical effort as they rely on complex structures. One-size-fits-all interventions that are accompanied by an individual telephone coaching may be another option to allow a certain level of individual tailoring. Therefore, it is of high importance to compare the different approaches with regard to cost-benefit considerations.

With fitcor, we provide healthcare and administrative workers specific digital interventions. This protocol describes a randomized controlled trial (RCT) in which we investigate the effectiveness of the fitcor interventions. Therefore, our aim is to identify the most beneficial digital intervention with respect to the following goals: (a) reduce stress and associated consequences and/or symptoms, (b) increase self-management and self-efficacy, and (c) increase adherence.

The proposed trial is needed to address these aims for four reasons. It includes samples from three different health care settings (1), namely hospitals, stationary elderly care homes, and ambulatory care, which allows to draw conclusions on similarities and differences between the effectiveness of the interventions in the specific settings. It allows comparison of different digital interventions with regard to topic, complexity, or biofeedback inclusion (2). Additionally, it enables investigating stress both from an objective perspective facilitating physiological measures as well as from a subjective perspective facilitating self-report measures (3). Finally, we can derive conclusions on long-term effects of the applied intervention through our longitudinal approach [4]. We expect that each intervention will benefit participants as they get free access to usually pricey digital health improvement programs. But at the same time, participants will have to invest some of their time to conduct all three measurement time points. Other than that, no harms are assumed to appear directly caused by the intervention. Next to the effects on different outcome parameters, the whole approach will give us more information about the required composition of individualization and modularization in different occupational groups.

Research questions

The main research question of this study is:

- ☐ Which digital intervention is most efficient for improving the stress management skills of health care and administrative personnel?

Regarding this main question, there might be some group-related differences to detect. Therefore, the following research questions should be answered:

- ☐ What are the differences in stress levels between nursing and administrative health personnel?
- ☐ What are the differences in sleep quality between nursing and administrative health personnel?

☐ How do intervention formats differ with regard to the effects on the processes of behavioral change?

Moreover, there are some outcome-related research questions:

☐ What is the association between the usage of mHealth intervention applications during working hours and stress levels of users?
☐ Is the effectiveness of the mHealth interventions determined by the age or gender of the participants?
☐ Is there a connection between stress and other outcomes such as back pain or physical activity levels?
☐ Do mHealth interventions contribute to a reduction in back pain?

Finally, the study should answer some acceptance and individualization related research questions:

☐ What is the rate of acceptance for the sensor-based mHealth interventions for nursing and administrative health personnel?
☐ What is the level of satisfaction for the sensor-based mHealth interventions for nursing and administrative health personnel?
☐ Do additional intervention requirements (e.g. for individualization) emerge as a result of the sensor screenings?
☐ What are the necessary requirements to ensure a long-term integration of sensor-based mHealth interventions to the daily routine of nursing and administrative health personnel?

Methods

Study design

The study is part of the project "Internet and app-based interventions to reduce stress in healthcare workers" (fitcor). The studies are conducted and described according to the Spirit checklist [80]. The study will be conducted as a longitudinal crossover design trial with five intervention groups and group comparisons (nurses vs administrative personnel). The study is part of the project "Internet and app-based interventions to reduce stress in healthcare workers" (fitcor). The studies are conducted and described according to the Spirit checklist [80]. The study will be conducted as a longitudinal crossover design trial with five intervention groups and group comparisons as described in Table 1 (nurses vs administrative personnel).

The five intervention groups are as follows:

(1) Web-based digital stress management intervention (WBT only)
(2) Web-based and need-oriented digital stress management intervention (WBT + Need)
(3) Web-based and need-oriented digital stress management intervention with telephone coaching (WBT + Need + Coaching)
(4) App-based stress management interventions with sensory biofeedback (App + Biofeedback)
(5) App-based stress management intervention with sensory biofeedback and health report (App + Biofeedback + Report)

All participants of the intervention groups will receive a digital intervention. The waitlist control group will start the intervention after 8 weeks. Both, questionnaire and sensory data will be assessed:

(1) At baseline (T_1: pre-intervention/pre-waiting)
(2) At 8 weeks (T_2: post-intervention/post-waiting=pre-intervention)
(3) At 16 weeks (T_3: sustainability or post-intervention for waiting group; see Table 1).

Participants

Eligibility and ethical approval

The crossover randomized controlled trial will include nursing staff and office workers aged 18 years or older from hospitals, stationary elderly care facilities, and ambulatory care providers. No clinical patients will be involved in the proposed study. Fluency in the German language as well as internet access via a smartphone device are prerequisites for study participation. All potential participants will be informed about the study and its procedure through a comprehensive informative video. The study is conducted in agreement with the principles of the Declaration of Helsinki and the guidelines of Good Clinical Practice. The recruitment of the participating nursing facilities involved cooperating health insurance companies, whereas the recruitment within the participating facilities will remain within the responsibility of the authors. Written informed consent will be obtained from all participants or their legal guardians before enrolment. Participants as well as their relatives or legal guardians can withdraw consent at any time. The local ethics committee of the TU Berlin, Germany, has approved the study protocol (No GR_14_20191217). The trial was registered at DRKS.de with registration number DRKS00021423 on 12 July 2021.

We used the program G*Power [81] to calculate the relevant sample size. To achieve the sample sizes required by power analysis with a β-error of 80% and an

Table 1 Schedule of enrollment, interventions, and assessments: Recommendations for Interventional Trials (SPIRIT) chart of the enrollments and assessments during randomized controlled trials

		STUDY PERIOD						
	Enrolment	Allocation	Post-allocation					Close-out
TIMEPOINT	$-t_1$	0	t_1	8 weeks	t_2	8 weeks	t_3	t_x
ENROLMENT:								
Eligibility screen	X							
Informed consent	X							
Interviews	X							
Allocation		X						
INTERVENTIONS:								
Intervention first								
WBT only			X	↔	X		X	
WBT + Need			X	↔	X		X	
WBT + Need + Coaching			X	↔	X		X	
App + Biofeedback			X	↔	X		X	
App + Biofeedback + Report			X	↔	X		X	
Waitlist control								
WBT only			X		X	↔	X	
WBT + Need			X		X	↔	X	
WBT + Need +coaching			X		X	↔	X	
App + Biofeedback			X		X	↔	X	
App + Biofeedback + Report			X		X	↔	X	
ASSESSMENTS:								
Questionnaire data			X		X		X	X
Sensor data			X		X		X	X
App usage Data				X		X		X

effect size of 0.25, we will need to include 700 participants. An effect size of 0.25 is considered a small effect, which is congruent with the literature on the effectiveness of eHealth/mHealth behavior change interventions [82, 83] and workplace health promotion interventions [84]. We expect a participation rate of 20% as this appeared to be a realistic participation rate in previous intervention studies in different small and middle-sized companies [85]. With an expected dropout rate of 20%, we will include additional 140 participants to ensure that the study results will still be eligible for data analyses.

Allocation and blinding
To prevent selection bias, the allocation of participants to the intervention groups and waiting control group will be assigned randomly by lot by the director of the study. There is going to be a random allocation at the individual level with the tool Research Randomizer using continuous block randomization. Sets of five numbers will be generated, representing the differing number of study groups. Each participant is then assigned the subsequent number on the block randomization list for group assignment. Therefore, each person can theoretically be assigned to any of the study arms. As participants will be assigned to an intervention group or the waiting control group by lot, no further mechanisms of implementing the allocation sequence is needed. To our best knowledge, there are no circumstances under which unblinding of the data assessors could be needed. Trial participants will be informed about which intervention group they are assigned to as they will need to receive the respective information to complete all necessary information and access the digital intervention programs. Outcome assessment will be blinded as the assessment is done in an online questionnaire that participants fill out independently. The sensor screening will also be done without including a third party as participants apply the sensor on their body by themselves. All data analyses will be run by blinded assessors.

Participant recruitment
Participants will be recruited in health care facilities in Germany. For this purpose, the health insurance companies contact the executives of their collaborating hospitals, stationary elderly care facilities, and ambulatory care providers. The executives will forward an explanatory video to their employees via in-house communication networks, whereupon they can voluntarily enter their contact details into an online tool to register for the study. Previous experiences of the researchers showed that approximately only half of all contacted nurses participated in intervention studies. Therefore, in order to reach the target sample size, we will contact double the participants than we will actually include in the study.

Interventions
Explanation for the choice of comparators
In order to illustrate the advantages of mHealth interventions for the specific requirements of healthcare settings, office workers were chosen as a comparison group. The reason for choosing this comparison group is that office workers are often more likely to adapt to digital interventions due to their workplaces being better equipped in terms of technology. In addition, as described above, we developed five different study scenarios to be compared within the study. The reason for this selection is to reflect different levels of individualization in mHealth interventions across the different scenarios.

Intervention description
As described above, there are five different intervention scenarios, each including a WBT or an app, and each with different levels of individualization. This trial becomes particularly complex due to the need orientation of the WBT interventions. Depending on the needs of a person, he or she is assigned a different WBT. For example, a person who does not exercise enough and is very overweight is recommended a weight loss WBT, while a person who suffers from high stress levels is recommended a WBT with autogenic training or mindfulness. For this reason, a detailed list of the content covered in the respective apps or WBTs is provided in Table 2 below.

Strategies to improve adherence to interventions
In order to improve adherence to interventions, a user-centered approach was chosen to integrate experiences and test the functionality of the app internally and externally. Moreover, the information process about the study design implied an explanatory video, numerous flyers, and digital meetings. After agreeing to participate, numerous reminder emails were also created, which were automatically sent to the participants if they forgot to order the sensors or register.

Participant involvement
To ensure target group participation, the intervention conception was preceded by a qualitative needs assessment of the target group health care workers. We inquired about acceptance of the biofeedback system, the chest strap, and needs and requests for app content to improve need-tailoring and individualization aspects. For the sake of simplicity, we do not report the outcomes of this assessment in this study protocol.

Outcome measures
The assessment will apply a selection of standardized questionnaire measures (cited below) as well as sensor-based physiological and vital parameter measures (measured by Corvolution CM300, which includes ECG circuit, 3-axis acceleration and rotation rate chip, air pressure chip, thoracic impedance chip, and temperature chip). Additionally, demographic characteristics, such as age, gender, and job hierarchy, will be assessed.

