Adolescent smartphone-based health behavior intervention

Usage and Continuous Attrition

Erlendur Egilsson

Thesis for the degree of Philosophiae Doctor

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Heilsueflandi snjalltækjalausn fyrir unglinga

Notkun og brottfall

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Ritgerð til doktorsgráðu

Leiðbeinandi

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Doktorsnefnd

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Júní 2024

Heilbrigðisvísindasvið

SÁLFRÆÐIDEILD

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Reykjavik, Iceland 2024

Ágrip

Flestir unglingar eiga eða hafa aðgengi að snjallsíma og margir þeirra eru flestar vökustundir við símann. Hins vegar notar minnihluti unglinga snjallheilsuhugbúnað sér til heilsubóta. Bilið á milli aðgangs að heilsutækni og nýtingu á henni virðist því umtalsvert á meðal unglinga og má rekja til ýmissa þátta, s.s. uppsetningu og hönnun meðferða auk skorts á trú á hugsanlegan meðferðarávinning. Þrátt fyrir að um 10% unglinga séu greindir með tilfinningaröskun og enn fleiri glími við hamlandi tilfinningavanda, þá er notkun snjallhugbúnaðar til handa geðheilsu unglinga sömuleiðis áberandi lítil. Þetta ósamræmi undirstrikar víðtækan skort á áhrifaríkum heilsutengdum snjalllausnum sem ætlaðar eru geðheilbrigði ungmenna.

Rannsóknir á miklu brottfalli úr heilsutengdum snjallúrræðum fyrir unglinga hafa litast af þröngri, tvívíðri sýn á brottfall, frá upphafi til enda meðferðar, og hefur fyrir vikið ekki tekist að fanga þá þætti sem stuðla að vilja til þátttöku og hindra brottfall. Há tíðni brottfalls meðal unglinga með kvíða og þunglyndi í snjallúrræðum er með sambærilegum hætti. Brottfall er venjulega mælt frá upphafi til enda meðferðar, án ítarlegrar athugunar á því hvenær og þá hvers vegna unglingar með þunglyndi og kvíða hætta meðferð. Rannsóknir á snjallúrræðum fyrir unglinga, sér í lagi geðheilbrigðisinngripum, hafa því takmarkast við skort á ítarlegum, tímatengdum gögnum um brottfall, breytilegar skilgreiningar á hugtakinu brottfall og skort á ástæðunum sem liggja að baki virkri þátttöku unglinga í heilsutengdum snjallúrræðum. Í rannsóknarverkefninu hefur verið leitast við að skilja hvernig tíðni og tími notkunar snjallhugbúnaðar, samfelldar mælingar á brottfalli, óeigingjörn umbun, endurgjöf á notkun auk hvatningar og stuðnings í gegnum leikjavæðingu snjallhugbúnaðar fyrir unglinga gætu dregið úr brottfalli. Aukinn skilningur á þessum sviðum myndi mögulega ekki aðeins bæta uppsetningu og skilvirkni inngripa, heldur einnig auka aðdráttarafl þeirra í huga unglinga sem t.a.m. glíma við geðheilbrigðisvandamál. Rannsóknarverkefnið beindist að fýsileika og notkunareiginleikum snjallheilsuhugbúnaðarins SidekickHealth í sex vikna rannsóknartímabilum meðal íslenskra unglinga. Aðaláhersla var lögð á að skoða notkunar- og brottfallsmynstur. Sér í lagi hvernig stuðningur og leikjavæðing meðferðar höfðu áhrif á brottfall. Aukinheldur voru áhrif hugbúnaðarins á daglegar heilsuvenjur metnar og með

hvaða hætti notkun á hugbúnaðinum stuðlaði að aukinni velsæld þátttakenda. Sömuleiðis var það markmið verkefnisins að rannsaka notkunargögn og brottfall meðal ungmenna með marktækt hamlandi kvíða- og depurðareinkenni.