Table 2 Detailed list of the contents of the various needs-specific app and WBT modifications

Focus	Sub-focus	App				WBT							
		AusGleich	BIG Balance	myCare+	GetRest	Nutrition	Weight loss	Physical Activity	Spine Gymnastics	Mindfulness	Hatha Yoga	Sleep and Stress	Autogenic training
Individualization	Direct biofeedback	x	x	x	x								
	AVEM patterns	x											
	Telephone coaching					x	x	x	x	x	x	x	x
	Vocational setting	x	x	x	x								
	Need orientation					x	x	x	x	x	x	x	x
Stress and relaxation	Problem-focused	x	x	x	x								
	Deep breathing	x	x	x	x					x	x	x	x
	Mindfulness	x	x	x	x					x	x	x	
	Goal setting	x	x	x	x		x	x		x		x	x
	Gratitude journal	x	x	x	x					x	x	x	
	Positive psychology	x	x	x	x					x	x	x	x
	Autogenic training	x	x	x	x					x	x	x	x
	Progressive muscle relaxation	x	x	x	x					x	x		
	Body perception	x	x	x	x					x	x		
	Stress physiology												x
Sleep	Sleep habits	x	x	x	x								
	Sleep and shift work	x	x	x	x								
	Healthy sleep	x	x	x	x							x	
Physical activity	Stretching and yoga	x	x	x	x			x			x		
	Fascia						x	x	x				
	Behavior change	X	x	x	x								
	Activity habits	x	x	x	x								
	Endurance training	x	x	x	x			x					
	Anatomy						x	x	x				
	Spine health								x				

Primary outcomes

All primary outcomes will be assessed at baseline (T_1), at follow-up measurement after 8 weeks (T_2), and at follow-up measurement after 16 weeks (see Table 1).

Stress and relaxation While perceived stress and stress symptoms will be assessed in a questionnaire format, heart rate variability (HRV) and sympathovagal balance are captured by the sensor.

- ☐ *HRV*: HRV measurement will be used to determine the ability of the heart to respond to daily physiological and psychological stimuli. The following HRV parameters will be used for the assessment of psychological health and stress: SDNN (ms), RMSSD (ms), LF (ms2), HF (ms2), and the LF / HF-Ratio.
- ☐ *Perceived Stress*: Stress perception will be assessed via the PSS-4 questionnaire. The PSS-4 is the short version of the original PSS-10, developed by Cohen et al. [86], which measures the extent to which respondents perceive their life situation as unpredictable, uncontrollable, and overloaded, and thus feel stressed. The 4-item version incorporates the statements: "In the last month how often have you felt you were unable to control the important things in your life?," "In the last month how often have you felt confident about your ability to handle your personal problems?," "In the last month how often have you felt that things were going your way?," "In the last month how often have you felt difficulties were piling up so high that you could not overcome them?". The 5-point response scale ranges from 0 = never to 4 = very often. Internal consistency is good at $\alpha = 0.77$ [87].
- ☐ *Subjective stress symptoms*: A self-developed questionnaire asks respondents to rate 10 stress symptoms (e.g., I often feel alone, abandoned, and isolated) on a 5-point Likert scale (not true—true).

Sleep quality Sleep quality will be measured via both sensor data (sleep duration and sleep recovery) and validated questionnaires (subjective sleep quality, sleep apnea risk).

- ☐ *Sleep duration*: Determination of sleep duration follows the method of Cole et al. [88]. Classification of sleep duration occurs as hours/day, where <6 h/day = insufficient, 6–9 h/day = sufficient, and >9 = excessive [89].
- ☐ *Sleep recovery*: ECG parasympathetic activation will measure sleep recovery. Via the sensor, participants' recovery will be classified as poor, moderate, or good.
- ☐ *Subjective sleep quality*: The Pittsburgh Sleep Quality Index (PSQI) will be used to collect subjective sleep quality data. The index is composed of 18 items covering seven relevant areas (subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleep medications, and dysfunction during the day within the past four weeks) [90]. An example item is "During the past 4 weeks, how often have you slept poorly because you woke up in the middle of bedtime or much too early?" Across the seven areas, a total of 0–21 points can be achieved. Scores above 11 reflect poor sleep quality, whereas a score of 5 and below reflects good sleep quality. The German version demonstrated good internal consistency ($\alpha = 0.75$ [91];).
- ☐ *Sleep apnea risk*: The snoring, tiredness during daytime, observed apnea, and high blood pressure with BMI, age, neck circumference, and gender (STOP-Bang) questionnaire will be used to identify obstructive sleep apnea (OSA) risk. The STOP-Bang questionnaire asks four yes/no questions ("Do you snore loudly (louder than talking or loud enough to be heard through closed doors)?", "Do you often feel tired, fatigued, or sleepy during daytime?", "Has anyone observed you stop breathing during your sleep?", "Do you have or are you being treated for high blood pressure?") to quickly screen OSA risk. Respondents are assigned a score for each item (no = 0, yes = 1) for a possible score of 0 to 8 points. Using a cut-off score $\geq$ 3, the STOP-Bang questionnaire exhibits high sensitivity to detect any OSA (84%), moderate-to-severe OSA (93%), and severe OSA (100%) [92].

Physical activity and fitness Sensor-based measures of physical activity and fitness measures include daily steps, energy expenditure, activity intensity and variety, physical inactivity, and BMI.

- ☐ *Steps*: Accelerometer-based measurement of steps (steps/day) will be recorded, and participants will be categorized as low active (<5000 steps/day), moderately active (5000–10,000 steps/day), and highly active (>10,000 steps/day) adapted from the Tudor-Locke & Bassett [93] framework (originally: sedentary (<5,000 steps/day), low active (5000 to 7499 steps/day), somewhat active (7500 to 9999 steps/day), active (10,000 to 12,499 steps/day), and highly active (>12,500 steps/day)).

☐ *Total daily energy expenditure*: Based on the work of Livesey [94], daily activity will be computed as the discrepancy from the individual basal metabolic rate (BMR; MJ/day) requirements determined by age, sex, and body weight (kilograms). Participants with total daily energy expenditure <1.5, BMR are considered low active, 1.5–1.7 BMR reflects moderate daily activity, and daily energy expenditure >1.7 BMR will be treated as highly active.

☐ *Activity variety*: Metabolic equivalent of task (MET) minutes/day will be assessed for daily activities [95].

☐ *Activity intensity*: Activity intensity will be computed as mean heart rate in relation to minimum and maximum rate during the measurement period.

☐ *Physical inactivity*: Physical inactivity will be assessed as the number of minutes per days those participants exhibit waking inactivity (sitting, standing) Classification is as follows: <60 min/day = good, 60–240 min/day = moderate, >240 min/day = poor. Also, inactivity disruptions will be measured, operationalized as a disruption of a $\geq$ 30-min inactivity period for at least 1 min (e.g., short walk after a 30-min sitting period).

☐ *BMI*: The BMI will be computed (kg/m^2). According to the WHO [96], participants will be classified as underweight (<18.5 kg/m^2), normal weight (18.5 to 25 kg/m^2), and overweight (>25 kg/m^2). Height and weight are assessed by questionnaire.

Secondary outcomes

Behavioral and experiential outcomes In addition to the three primary outcome domains of stress, sleep, and physical activity, information was collected on experienced back pain, health behaviors, work-related behavior and experience patterns, and personality. These were used to tailor the app. All behavioral and experiential secondary outcomes will be assessed at baseline (T_1), at follow-up measurement after 8 weeks (T_2), and at follow-up measurement after 16 weeks (see Table 1).

☐ *Back pain*: The back complaints of the last 7 days are surveyed using three self-developed items, addressing the location and situations in which back complaints occur.

☐ *Health behavior*: Based on the Health Action Process Approach, 22 items were adapted from Schwarzer [97] to capture motivational and volitional mechanisms that influence individual stress management practices. Items include statements regarding self-efficacy, intentions, outcome expectancies, planning, and actual stress coping behavior (e.g., "How certain are you that you can execute the exercise in the app?"). All items are assessed on a 5-point Likert scale (e.g., 1: not at all certain–5: very certain).

☐ *Work-related behavioral and experiential patterns*: To assess the Work-related Behavior and Experience Patterns (German acronym AVEM), we included four items that were self-developed based on the 44-item original version by Schaarschmidt & Fischer [98]. The original questionnaire comprises 44 questions covering eleven dimensions (subjective meaning of work, occupational ambition, energy expenditure readiness, perfectionism, emotional distancing ability, resignation tendency, offensive problem coping, internal peace and balance, perceived work success, life satisfaction, and perceived social support). Respondents are clustered into one of four patterns (health, conserving, overexerting, and burnout) that can be used to identify individual intervention targets. The condensed 4-item version used for this study was validated in an online survey (e.g., "My job is important to me, but I also manage to distance myself from my work and thus maintain a high quality of life."). The internal consistency of the original version ranges from 0.79 to 0.87 [99].

☐ *Personality*: We will include the Big-Five-Inventory-10 (BFI-10) comprising ten items that economically measures personality based on the five-factor model [100]. The procedure was shown to be reliable in evaluation studies with a retest reliability of 0.49 to 0.84 and exhibited good content as well as convergent validity. An example item of this scale is "I trust others easily, believe in the good in people."

App-related outcomes During the intervention, usage data was also collected that included information about satisfaction with the app, modules completed, intensity of use, and duration of use. App-related secondary outcomes will only be assessed during the intervention period (see Table 1).

☐ *Satisfaction with internet-based programs*: To assess the satisfaction with internet-based training, we include the Client Satisfaction Questionnaire-Internet (CSQ-I), which measures the acceptance towards digital interventions with eight items (e.g., "I am satisfied with the amount of help I received from the training"). The questionnaire has very good reliability with $\alpha = 0.94$ [101].

☐ *App usage data*: Tracking of intervention module finalization and total time spent with allocated modules will be performed.

Data collection, management, and analysis

Relevant outcome variables will be assessed at three time points. The different measurement points are the same for all five intervention groups. The baseline measurement (T_1) is first carried out on the participants directly prior to beginning with the interventions. The post-intervention measure will be performed immediately after the interventions are completed (T_2). After another 6 weeks of no intervention, the sustainability measurement (T_3) will be conducted. For the waiting control group, the first measurement (T_1) will be followed by a period of eight weeks of waiting. The second measurement (T_2) will be conducted after this waiting period. Then participants of the waiting control group will receive one of the interventions and then have their third measurement directly after finishing the respective intervention (T_3). At all three measurement points, the same variables, namely physiological stress, perceived stress, satisfaction with the digital intervention, personality, work-related behavior patterns, and team conflict will be measured.

The respective measurement tools that will be applied are described in the outcomes section including information on reliability and validity. In order to promote data quality, we include evaluated scales that appeared to be reliable and valid in previous studies. We will not conduct duplicate measurements. The collected data will be processed pseudonymously in digital form (from the initial measurement to the sustainability study—approx. 12 weeks).

In order to ensure pseudonymization and simultaneously ensure subsequent deletion of the data, each participant creates a five-digit individual code word immediately after signing the consent form when answering the initial survey, consisting of the first letter of their mother's first name, the first letter of their favorite color, the first letter of their place of birth, the last digit of their year of birth, and the last digit of their day of birth (e.g., MGF01). This code is used instead of other identifier in all subsequent measurements. There is a coding list on paper that links the name to the code but is only accessible to the investigators and the project manager. The coding list is kept in a lockable cabinet or safe and is destroyed after the data collection is completed. If a respondent wishes to delete their data retrospectively, they can use the five questions mentioned above to reconstruct their code word and thus request deletion of the data. After completion of the sustainability measurement, the code used to pseudonymize the employees will also be replaced by assigning a combination of numbers (e.g., 1647) and thus anonymized. Non-anonymized data sets are deleted by the university and the cooperation partners involved in the data collection after completion of the data collection. Data will only be processed in anonymized form within the framework of the study and for subsequent scientific use as well as for publication of the study results.

The anonymized data sets will be stored on a password-protected project folder of the TUB cloud of the TU Berlin for the duration of the project until the completion of all scientific work and associated data analyses. Subsequently, the data will be transferred to a research data repository of the TU Berlin and stored there for a period of 10 years. Access to the server is granted by assigning passwords to the external project partners. The rights to assign the passwords lie with the project leader PD Dr. Bettina Wollesen. After completion of the project, all raw data collected can be made publicly available in anonymized form in a research data repository for an unlimited period of time as part of the Open Science efforts of the scientific community and in accordance with the Berlin Declaration. Personal information about the participants will be protected by pseudonymization of the data sets described above.

Statistical analysis

Primary and secondary outcomes will be analyzed using SPSS software. The study will allow a comparison between all summarized intervention groups with the waiting control group, as well as a comparison between the different intervention groups. Additionally, participation rates will be included in the analyses. Sample characteristics will be explored applying descriptive statistics. Standard analyses adjustments will be made to adjust for baseline differences between groups, in case there are any. For missing data, sensitivity analyses will be conducted to compare results with the complete case analysis. Further, different options for imputation will be considered. Differences between intervention groups and the control group will be investigated using χ^2 tests for categorical variables and independent sample t-tests for continuous variables. General linear mixed models will be applied for the statistical analyses of primary and secondary outcomes. Group-based trajectory modelling will also be applied if feasible given the data situation. The models will be adjusted by baseline value and potential confounders, such as staff field of working (hospital, stationary elderly care, ambulatory care) or age. P values <.05 will be considered as statistically significant and effect sizes of >.3 will be regarded as clinically significant. If appropriate, 95% CI will be reported with the p values as well. If feasible, missing data will be imputed through multiple imputation.

Monitoring

The research team will promote participant retention through close personal support. Contact persons will always be available for any occurring questions or problems. Further regular reminder emails will be sent out as soon as participants appear to fade out of completing the interventions. A respective data monitor will be named and be responsible to supervise the active participation. If there is no response to the reminder emails, participants will be contacted by phone by the research team. If participants decide to withdraw from the intervention, no further data of them will be collected.

All researchers involved in the study will monitor the data and report in case of appearing inconsistencies or other problems. In the beginning of the project, data monitoring will take place on a daily basis. As soon as the study runs smoothly, data will be monitored on a weekly basis.

We do not expect that any adverse effects appear during the study. However, in case any solicited, and spontaneously adverse events are reported, the research team will inform the supervisor and decide based on her expertise how to deal with the events. The investigators will audit the trial conduct on a weekly basis to inspect how the trial is going and whether any adaption or intervention is necessary. This will be done in collaboration with the trial sponsor. In case any protocol amendments will be necessary, the ethical committee that granted approval for the present trial will be informed immediately. Additionally, all participants will be informed about changes. The results of the trial will be reported to participants and their institutions in an anonymized report that is specifically designed to be understandable by people without a scientific background. The study results will further be made available to the public and interested researchers through an open access publication in peer-reviewed journal.

Discussion

The development of a digital intervention to improve the individual's abilities for stress management in different working settings, especially in the health sector, is facing several requirements. Next to the integration of evidence-based feasible interventions, these contents need to be tailored and individualized to gain adherence and long-term usage. Therefore, the main aim of the study is to compare web-based and app-based stress management interventions to identify the most beneficial digital intervention to (a) reduce stress and associated consequences and/or symptoms, (b) increase self-management and self-efficacy, and (c) increase adherence.

Regarding the overall aim, previous studies have shown that the nursing occupation is strongly linked to stress experiences [9]. The working conditions within the health care sector are accompanied by staff shortage and poor health outcomes, which were exacerbated by increased workloads during the pandemic [102]. Previous studies have shown chronic stress and resulting physical, cognitive, and emotional strains in nursing personnel [103, 104]. Regarding the physical conditions, chronic stress leads to reduced heart rate variability [21].

As administrative personnel do not have the same level of intimate encounters with patients, they are less likely to experience work stress. Also, shift work is an independent stressor, which is less of a problem for administrative personnel. Therefore, we suppose the two target groups within our study might show differences in their chronic stress conditions and referring physical reactions (expressed by heart rate). Moreover, it has been shown that the physical conditions might also lead to reduced sleep quality or duration [105]. With respect to the different nature of work-related burdens within nursing and administrative personnel, these circumstances might also lead to differences in individual sleep quality.

Due to previous studies providing positive effects of app-based stress management and mindfulness interventions on wellbeing, reduced stress, anxiety, and depression [67, 68], these types of interventions should be tailored and adopted to specific requirements of the target groups within this study. Also, work-specific stressors and back pain are known to be interrelated, with a potential bidirectional causality. For both groups, the underlying mechanisms might be different. While nursing personnel has to compensate heavy loads on the spine according to care processes with awkward body positions under time pressure, administrative personnel have long sitting periods without moving [103, 106]. However, despite the different strains on the musculoskeletal system, stress is commonly associated with increased blood pressure and an augmented perception of pain [20, 107].

Overall, the study results will help to gain more evidence of the effectiveness of these interventions for health personnel according to positive benefits on stress reduction. This will be gained by an appropriate small sample size, appropriate study designs, and follow-up measurements to address the relevant aspects identified [54, 59]. Moreover, we expect to find a positive correlational link between stress level of participants and back pain severity as well as a negative correlational link between stress level of participants and physical activity level [11].

Also, the digital interventions allow more temporal flexibility for usage and therefore might help to overcome organizational, social, and individual reasons and barriers for participation proposed by Zhang et al. [108]. Additionally, healthcare personnel are difficult to reach due to low motivation to change, low self-efficacy, and high psychological and physiological demands [109]. Increasing the motivation and improving the stress coping related self-efficacy of healthcare personnel can be achieved by including measures of behavior change mechanisms. Whether a health intervention will be successful in changing a behavior in the desired direction is contingent on changes in motivational and volitional aspects, such as intention to change and planning behavior. As individualized interventions are theorized to be more motivating than generalized interventions, we expect the need of tailored conditions to be associated with improved self-efficacy, intentions, planning, and actual behavior compared to generic and waitlist control conditions. These changes will be accompanied by health behavior stages (i.e., from non-intending to intending to acting). At the same time, organizational barriers (e.g., inadequate social support, high job demands) for behavioral change are known to prevail in the nursing sector compared to facilitators [110] which influence the change outcomes. Organizational barriers may be less problematic in the administrative setting, which could show in better intervention results for administrative vs nursing personnel. The individualization and the just-in-time-adaptive intervention [111] approach of the sensor-based app interventions are expected to be particularly successful in decreasing perceived work stress. Web-based, non-individualized interventions will likely also yield desirable results, however to a lesser degree.

One-size-fits-all interventions have been found to produce fewer desirable results than need-tailored interventions [63]. We expect biofeedback-based, need-tailored digital interventions to be superior in terms of stress reduction and physical activity improvements than generalized, nonspecific online courses. However, the presented biofeedback system has not been tested before systematically. It might therefore be the case that additional intervention necessities emerge by means of the sensor screenings. As an example, if sleep recovery is found to be of particular low quality, recommendations will be made to specifically target sleep in future interventions.

Next to the positive effects of tailoring the interventions to gain higher effects of individual stress responses, individualization might be expected to increase the adherence of the participants [112]. A continuous participation in an intervention program is necessary to gain positive adaption and long-term effects. The interventions of this study integrate different forms of strategies (e.g., tailoring, self-tracking) that are helpful to maintain a certain behavior [113, 114]. To our knowledge, there is no study that compared these different approaches within care settings, yet. Therefore, with this study, we detect new insights into the most beneficial composition of the program with respect to adherence according to the acceptance rates.

Further, moderators for intervention effects will be analyzed. For instance, a higher degree of usability for younger participants vs elderly participants may be apparent. However, it has recently been shown that elderly people are improving their e- and mHealth literacy [115]. Thus, whether or not relatively young participants profit more from the current intervention will be analyzed.

In summary, this trial integrated evidence-based contents demonstrating positive effects on stress management and converted these contents for the use of digital health in the context of healthcare work. Moreover, the approach integrates individualization to the digital offers to improve effectiveness and adherence.

Limitations

This study comes with limitations: The participants will be asked to fill in questionnaires that come with known issues such as social desirability, tendency to the middle, common method bias, and subjectivity due to self-perception. Further, a lack of time in a highly stressed population that nurses are may lead to answering under time pressure and thus not reading the questions of the survey with necessary attention. Another possible limiting factor can be the interchange about the health promotion programs between nurses in different groups which might cause changes in the waiting control group. Further, work culture, team environment, and management can affect intervention uptake and thus the interventions effectiveness.

Practical implications

The current study can provide useful information for workplace health promotion interventions aimed to improve work ability of health care workers. This large-scale trial is the first to assess the feasibility of an mHealth intervention for a highly stressed target group that requires special societal attention as nursing shortages are present in many countries. To counter health care worker disease and job turnover, health promotion experts should consider both the positive preliminary results and issues pertaining to adherence and participant attrition.

Trial status

By the time of submission of this study protocol, we have already received a positive ethics vote from the local ethics committee of the Technical University of Berlin, as well as successfully registered the study with the DRKS (German Registry for Clinical Trials; available on https://drks.de/search/de/trial/DRKS00024605). We are currently in the participant recruitment phase. At the time of the initial study protocol submission, we entered the recruitment phase. We began recruiting in April 2021 and completed in March 2022. In parallel to the recruitment phase, the first facilities initiated the measurement phase. To date, data measurement has started in September 2021.