Rannsóknarverkefnið samanstóð af tveimur slembirannsóknum á áhrifum snjallheilsuhugbúnaðarins SidekickHealth, þar sem ætlunin var að efla næringu, geðheilsu og líkamlega heilsu unglinga sem notuðu hugbúnaðinn. Í forrannsókn voru 41 þátttakandi en í stærri rannsókn verkefnisins voru 304 þátttakendur úr þremur grunnskólum á höfuðborgarsvæðinu. Seinni tvær greinar verkefnsins byggjast á gögnum stærri rannsóknarinnar þar sem sú þriðja einblínir á 121 þátttakanda með marktæk hamlandi depurðar- og kvíðaeinkenni. Mælingar fóru fram í upphafi, með stöðugum hætti yfir sex vikna rannsóknartímabil og við lok rannsóknar. Í seinni rannsókninni var þátttakendum skipt í samanburðarhóp, hefðbundna meðferð (e. treatment-as-usual: TAU) og rannsóknarhóp. Aðalbreytur voru brottfallstími, tími og tíðni heilsuæfinga innan SidekickHealth ásamt breytingum á kvíða- og depurðareinkennum í síðustu rannsókninni. Aðrar breytur voru trú á eigin færni og hamlandi svefnvandi ásamt BMI-SDS í forrannsókn. Samanburðarpróf í formi *t*-prófa, χ2 prófa, Pearson fylgnistuðula auk endurtekinna dreifigreininga (e. ANOVA) með leiðréttum alfa gildum voru notuð til að meta mismun helstu mæliþátta. Aðfallsgreining Cox (e. Cox proportional hazard regression models) var notuð til að spá fyrir um brottfall byggt á notkun hugbúnaðarins og marghliða aðfallsgreiningu beitt til að rannsaka spábreytur fyrir breytingar kvíða- og depurðareinkenna í síðustu rannsókninni. Að lokum var brottfall metið með Kaplan-Meier lifunargreiningu og log-rank prófum.

Brottfall var með marktækt ólíkum hætti milli rannsóknarhópa. Í fjölmennustu rannsókninni mældist brottfall 44,4% í rannsóknarhópi á meðan það var 94,3% í hefðbundnum meðferðarhópi (TAU) (χ^2_1=61.220; p <.001). Sambærilegar niðurstöður fundust meðal þáttakenda með hamlandi depurðar- og kvíðaeinkenni þar sem brottfall í TAU hópnum var 93,70% og 37% í rannsóknarhópi (χ^2_1= 27.11, p <.01). Ennfremur tóku þátttakendur í rannsóknarhópum marktækt lengur þátt í bæði annarri og þriðju rannsókn. Í annarri rannsókn var meðalnotkunarlengd 6.286 dagar í TAU hópi en 24.975 dagar í rannsóknarhópi. Svipaðar niðurstöður fundust meðal þátttakenda með hamlandi kvíða- og depurðareinkenni en notkunardagar voru 6,31 (95% CI 2,90-9,73) í TAU hópnum og 29,96 (95% CI 22,58-33,34) í rannsóknarhópi. Sá hópur sem þátttakendur tilheyrðu hafði

því marktækt forspárgildi fyrir brottfall (áhættuhlutfall 0,308, 95% CI 0,222-0,420) auk þess sem notkunardagar virtust spá með marktækum hætti fyrir um mun á kvíða- og þunglyndiskorum (*β* = - .252, *p* <.01). Umtalsverð minnkun á notkun átti sér stað fyrstu dagana eftir að rannsóknartímabil hófst. Í öllum rannsóknarhópum, sem fengu endurgjöf frá heilbrigðisstarfsmanni og leikjavæddan stuðning, jókst hins vegar notkun á hugbúnaðinum í kjölfar upphafsfalls og sérstaklega undir lok meðferðartímabils.

Niðurstöður þessa verkefnis gefa til kynna marktækan mun milli rannsóknarhópa á brottfalli og notkun hugbúnaðarins þar sem íhlutunararmar sem fengu endurgjöf og stuðning voru marktækt ólíklegri til að hætta í inngripinu, luku marktækt fleiri heilsuverkefnum og voru virkir lengur en samanburðarhópar. Það eru niðurstöður sem eiga bæði við um þátttakendur með klínísk kvíða- og depurðareinkenni og ekki. Niðurstöður rannsóknarverkefnins gefa sömuleiðis til kynna hugsanleg næmiskeið á meðan meðferð stendur. Við frekari rannsóknir á brottfalli meðal unglinga úr snjallheilsuúrræðum væri því ráðlegt að leggja áherslu á sífelldar mælingar á brottfalli og daglegt mynstur heilsuhegðunar auk þess sem ítarlegri skilningur á áhrifum leikjavædds stuðnings, óeigingjarnra verðlauna og stöðugri persónulegri endurgjöf heilbrigðisstarfsfólks myndi vafalaust draga úr brottfalli og efla skilvirkni snjallheilsuúrræða ætluðum unglingum.