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Authors' contributions
The steering committee for this trial will be composed of three parties: BW, LH, and HB (TU Berlin); Silvester Fuhrhop, Jessica Vogesser, and Malte Kirst (corvolution); and Johannes Heering, Particia Nixon, and Nina Wegener (FitBase). During the recruitment and assessment period, this committee meets on a weekly basis to monitor the current status of the trial. The steering committee provided day to day support for the trial and organizational support. This study protocol was carried out in collaboration of all authors. Prof Dr. BW developed the project idea and is the head of the multicenter study. Study contents were additionally refined by LH and HB (PhD candidates). They also wrote the first draft of the manuscript. Prof Dr. BW and HB calculated the sample size according to the data analysis plan. All authors have been involved in the drafting and contributed significantly to the revision of this manuscript. The authors approved the final manuscript. Prof Dr. BW was the project supervisor, the scientific expert with the highest academic degree in our team and was responsible for study design, coordination, and data management. LH and HB were supporting with the study design, coordination, and data management. Corvolution GmbH and Fitbase GmbH were responsible for data assessment and data processing of the sensor- and app-related data. Prof Dr. BW, LH, and HB represent the data monitoring committee for the proposed study. Their data monitoring strategy is described in this monitoring section above.

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The basis of the funding was the scientific concept. The study including the fitcor intervention is part of the project DiCiS—"Digital coaching of individual stress management skills using sensor technology, feedback, and app for nurses". Besides the nursing facilities' recruiting process, the funding body played no part in study design; collection, management, analysis, and interpretation of data; writing of the report; and the decision to submit the report for publication. Trial data will be analyzed independently of the trial sponsors and funding body. Open Access funding enabled and organized by Project DEAL.

Availability of data and materials
All participant information and data will be stored securely and identified by a coded ID number only to maintain participants' confidentiality. It is planned to transfer the data to an open access repository. The datasets analyzed during the current study and statistical code are available from the corresponding author on reasonable request, as is the full protocol.

Declarations

Ethics approval and consent to participate
The multicentric RCT is conducted in agreement with the principles of the Declaration of Helsinki and the guidelines of Good Clinical Practice. Written informed consent will be obtained from all participants or their legal guardians before enrolment in the study. On the consent form, participants will be asked if they agree to use of their data should they choose to withdraw from the trial. Participants will also be asked for permission for the research team to share relevant data with people from the Universities taking part in the research or from regulatory authorities, where relevant. This trial does not involve collecting biological specimens for storage. There is no anticipated harm and compensation for trial participation. Therefore, this trial is considered to be a low-risk trial. The local ethics committee of the TU Berlin, Germany, has approved the study protocol (No GR_14_20191217). The trial was registered at the German Register for Clinical Trials (DRKS.de) with registration number DRKS00021423 on 12 July 2021: Online available at: https://drks.de/search/de/trial/DRKS00024605.

Competing interests
The authors declare that they have no competing interests.

Author details
[1]Institute of Biological Psychology and Neuroergonomics, Technical University of Berlin, Fasanenstr. 1, 10623 Berlin, Germany. [2]Institute of Human Movement Science, University of Hamburg, Turmweg 2, 20148 Hamburg, Germany. [3]Institute of Interdisciplinary Exercise Science and Sports Medicine, Medical School Hamburg, Am Kaiserkai 1, Hamburg, Hamburg 20457, Germany.

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Publisher's Note

Article

Efficacy of individualized sensory-based mHealth interventions to improve distress coping in healthcare professionals: A Multi-Arm Parallel-Group randomized controlled trial

Hannes Baumann [1,2,3,*], Luis Heuel [1], Laura Bischoff [2] and Bettina Wollesen [2]

[1] Technical University Berlin; hannes.baumann@tu-berlin.de; luis.heuel@tu-berlin.de
[2] University of Hamburg; Hannes.baumann@uni-hamburg.de; laura.bischoff@uni-hamburg.de; Bettina.wollesen@uni-hamburg.de
[3] Medical School Hamburg; hannes.baumann@medicalschool-hamburg.de
* Correspondence: Hannes.baumann@uni-hamburg.de; Tel.+4917691451066

Abstract:

Consequences of chronic distress in healthcare professionals are well established. Yet, implementing and evaluating high-quality interventions to improve distress coping in this setting remains deficient. Individualized mHealth interventions including sensor feedback represent a promising approach. This study examined whether individualized, sensory mHealth interventions focusing on stress and physical activity can improve distress coping in healthcare professionals. This multi-arm, parallel group randomized controlled trial compared five intervention groups, representing different levels of individualization (study arms: 1=WBT, 2=WBT+Need, 3=WBT+Need+Coaching; 4=APP+Biofeedback, 5=App+Biofeedback+Healthreport), with a control group. Both, questionnaires (Limesurvey) and ECG- and accelerometry-based sensory data (Mesana Sensor; HRV and physical activity data) were assessed at baseline and after eight weeks. 170 of 995 eligible participants (26%) completed post measurement (1: N=21; 2: N=23, 3: N=7; 4: N=34; 5: N=16, Control: N=69). MANOVA indicated small to moderate time*group interaction effects for physical activity related outcomes MVPA and inactivity-disruption in studyarms 4 and 5, but not for Steps/day and inactivity. Stress-related HRV parameters did not change over time. Despite high dropout rates and complex study design, individualized interventions revealed initial effects on physical activity, but not the expected effects on stress-related outcomes. Thus, intervention duration was not sufficient to induce physiological adaptations associated with improved distress unlike changes in physical activity behavior.

Keywords: biofeedback; tailoring; digital health, nurses, ECG, Sensor, eHealth, heart rate variability, accelerometry, healthapp

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1. Introduction

Occupational psychosocial stress can increase the risk of developing psychological, musculoskeletal, or cardiovascular diseases [1,2]. Healthcare professionals are particularly prone to experience exceptionally high levels of occupational stress [3] leading to serious individual, organizational, and societal problems as for example shortages of skilled professionals [4]. Also, more than one in four nurses consider leaving the profession [5]. Additionally, healthcare institutions often fail to retain long term personnel, exposing healthcare professionals to a vicious cycle of stress [6]. This is consistent with findings from previous studies indicating higher occupational distress in health care occupations than in other occupations [7]. Recurring stressors in health organizations include high work demands, leadership style, few participation opportunities for work structuring, emotional burdens, lack of appreciation, and work-family conflicts [8,9]. In turn, these stressors may influence recreational activities of the affected persons. For instance, sleep and physical activity levels have been found to be poor in stressed individuals [10,11]. Frequent or chronic occupational distress results in serious health consequences. If work-related demands outweigh individual, social, and organizational resources [12] affected individuals may incur psychological and physiological consequences such as sleep disorders, gastrointestinal complaints, burnout, diabetes, and coronary heart disease [13–16]. In severe cases, inability to work can lead to long-term sickness absenteeism [17].

In general, psychosocial stressful stimuli activate neuronal, neuroendocrine, and endocrine pathways. Thus, a physiological response to stress occurs, among others, at the neurological level, through receptors of the sympathetic nervous system that stimulate the sympatico-adrenomedullary axis. The hormones adrenaline and noradrenaline are released in the adrenocortical medulla, leading to an increase in heart rate and a decrease in heart rate variability (HRV) under physical or psychological stress [18]. Such biological responses to stressful stimuli may be adaptative. However, extreme, frequent, or chronic activations of stress axes may be detrimental to health and may be assessable via HRV [19,20]. Chronically low HRV is associated with impaired regulatory and homeostatic functions of the autonomic nervous system, which reduce the body's ability to cope with internal and external stressors. For instance, individuals with lower HRV were more likely to report poorer quality of sleep in the context of chronic stressor exposure than individuals with higher HRV [21]. Thus, HRV measurement is a noninvasive method that can be used to measure the autonomic nervous system in a variety of settings [22]. For instance, it has been shown that in response to stress-inducing tasks, such as the Trier Social Stress Test, individuals show low parasympathetic activity, characterized by a decrease in High Frequency Power (HF) and an increase in Low Frequency Power (LF) HRV values [22–24]. The Standard Deviation of Normal-to Normal heart beats (SDNN value) represents an index of physiological resilience to stress. When HRV is elevated and irregular, SDNN increases. On the other hand, chronic (occupational) stress is linked to a decrease in the SDNN [22,25]. A low Root Mean Square of Successive Differences (RMSSD) value can also be an indicator of stress, with values lower in chronically stressed vs. non-stressed individuals [18,24,26]. However, it should be noted when evaluating HRV data that - beyond psychological stress - certain influencing variables must be considered. Age has a significant influence on HRV. It initially increases with age, peaks in young adults, and then decreases with increasing age [27,28]. In addition, BMI correlates positively with sympathetic activity [29] and thus negatively with HRV [30,31], whereas regular physical activity is associated with an increase in HRV [32].

While health complaints are frequently observed, there are personal and organizational resources which can improve resilience toward occupational stress [33,34]. Personal resources concerning coping qualities include social support, coping style, self-efficacy and optimism [35]. Pertaining to organizational resources, a recent systematic review identified supervisor support, job autonomy, and provision of work equipment to minimize stress [36]. Stress may also affect healthcare professionals differentially[43]. For instance, nurses exhibit less health behaviors [e.g., physical activity] than physicians, pharmacists, and administrative health personnel [37]. According to Gerber and Pühse [38] physical activity may exert a stress-buffering effect and thus protect against physical and psychological illness. Although a variety of stressors exist in healthcare professionals, evidence suggests that perceived stress can be reduced through the participation in stress management interventions.

For instance, mindfulness programs improve quality of life, anxiety, stress perception and sleep quality [39,40]. Physical activity-based studies showed improvements in autonomous nervous system function [41], accelerometric factors such as steps per day [42], BMI, sedentary behavior, MET, and physical activity levels [43]. Physical activity can help reduce stress by improving physical and emotional well-being across at least three pathways. (1) It reduces the release of stress hormones: During physical activity, endorphins are released, which increase well-being and decrease the release of stress hormones such as cortisol, (2) physical activity promotes relaxation: Physical activity can help relax muscles and release tension that builds up during stress, and (3) physical activity improves mental health: physical activity can help reduce symptoms of depression and anxiety and improve self-esteem [44,45].

Within the health care sector, efficacious stress reduction programs include Yoga and qigong [45], cognitive-behavioral interventions such as resilience training [46], Mindfulness-based stress reduction (MBSR) [47] or multimodal combinations of aforementioned intervention types [48]. According to literature, four tasks that need to be completed when designing individual-level interventions for healthcare professionals: identifying barriers, selecting intervention components, using theory, and engaging end-users [49] The length of a health intervention will depend on a variety of factors, including the specific health problem being addressed, the goals of the intervention, and the resources available. Some health interventions may be short-term, lasting only a few days or weeks, while others may be long-term, lasting months or years [50]. In general, it is important to carefully consider the length of a health intervention and to ensure that it is sufficient to achieve the desired goals. Short-term interventions may be appropriate for addressing acute health problems or for providing targeted support for specific populations. However, long-term interventions may be necessary for addressing chronic health problems or for addressing more complex health issues that require sustained support and intervention [49]. It is also important to consider the sustainability of a health intervention and to ensure that it can be maintained over the long term. This may involve developing strategies for funding, staffing, and resource management, as well as engaging community members and other stakeholders in the planning and implementation of the intervention .

Despite the plethora of studies confirming the efficacy of stress reduction interventions, the evidence for health personnel is insufficient. Study rigor issues, for instance low total intervention time, small sample sizes, and high dropout rates undermine intervention quality [51]. Further, elevated risk of bias due to lack of both appropriate study designs and follow-up measurement points are common [45]. The poor evidence base in the field of study is due to organizational, social, and individual reasons. According to Zhang et al. [52], participation in health promotion campaigns in health care facilities is often aggravated by various barriers. Specifically, poor communication between management and staff, colleague peer pressure, insufficient staffing, top-down decision-making, and budget constraints can impede participation rates. Additionally, healthcare personnel are difficult to reach due to low motivation to change, low self-efficacy, and high psychological and physiological demands [53]. Moreover, due to differences in individual and organizational resources, stress management interventions should be individualized to the specific needs of participants. One possibility is to categorize subjects in terms of coping style when facing challenging work situations [54]. Further, individual preferences for health promotion are apparent. For instance, health and other non-health related outcomes [e.g., the value of a healthy future self and time costs, respectively] have differential impacts on the decision to engage in stress management [55]. Thus, one-size-fits-all interventions [56] should not be adapted for vulnerable populations as intervention success is limited [57]. In sum, to counteract stress effects in health personnel, low-cost, easy-to-implement, setting-specific, and need-individualized health promotion interventions are necessary. One way to address these issues are digital interventions, especially when delivered via a mobile device (mHealth).

Recent developments and studies highlight the opportunities of digital interventions to address the described concerns for implementing and evaluating interventions in the health care sector and the current stage of change readiness. mHealth interventions yield the potential to address stress in a low-cost, easy-to-implement fashion [58] with existing evidence for stress-reducing effects in different occupational settings [59]. Interestingly, internet-based interventions have been rarely implemented in the healthcare sector so far [60].

Digital health promotion programs can come in different modalities: Web-based trainings (WBT) are presented on a secured online platform and assessed through an internet browser either on a smartphone or on a computer/laptop [61,62], whereas app-based interventions are delivered via smartphone application only [60]. However, there are also hybrid forms such as web apps. mHealth Interventions can be a low-threshold opportunity for health promotion and are a promising possibility to achieve prevention goals [63]. The free allocation of time and flexibility of availability were evaluated on a positive note. Combining such apps with so-called "wearables", such as smartwatches or fitness trackers, could be a promising approach to continuously record health data and thus constitute various opportunities in the context of prevention work (Gamification, Just in time adaptive interventions). By implementing wearable devices into mHealth applications (apps), health-related data (e.g., sleep patterns, eating patterns, and exercise) could be recorded and respective need-tailored interventions be derived [64]. Previous studies already showed positive effects of stress apps on wellbeing. Harrer et al. [65] for example found that app-based stress management interventions improved stress, anxiety, and depression in college students. Another example stems from research by Economides et al. [66] who found that a mindfulness app intervention reduced stress and irritability, while it also increased positive affect. At the same time, expectations towards health apps are high, 70% of health app users believe that these can strengthen self-motivation and 56% think that app use can improve health education [67].

In order to establish long-term health behavior changes in healthcare workers, an elevated level of adherence motivation during the intervention implementation is necessary, and therefore individualized approaches may be beneficial. Often, the adherence to digital health promotion programs is low, which reduces their effectiveness [68]. Individual tailoring [69,70] or gamification could be approaches to address this problem. A meta-analysis, showed that web-based individualized interventions clearly outplayed generic interventions with respect to health behavior change [70]. In particular, non-individualized interventions were found to decrease user satisfaction [71]. However, the definition of an individualized health app remains unknown due to the lack of a framework for individualized app elements [72]. In the context of mHealth, individualization is defined as an adaptation to the needs or special circumstances of an individual and the lack of such is cited as one of the main barriers that prevent patients from behavior change. [73,74]. Individualized interventions (sometimes also called adaptive, needs-specific, target group–specific, tailored, or personalized interventions) offer a potential way of delivering person-centered interventions by varying levels of individual needs and empowering individuals to monitor their health actively [75]. In one of the few reviews that address this issue, the authors enumerated the individualized elements in the app and determined the level of individualization of mHealth intervention [76]. The evidence of this review is clear, however, there is a wide range of potential approaches for individualization, and these are often accompanied by established behavior change mechanisms.

Potential opportunities for individualization are (1) the adaptation of intervention content to individual needs for behavior change (2) individual coaching based on intervention results (3) direct biofeedback via app and sensor interfaces (4) visualization of health data e.g. in the form of health dashboards or health reports or (5) the adaptation of content based on psychological characteristics, such as personality traits. Needs assessment, health reports and coaching have already been discussed above. The most commonly used devices in biofeedback differed depending on the outcome of the evaluation. For physical activity parameters ActiGraph accelerometer (Actigraph, LLC, FL), SenseWear wristbands (BodyMedia, Inc., PA), Actical (Mini Mitter Co., Inc., OR), or Active style Pro (Omron Healthcare Co., Ltd., Kyoto, Japan) are the most common [77]. Accelerometer sensors are devices that measure acceleration or changes in movement or position. They are commonly used in a variety of applications, including smartphones, fitness trackers, and wearable devices.

Advantages of accelerometer sensors include: (1) High sensitivity: Accelerometer sensors are highly sensitive and can accurately measure even small movements or changes in position; (2) Compact size: Accelerometer sensors are small and lightweight, making them easy to incorporate into a variety of devices and systems; (3) Low power consumption: Accelerometer sensors have low power requirements and can operate for long periods of time without needing to be recharged; (4)Versatility: Accelerometer sensors can be used in a wide range of applications, including motion sensing, activity tracking, and gesture recognition. Potential disadvantages of accelerometer sensors include: (1) Limited accuracy: While accelerometer sensors are highly sensitive, they may not be as accurate as other types of sensors, such as gyroscopes, in certain applications; (2) Vulnerability to noise: Accelerometer sensors may be prone to interference or "noise" from external sources, which can affect their accuracy and performance, (3) Limited range: Accelerometer sensors may have a limited range of movement or acceleration that they can measure, depending on the specific device or application. Nevertheless, accelerometer sensors are useful and versatile devices that have a wide range of applications. However, it is important to consider the potential limitations and challenges of using accelerometer sensors in order to ensure the best possible performance and accuracy.

For stress-related parameters, photoplethysmography (PPG) based wearable devices such as earlobe sensors, blood pressure monitors, finger bracelets and wristwatches, or electrocardiogram (ECG)-based devices such as chest belts or patches are commonly used, with the latter exhibiting higher sensitivity and specificity values [78]. ECG sensors are devices that measure the electrical activity of the heart and are used to diagnose a variety of cardiac conditions. Advantages of ECG sensors include: (1) Non-invasive: ECG sensors are non-invasive and do not require any penetration of the skin or tissue, making them relatively safe and painless to use; (2) High sensitivity: ECG sensors are highly sensitive and can accurately measure the electrical activity of the heart, even in the presence of noise or interference; (3) Portability: ECG sensors are portable and can be used in a variety of settings, including hospitals, clinics, and home care settings and (4) Versatility: ECG sensors can be used to diagnose a wide range of cardiac conditions, including arrhythmias, heart attacks, and coronary artery disease. Potential disadvantages of ECG sensors include: (1) Limited accuracy: While ECG sensors are highly sensitive, they may not be as accurate as other diagnostic tests, such as echocardiography, in certain situations. (2) Vulnerability to interference: ECG sensors may be prone to interference or "noise" from external sources, such as electrical devices or electromagnetic fields, which can affect their accuracy and performance and (3) Limited scope: ECG sensors can only measure the electrical activity of the heart and do not provide information about the structure or function of the heart or other organs. Overall, ECG sensors are useful and valuable diagnostic tools that have a wide range of applications. However, it is important to consider the potential limitations and challenges of using ECG.

Beside sensory based biofeedback, another approach to design individualized digital solutions could be the integration of personality traits. A smartphone app that focuses on stress reduction may firstly focus on personality characteristics, as studies showed that personality characteristics are associated with specific coping behavior [79], app usage behavior, and receptivity to gamification elements [80]. Implementing personality traits into mHealth interventions offers the opportunity to systematically individualize the content. Besides the adaptation to personality, it is also necessary to address health behavior change intention. Thus , if participants are not intending to change their activity levels and stress coping behavior, the intervention might fail to succeed. However, the intervention could be tailored to target the individual at the current stage of health-related behavioral change. In summary, for the development of a digital health intervention, the specific combination of different components has to be considered. These are: (1) evidence based feasible interventions, (2) tailoring and individualization and (3) additional elements to gain adherence and long-term usage.

Therefore, the present study aims to compare both web-based vs. app-based and individualized vs. non-individualized stress management interventions in terms of their effectiveness. The main research question is whether eight weeks of differentially individualized sensor-based mHealth interventions (1 = WBT, 2 = WBT + Need, 3 = WBT + Need + Coaching; 4 = APP + Biofeedback, 5 = App + Biofeedback + Healthreport) focusing on stress management and physical activity can impact HRV related stress parameters (SDNN, RMSSD, LFHF & Baevsky Index) and accelerometry related physical activity parameters (Steps, MVPA, Inactivity & Inactivity disruption) and therefore improve distress coping in health professions. We hypothesize that individualized interventions will have small to moderate positive effects for physical activity and stress-related outcomes in relation to distress coping in health professions, whereas non-individualized interventions will not show significant effects.