Lykilorð:

Snjallheilsuhugbúnaður, unglingar, brottfall, notkun, geðheilsa

Abstract

In an era where smartphone ownership is ubiquitous among adolescents, with many engaging online almost incessantly, there is a paradoxical trend. Only a minority are utilizing mobile health (mHealth) applications and significantly few to tackle mental health issues. This gap between access to technology and its application for health benefits may be attributed to a range of factors, including perceived relevance, intervention designs, or a lack of awareness about potential benefits. Despite approximately 10% of adolescents being diagnosed with emotional disorders and even more grappling with sub-clinical emotional symptoms, the uptake of mental mHealth solutions is also notably low. This dissonance underscores a broader disengagement with digital health resources intended for adolescent mental health. High attrition rates in adolescent mHealth interventions reveal significant inconsistencies, and the binary portrayal of attrition, from beginning to end of treatment, has failed to capture the dynamics of engagement over time. High attrition rates from mHealth interventions aimed at adolescents with anxiety and depression follow the same path, where attrition is often measured from start to finish, without a nuanced understanding of when and why depressed and/or anxious adolescents discontinue treatment. Current research into adolescent mHealth interventions and especially mental health interventions, is hampered by a lack of detailed, temporal data on attrition, combined with diverse definitions of attrition and deficient explorations into the reasons behind varying levels of app engagement.

To address these challenges, the research project has sought to understand how frequency and time of application usage, continuous measures of attrition, altruistic rewards, healthcare feedback and motivational support through gamification of mHealth applications could unlock strategies to mitigate attrition. This would perhaps not only improve the design and delivery of mHealth interventions but also enhance their appeal and effectiveness for adolescents struggling with mental health issues. By integrating a time-specific lens into the study of mHealth usage and attrition, researchers could better comprehend the ebb and flow of engagement, thereby fostering more enduring and impactful digital health strategies. The research project focused on the acceptability of the mHealth application SidekickHealth during six-week interventions with Icelandic

adolescents, and more importantly examining the patterns of attrition throughout the interventions. In particular how motivational support influenced attrition rates. Additionally, the research assessed the app's impact on daily health habits, contributing to adolescent well-being. Another objective was to study continuous attrition among adolescents with clinical anxiety or depression, analyzing usage data for insights into attrition causes, and determining the intervention's success in ameliorating these conditions.

The research project consisted of two randomized controlled trials investigating the impact of a mobile health application, SidekickHealth, designed to promote nutrition, mental health, and physical health among adolescents. The project encompassed a single-site pilot (n=41) and broader trial with 304 participants from three elementary schools. The project's two latter papers are based on data from the larger trial, where the third one focuses on 121 participants with clincial depression and anxiety symptoms. Outcome measures were obtained at baseline, throughout the 6-weeks trials and at conclusion. In the larger trial participants were assigned to one of three groups: Control, treatment-as-usual (TAU) and intervention. Primary outcomes were time of attrition, time and frequency of task completion within SidekickHealth along with changes in anxiety and depression symptoms in the last trial. Secondary outcome measures were self-efficacy levels and significant sleep problems along with BMI-SDS in the pilot. Independent samples *t*-tests, $\chi 2$ tests, Pearson's correlation coefficients and repeated measures ANOVAs with adjusted alpha levels were used to obtain mean differences on primary and secondary outcome measures. Cox proportional hazard regression models with interacting covariables were used to predict attrition based on usage of in-app health exercises and multiple regression models were applied to study predictor variables for primary mean change in anxiety and depressive symptoms in the last trial. Lastly, attrition times were assessed with Kaplan-Meier survival analysis and log-rank tests.

Measured attrition differed significantly between research groups. In the second study, attrition was 44.4% in the intervention group while it was 94.3% in the TAU group (χ^2_1=61.220; p <.001). Similar results were found among anxious and/or depressed participants, where attrition in the TAU group was 93.70% and 37% in the intervention group (χ^2_1= 27.11, p <.01). Further, mean duration of participation differed between groups. In the 2nd study, mean usage duration was 6.286 days in the TAU group and

24.975 days in the intervention group. Similar results were found among anxious and/or depressed participants in the larger trial. Days of usage were 6.31 (95% CI 2.90-9.73) in TAU group and 29.96 (95% CI 22.58-33.34) in intervention group. Allocation to research group was therefore significantly related to attrition time (hazard ratio 0.308, 95% CI 0.222-0.420) and days of usage significantly predicting differences in pre- and post-measures in anxiety and depression scores (β = -.252, p <.01). In both trials, there was a significant decrease in usage in the first days after instigation. However, in all intervention groups receiving motivational support, in-app usage rose after initial drop and especially towards the end of treatment.