2. Materials and Methods

2.1. Trial Design

This multi-arm parallel group randomized controlled trial (including five intervention groups) was conducted and described [76] according to the CONSORT guidelines [81], including the necessary extensions [82,83]. All participants of the intervention groups received a digital intervention. Both, questionnaire and sensory data were assessed at baseline (T1 pre-intervention assessment) and at eight weeks (T2: Post-Intervention assessment). However, this paper only refers to the sensory data. The five intervention groups were conducted as follows (see table 1):

Table 1: Brief description of intervention groups

No.	Intervention	Type	Need	Biofeedback	Coaching	Report
1	Web-based digital stress management intervention	Web-based	No	No	No	No
2	Web-based need-oriented digital stress management intervention	Web-based	Yes	No	No	No
3	Web-based need-oriented digital stress management intervention with telephone coaching	Web-based	Yes	No	Yes	No
4	App-based personality specific digital stress management interventions with sensory biofeedback	App-based	No	Yes	No	No
5	App-based personality specific digital stress management intervention with sensory biofeedback and health report	App-based	No	Yes	No	Yes

2.2. Participants

The trial included multiple healthcare professionals (nursing staff and office workers) aged 18 years or older. No clinical patients were involved in the proposed study. An a priori power analysis with G*Power [84] indicated the necessity of at least 700 participants to show moderate effect strengths (0.25) with a beta error of 80%. The executives of collaborating hospitals, stationary elderly care facilities and ambulatory care providers forwarded an explanatory video to their employees via in house communication networks, whereupon they voluntarily entered their contact details into an online tool to register for the study. Fluency in German language as well as internet access via a smartphone device were prerequisites for study participation. In order to improve adherence to interventions, a user centered approach was chosen to integrate experiences and test the functionality of the app internally and externally. After agreeing to participate, numerous reminder emails were created, which were automatically sent to the participants if they failed to order the sensors or missed the registration.

To prevent selection bias, the allocation of participants to the intervention- and control groups was randomized . The random allocation at individual level was conducted with the tool Research Randomizer [85] using continuous block randomization. Sets of six numbers were generated, representing the differing number of study and control groups. Each participant was then assigned the subsequent number on the block randomization list for group assignment. As participants were assigned to an intervention group or the waiting control group by lot, no further mechanisms of implementing the allocation sequence were needed. Unblinding of the data assessors was not necessary.

Trial participants were informed about which intervention group they were assigned to as they needed to receive the respective information to complete all necessary information and access the digital intervention programs. Furthermore, participants were informed in advance to ensure the intervention is implemented during working hours and outside of vacation periods. The data collection of primary outcomes was also blinded, as participants self-completed the online questionnaire and the sensor screening was similarly conducted without the involvement of a third party, as participants self-applied the sensor to their bodies. All data analyses were conducted by blinded evaluators.

2.2. Interventions

There were five different intervention scenarios (studyarms), each including a WBT or an app, and each with various levels of individualization. The App Interventions included individualization according to the AVEM personality type (work-related behavior and experience pattern) [86]. This trial became particularly complex due to the need orientation of the WBT interventions. Depending on the needs of a person, the participant was assigned to a different WBT. For example, someone with insufficient physical activity and severe obesity has been recommended a WBT for weight loss, while someone suffering from high stress levels has been recommended a WBT with autogenic training or mindfulness. For this reason, a detailed list of the content covered in the respective app or WBTs is provided in Table 2 below.

Likewise, the distinguished stress and physical activity-specific content of the interventions can be inferred from the table. The app-based study arms featured higher levels of individualization than the WBTs. The content of the app-based mHealth interventions (study arms 4 and 5) was also developed exclusively for use on a smartphone (see Figure 3 for insights into UI design), whereas the WBT-based mHealth interventions (studyarms 1,2 and 3) could also be accessed using a web browser on a desktop computer.

Table 2: Detailed list of study arm specific intervention modules ((x) = it depends on study arm if this individualized feature occurs)

Focus	Sub focus	App	WBT							
			Nutrition	Weight loss	Physical Activity	Spine Gymnastics	Mindfulness	Hatha Yoga	Sleep and Stress	Autogenic training
Individualization	Direct biofeedback	x								
	AVEM patterns	x								
	Telephone coaching		(x)	(x)	(x)	(x)	(x)	(x)	(x)	(x)
	Health Report	(x)	(x)	(x)	(x)	(x)	(x)	(x)	(x)	(x)
	Need orientation		(x)	(x)	(x)	(x)	(x)	(x)	(x)	(x)
Stress and relaxation	Problem-focused	x								
	Deep breathing	x					x	x	x	x
	Mindfulness	x					x	x	x	
	Goal setting	x		x	x		x		x	x
	Gratitude journal	x					x	x	x	
	Positive psychology	x					x	x	x	x
	Autogenic training	x					x	x	x	x
	Muscle relaxation	x					x	x		
	Body perception	x					x	x		
	Stress physiology									x
Physical activity	Stretching and yoga	x			x			x		
	Fascia training			x	x	x				
	Behaviour change	x								
	Activity habits	x								
	Endurance training	x			x					
	Anatomy			x	x	x				
	Spine health					x				

(a) (b) (c)

Figure 1: UI-Design of the App (**a**) breathing meditation user interface; (**b**) user interface of the landing page with a brief summary of vital parameters; (**c**) training progress user interface

2.2. Outcomes

The assessment applied a selection of standardized questionnaire measures as well as sensor-based physiological and vital parameter measures (measured by Corvolution CM300 [87], which includes ECG circuit, 3-axis acceleration and rotation rate chip, air pressure chip, thoracic impedance chip and temperature chip) [88,89]. The sensitivity of patch-based ECG sensors such as this is 93.4-97.0%, and the specificity is 95.6-98.8% [78]. Additionally, demographic characteristics, such as age, gender, and job hierarchy were assessed via standardized questionnaires within Limesurvey 5.4.15 [computer software] [90]. The detailed description of all parameters can be found in the study protocol [76]. However, the current study focused on the sensory datasets in the stress and physical activity domains. The following parameters were considered (see table 3 below):

Table 3: Summary and description of relevant outcome parameters

Parameter	Unit	Description [91]
SDNN	ms	Standard deviation of all RR intervals includes fluctuations over shorter as well as more widely divergent time periods.
RMSSD	ms	Square root of the squared mean value of the sum of all differences of successive RRintervals. Marker for selective assessment of efferent vagus activity and parasympathetic influence on the heart.
LF/HF ratio	%	Quotient of LF and HF: LF = power density spectrum from > 0.04 to 0.15 Hz, percentage LF of the full spectrum. This parameter characterizes the potency of the low frequency components and can be attributed to parasympathetic as well as sympathetic activity; HF = power density spectrum from > 0.15 to 0.4 Hz, percentage HF of the full spectrum, mediated by respiratory-induced modulations of parasympathetic activity.
Beavsky	Index	Measure for characterizing recorded ECG signals or RR intervals. Reflects the degree of central control of the heart rhythm and characterizes the activity of the sympathetic part of the autonomic nervous system (VNS). It serves as an indicator of shifts in the balance of the VNS, i.e., changes in the balance between the effects of the sympathetic and parasympathetic nervous systems.
Steps	Counts/day	Accelerometer measured number of steps taken per day.
MVPA	Min/day	Accelerometer measured time spend in moderate to vigorous physical activity per day.
Disrupt	Counts/day	Accelerometer measured inactive period disruption counts. Counting occurs when a > 30-minute period of inactivity is interrupted with physical activity. This parameter serves as a measure of behavior change.
Inactivity	Min/day	Inactivity or sedentary behaviour is defined by any waking behavior characterized by an energy expenditure ≤1.5 metabolic equivalents of task [METs] while in a sitting, reclining, or lying posture [92].

2.2. Analysis

Although three measurement points were originally planned, this analysis includes a pre-post comparison only, since insufficient sample size was available for a three-stage analysis. The baseline measurement (T1) was first conducted on participants immediately prior to the start of the interventions. The post-intervention measurement was conducted immediately after the completion of the interventions (T2). The same variables were measured at both measurement time points, namely physiological stress, exercise parameters, perceived stress, satisfaction with the digital intervention, personality, work-related behaviors, and team conflict. The measurement instruments utilized at each time point are described in the study protocol, including information on reliability and validity. To promote data quality, only evaluated scales that have been shown to be reliable and valid in previous studies were used. The collected data was pseudonymized and processed in numerical form. For the purpose of this statistical analysis, only primary sensor-based outcomes were analyzed using SPSS, JASP, and R-Studio software. The study allows for comparison between the five intervention groups and the control group. Additionally, participation rates were included in the analyses. Descriptive statistics were used to examine the characteristics of the sample. Within subject differences between the intervention groups and the control group were tested for using group*time effects in a MANOVA, Bonferroni tests, and linear mixed models.

3. Results

3.1. Flow-chart

Based on the results of an a priori power analysis and an expected dropout rate of 20% (this appeared to be a realistic participation rate in previous intervention studies in different small and middle-sized companies [93]), we were able to out-recruit slightly and obtain a total of 995 participants from multiple institutions. We started the eligibility assessment in June 2021 and completed the data collection in June 2022. Among the 995 eligible participants, 113 failed to respond to contact attempts and 239 retrospectively declined to participate due to lack of time or illness. Therefore, merely 643 participants were assigned to the study groups and received interventions (see Figure 2). Due to organizational (e.g., shift work, lack of time), technological (e.g., synchronization errors, outdated operating system), and physiological reasons (e.g., allergies, illness, or arrhythmias), a total of 258 subjects were unable to complete the baseline measurement despite receiving the sensor and the intervention. We further lost 218 subjects to follow-up measurement. This resulted in the analysis of a total of N = 170 participants, which corresponds to a total dropout rate of 74%. Studyarm-wise, 16% of participants completed the post measurement after the app intervention + biofeedback, 18% after the WBT intervention, 19% after the app intervention + biofeedback + health report, 20% after the WBT intervention + need orientation + coaching and 33% after the needs-based WBT intervention.

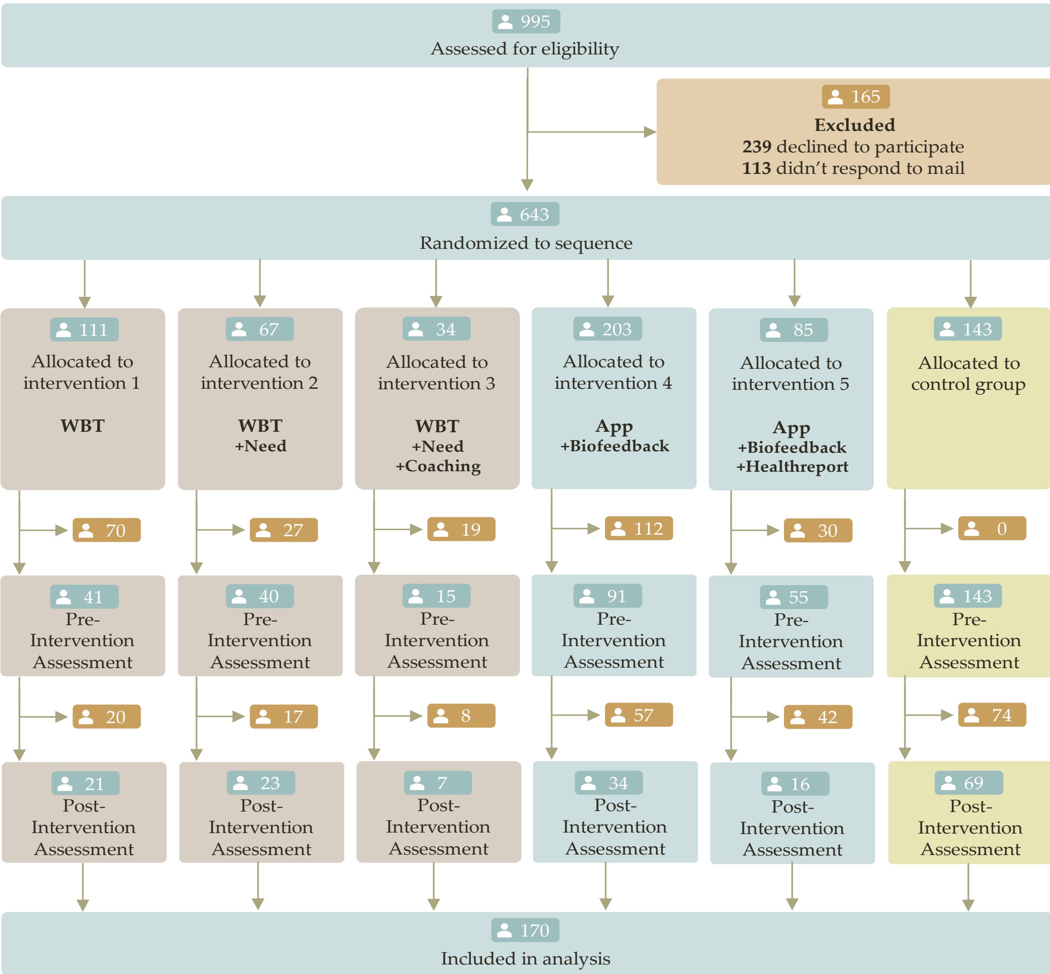

Figure 2: Consort Study flow for multi-arm parallel group randomized controlled trials [81–83]

3.1. Baseline Data and main analysis

Table 4 reports the descriptive values and statistics of each measurement point (Pre-Intervention Assessment and Post-Intervention assessment) and each study arm. The participants were analyzed in their original assigned groups. There were no significant differences in baseline demographics between the intervention and control groups. Furthermore, participants lost to follow-up were not significantly different from those considered. Across all study arms, there were more female than male participants in the sample. The average age of participants at baseline was 41.1∓10.9 years. The group size of the study arms was not identical and varied from 34-203 participants per group at baseline to 7-69 participants per group at post assessment. The statistical analysis (MANOVA) indicated significant time*group effects for the two physical activity-related outcomes MVPA minutes as well as inactivity disruption counts. Post-hoc-analysis revealed individualized app study arms (4 and 5) to be significantly different from the control group and less individualized WBT study arms (1, 2 and 3) in these outcomes. Participants in study arm 4 increased their activity time by 72.5∓45 minutes and participants in study arm 5 by 69.3∓11.7 minutes, whereas in all other study arms and the control group, activity time decreased. A similar pattern can be seen for inactivity disruptions: While the number of inactivity disruptions per day increased significantly in app trials by 4.9∓3.5 in studyarm 4, and 5∓1.5 in studyarm 5, respectively, it decreased in all other study arms and the control group. In addition, time*trialgroup (intervention vs control group) and time*interventiontype (app vs WBT) effects have also been tested. The results showed significant effects on the same outcome variables, although the magnitude of the effect was smaller. All stress-related outcomes (SDNN, RMSSD, LFHF and Baevsky Index), as well as the other physical activity-related outcomes (Steps and Inactivity), did not differ significantly across measurement time points or among study arms.

Table 4: Baseline values for Pre- and Post-Intervention Assessment and ANOVA statistics

		Pre-Intervention Assessment							**Post-Intervention Assessment**							**MANOVA**		
		studyarm					**Con-trol**	**Over-all**	**studyarm**					**Con-trol**	**Over-all**	**time*group**		
		1	**2**	**3**	**4**	**5**			**1**	**2**	**3**	**4**	**5**			**F(1,5)**	**p**	**η²p**
Gender																		
male	n	12	4	2	43	21	20	102	7	0	1	3	3	52	66			
	%	29	10	13	47	38	14	26.5	33.3	0	14.3	18.7	8.8	75.4	38.8			
female	n	29	36	13	48	34	123	283	14	23	6	13	31	17	104			
	%	71	90	87	53	62	86	73.5	66.6	100	85.7	81.3	91.2	24.6	41.2			
Age	$\bar{x}$	42.4	40.6	39.0	40.8	41.6	42.4	41.1	45.8	40.2	42.6	42.6	44.3	40.9	42.7	0.888	0.489	0.008
	s	12.1	11.2	9.8	10.6	11.5	10.2	10.9	10.6	9.5	9.3	9.7	10.7	10.5	10.0			
BMI	$\bar{x}$	26.1	27.5	24.9	26.4	27.8	26.7	26.6	25.8	29.1	26.1	28.0	26.7	26.8	27.1	0.177	0.971	0.002
	s	7.1	5.3	4.6	6.6	7.0	6.0	6.1	3.9	9.0	5.0	7.4	6.3	6.1	6.3			
Steps counts/day	$\bar{x}$	7925	8541	8535	7588	6609	8074	7879	6402	8720	8956	8129	6876	7562	7774	0.794	0.555	0.008
	s	4253	2827	3255	3025	2716	3509	3264	2745	3121	4774	3726	3010	3062	3406			
MVPA min/day	$\bar{x}$	375.0	435.4	402.3	342.4	292.6	387.2	372.5	311.8	433.3	345.6	414.8	362.0	316.8	364.0	**5.826**	**< .001**	**0.057**
	s	131.4	86.6	104.9	141.5	117.4	118.8	116.8	95.4	106.8	125.0	95.7	129.1	123.5	112.6			
Inactivity min/day	$\bar{x}$	287.8	213.0	227.2	182.7	231.0	254.2	232.7	358.3	183.2	284.7	192.6	280.9	226.6	254.4	2.181	0.055	0.022
	s	150.3	113.5	138.5	81.1	112.4	137.5	122.2	156.1	108.3	137.0	72.1	142.7	120.2	122.7			
Disruption counts/day	$\bar{x}$	27.3	28.3	26.9	23.2	21.4	26.6	25.6	25.3	27.5	25.6	28.1	26.4	22.2	25.9	**11.2**	**< .001**	**0.100**
	s	4.8	3.3	2.9	7.5	6.5	4.7	4.9	4.6	4.4	2.9	4.0	5.0	7.2	4.7			
SDNN ms	$\bar{x}$	50.3	47.3	47.3	49.5	49.7	48.9	48.8	50.6	47.0	43.6	47.2	48.0	51.2	47.9	0.609	0.693	0.006
	s	11.0	11.3	12.8	9.3	12.5	11.4	11.4	11.0	10.9	10.3	10.9	12.2	12.0	11.2			
RMSSD ms	$\bar{x}$	28.4	28.5	27.4	28.3	29.3	27.9	28.3	28.6	27.3	27.0	26.1	27.6	29.9	27.7	0.697	0.626	0.007
	s	7.5	10.6	9.0	7.4	9.8	8.7	8.8	7.7	9.0	9.6	7.3	9.2	9.8	8.8			
LFHF %	$\bar{x}$	5.1	4.9	5.1	5.7	4.8	5.0	5.1	4.6	5.2	4.4	6.1	4.7	4.9	5.0	0.214	0.956	0.002
	s	2.3	2.6	3.7	3.8	2.5	3.1	3.0	2.1	2.5	2.4	5.9	2.6	2.9	3.1			

Baevsky Index	$\bar{x}$	241.3	279.0	283.1	268.0	270.5	263.9	267.6	225.4	289.3	307.4	258.6	282.4	248.5	268.6	0.196	0.964	0.002
	s	96.3	127.5	159.0	119.0	171.2	144.9	136.3	81.6	192.9	154.1	106.2	154.5	134.5	137.3			

Figures 3 and 4 visualize the significant results from Table 4. In addition to the differences in sample size and variance across variables and study arms, this illustrates the magnitude of effects.

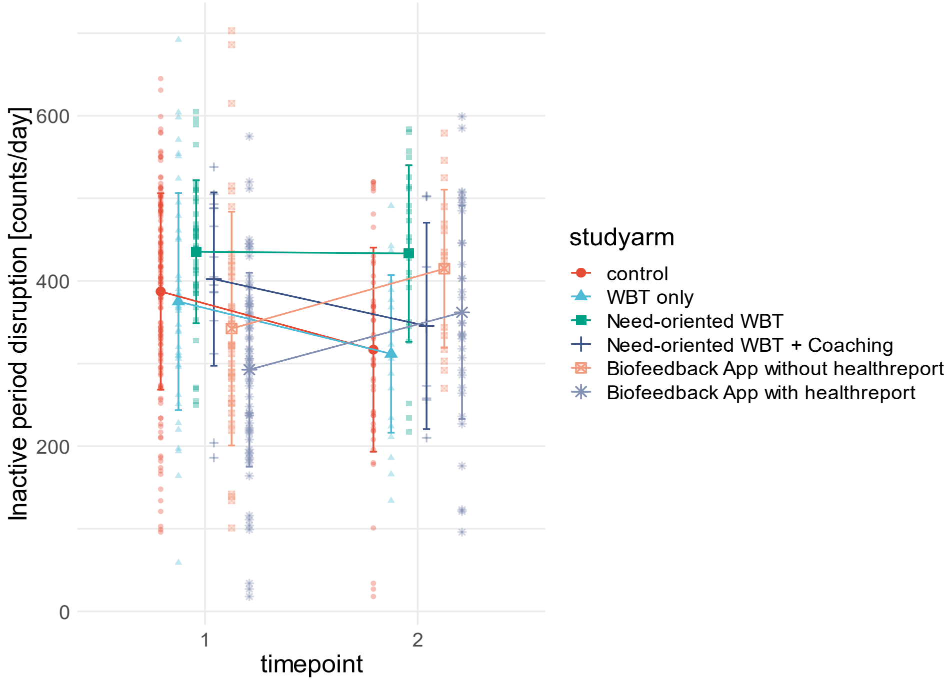

Figure 3: Grouped raincloud mean value plot of pre-post differences in moderate to vigorous physical activity [min/day] across study arms and control group.

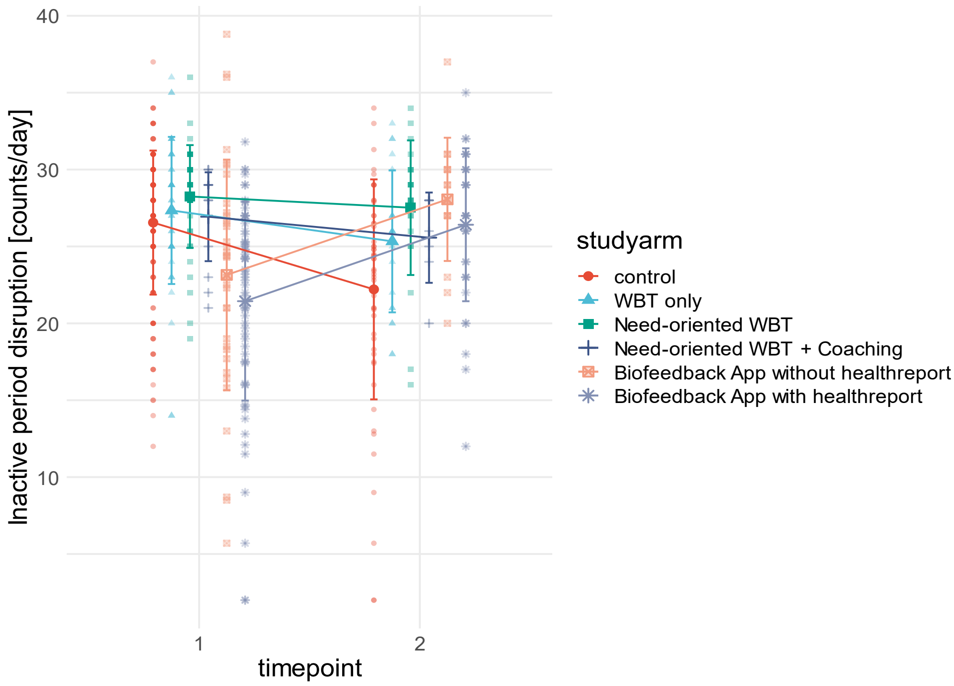

Figure 4: Grouped raincloud mean value plot of pre-post differences in inactive period disruption [counts/day] across study arms and control group.

4. Discussion

This multi-arm parallel randomized controlled trial aimed to investigate the efficacy of multiple differentially individualized sensory-based mHealth interventions to improve distress coping with regard to physical activity and stress related outcomes in healthcare professionals. We hypothesized that individualized interventions would have small to moderate positive effects for physical activity and stress-related outcomes in healthcare professionals, whereas non-individualized interventions would not show efficacy.

Contrary to our expectations, stress-related HRV-parameters did not show significant improvements over time, regardless of the study arm or the resulting level of individualization. Within this context, the stress buffering hypothesis assumes that physical activity and stress perception are closely related constructs [38]. However, to achieve cognitive and psychophysical adaptations through physical activity, continuous, specific training according to exercise principles is necessary for sustainable effects [94,95]. These criteria could not have been met within the guidance of the App. To gain positive effect on HRV parameters or subjective reported stress, physical exercise like Yoga or endurance training needs to be performed on a regular basis (Bischoff et al., 2019). Aside the challenges in obtaining the stress-related parameters (discussed in more detail in the limitations section), an 8-week intervention may retrospectively be insufficient to activate physiological mechanisms that have a stress-buffering effect. Long-term interventions may be necessary for addressing chronic stress symptoms or for addressing more complex health issues that require sustained support and intervention. An even stronger involvement of the participants would have been useful in terms of intervention mapping [50]. Moreover, the lack of supervision during the intervention in the mHealth interventions forced the participants to self-pace the intervention. This is a major disadvantage compared to supervised interventions [71–73]. Therefore, we conclude, that this type of mHealth intervention should include motivational aspects and guidance to do additional structured physical exercise next to the App use.

In contrast to the results on the physiological HRV based stress parameters, the interventions show positive effects on the accelerometry-based measured physical activity-related outcomes in high individualized app-based study arms (App-based digital stress management interventions with sensory biofeedback without (4) and with healthreport (5)). Strikingly, the small to moderate effects in physical activity typical for mHealth interventions [67] could only be shown for the outcomes of moderate to vigorous physical activity [min/day] and inactivity interruptions [counts/day] but not for those of Steps [counts/day] and inactivity [min/day]. Besides the fact that the considered interventions did not have steps and inactivity reduction as a primary goal, the nature of the nursing profession could be another possible explanatory mechanism: Other studies indicate higher step counts in nurses than in other occupations [96] as well as long work commutes and night shifts with long inactive periods [97]. Consequently, while a participant completes the intervention during working hours as instructed, this results in higher levels of moderate to vigorous physical activity and increased inactivity disruptions on the one hand, it inevitably results in elevated, consistent step counts due to patient work and elevated, unavoidable inactivity levels due to commutes and night shifts on the other. The findings from our study suggest that the relationship between physical activity and stress may vary depending on the context in which the activity takes place. This supports the idea of the "physical activity paradox," [98,99] which refers to the idea that the benefits of physical activity may depend on the specific circumstances in which it occurs. Our results suggest that physical activity may be perceived as more stressful when it is part of work, rather than leisure time, which suggests that interventions aimed at increasing physical activity in a work setting may not necessarily reduce stress levels. However, if physical activity is increased without also increasing stress, this could still be considered an improvement. Overall, these findings highlight the importance of considering the context in which physical activity occurs and the need to differentiate between occupational and leisure time physical activity when studying the relationship between physical activity and stress.

However, the effectiveness of an app-based intervention seem to be largely dependent on design aspects and user-centeredness. Despite all efforts to represent different levels of individualization across study arms, it could not be demonstrated which level of individualization is more effective based on effect sizes, as only both app-based interventions were able to show significant effects. With respect to our initial hypothesis, we would have assumed that studyarm 1 (WBT only) failed to show effects due to lack of individualization. This idea was supported by the results. It would have been reasonable to suspect that efficacy would increase across the remaining four study arms due to increasing individualization. However, no significant effects were found for studyarms 2 (need-oriented WBT) and 3 (need-oriented WBT and Coaching). Studyarms 4 (biofeedback app without health report) and 5 (biofeedback app with health report) each indicated homogeneous effect sizes for the outcomes MVPA and inactivity disruption. Thus, it could be argued, that based on the results of this study, it seems to make no difference whether a health report is displayed or not. However, one possible reason for this result could also be the small sample size in the individual study arms. Due to the high dropout rate, the number of subjects was not sufficient to show the expected moderate effects according to the power analysis. The results should therefore be interpreted with caution.

Nevertheless, the findings further indicate that individualized app-based interventions with direct biofeedback and differentiation by personality structure show better efficacy than web-based trainings (WBT) accessed via the smartphone browser. However, one reason for the high dropout rate were technical complaints while using the app-based interventions. With additional effort in the technical aspects this disadvantage could be minimized. Therefore, it remains unclear to what extent the need orientation or the coaching, which were exclusive for WBT, would have resulted in a further improvement of the effect size in the app-based interventions.

One possible explanation for the limited effectiveness of our intervention, in addition to the high dropout rate, is the insufficient incorporation of health behavior change strategies. While our biofeedback app included both active and passive behavior change techniques and promoted stress management skills, some of the content proposed by Bischoff et al. [100] was not implemented. Specifically, we applied individualization of app content, fulfilling common weekly goals and tasks, increasing knowledge about a healthy lifestyle, reminders for objectives, and controlling and checking progress, but did not include many suggestions for activities with diaries for documentation and development of strategies, or informational or instructional videos. The inclusion of these behavior change mechanisms could potentially enhance behavior change in future interventions.

.4.1. Strenght & Limitations

To the best of our knowledge, this is the first mHealth intervention in the healthcare setting of this quality and complexity in the study design, demonstrating initial effects in the area of physical effectiveness despite a small sample size and not to be despised dropout rates. Furthermore, it is the first mHealth intervention including multiple study arms with different levels of individualization demonstrating differences in efficacy.

Nevertheless, the conditions of data collection were difficult, which can be seen as a possible reason for the high dropout rates. The dropout rate of 74% was almost four times higher than expected. This was not least due to the fact that during the COVID-19 pandemic it was not possible to establish personal contact with the participants. Email based communication does not seem to work well in the healthcare setting, as 113 people were excluded due to non-response. One potential contributor regarding communication issues and multiple technical inconsistencies could be the evident low level of digital literacy among nurses [101]. Although we were aware of these circumstances when designing the intervention, a potential approach for future interventions could be to provide pre-interventional training and develop digital literacy first. Other reasons for the high dropout rate could be the intervention or the measurement procedure.

The participation threshold was not sufficiently low for healthcare workers. Excessive demands resulted from numerous extensive questionnaires, autonomous sensor orderings, and the proprietary installation of the app. In addition, the app did not support push notifications and synchronization problems between the app and sensor occurred frequently. With regards to the measurement procedure, it should be noted that the intervention had a different initiation time and duration for all participants. They were instructed to wear the sensor during working hours and for at least 48 hours. We were unable to identify from the data sensor wearing timing aspects, and whether vacation periods were taken into account.

4.2. Future research

Future interventions should use a less complex and longer-term study design to systematically demonstrate which individualization mechanisms lead to greater effectiveness of mHealth interventions in terms of distress coping. The focus of future mHealth interventions in the healthcare setting should be as low threshold access as possible, including push notifications and ideally an on-site project coordinator, who can provide technical support, establish accountability and remind participants to follow procedures.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Ethics Committee of Technical University of Berlin (No GR_14_20191217, date of approval 04.06.2021) for studies involving humans. Furthermore, the trial was registered at the german register of clinical trials (DRKS.de, No DRKS00021423, date of approval 12.07.2021). In addition, a study protocol exists for this study, which was submitted before the study was conducted and is currently under review [76].

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study. All participants or their legal guardians obtained written informed consent before enrolment in the study and were free to withdraw it at any time.

Data Availability Statement: The datasets generated and analyzed during the study are available from the corresponding author on reasonable request.

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