In these randomized controlled mHealth trials significant differences in attrition rates and app usage were observed between research groups. Intervention arms receiving motivational support were significantly unlikelier to drop out of interventions, completed significantly more in-app health tasks and were active longer than comparison groups, findings indicated for both adolescents experiencing clinical anxiety and depression and those who were not. The research illuminated potential sensitive periods for health task completion, emphasizing that time-specific attrition and in-app health behavior patterns offers a promising direction for future research, particularly in enhancing engagement and reducing excessively high attrition rates in adolescent mHealth interventions. Integrating motivational support through gamification, altruistic rewards, and ongoing healthcare feedback appears to be a major factor in reaching that outcome.

Keywords:

mHealth, adolescent, attrition, usage, mental health

Acknowledgements

Reflecting on the support I've received throughout this journey fills me with humility and deep gratitude. My first expression of thanks goes to my supervisor, Dr. Urður Njarðvík, for her wisdom, steadfast support, and guidance, paired with remarkable patience, all through this journey. I also wish to wholeheartedly thank Dr. Ragnar Bjarnason for setting me on this path at Barnaspítali years ago, for his astuteness and experience as well as his unwavering encouragement throughout the process. Without both of you, my journey would have veered off course long ago. My sincere appreciation goes out to you for reinforcing my determination and inspiring me to stick to it. I also wish to thank Þrúður Gunnarsdóttir for lending a critical eye and enriching insight to my research. I am thankful to my former colleagues at SidekickHealth for crafting such an innovative mHealth application and for the wonderful times we shared during our collaboration.

My gratitude extends to the adolescents who participated in the research, their teachers, and the staff at the involved elementary schools, Menntasvið Kópavogsbæjar, as well as all collaborators who contributed to this research project. I am thankful to the University of Iceland for the chance to undertake this endeavor, the brilliant psychology department and its outstanding team. A special nod of gratitude to the Icelandic Research Fund for the financial backing provided.

To my parents, I am deeply grateful for instilling in me the deep belief that persistent effort begets success and for your support in all times of my life. Your teachings and the values you hold dear have been my compass. For your ceaseless encouragement and for being my steadfast supporters from my earliest memories, I am eternally thankful for having such remarkable role models and loving parents. To Aggi, my brother and dearest friend, thank you for your support during my falls, for lending an ear and offering guidance when I was lost or weary, and for your constant, unwavering presence by my side. To my children, Kara, Gunnar Tumi, Kári, Móa, and Tinni, you have taught me the essence of unconditional love, offered me perspective in all I do, and have been the beacon in my life's journey. You are the reason I am.

And finally, to my Díana, my gratitude and love knows no bounds. Your optimism lifted me when I faltered; your practicality grounded me when I was adrift. Your encouragement

was my strength when conceding seemed the only option, and your companionship has been my constant through every step. You are my better half, the balance to my being, and the one who brings joy, laughter, love, and adventure into my life. May we be blessed with countless more moments, sharing coffee and conversations about everything and nothing into our twilight years. My love, without you, none of this would have been possible. Thank you.

Contents

List of Abbreviations

AAT	Appetite Awareness Training
AI	Artificial intelligence
BMI SDS	Standardized Body Mass Index
CDC	Centers for Disease Control and Prevention
CDI	Children's Depression Inventory
CBT	Cognitive Behavioral Therapy
DBT	Dialectical Behavior Therapy
GSE	General Self Efficacy Scale
MASC	Multidimensional Anxiety Scale
mHealth	Mobile Health
ML	Machine Learning
RCADS	Revised Children's Anxiety and Depression Scale
SDT	Self-Determination Theory
SES	Socio Economic Status
SSRIs	Selective Serotonin Reuptake Inhibitors
SUS	Systematic Usability Scale
TAU	Treatment As Usual

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List of Original Papers

This thesis is based on the following three original manuscripts, referred to by their Roman numerals (I-III)

I. Egilsson, E., Bjarnason, R., & Njardvik, U. (2021). Usage and weekly attrition in a smartphone-based health behavior intervention for adolescents: pilot randomized controlled trial. *JMIR formative research*, *5*(2), e21432.

II. Egilsson, E., Bjarnason, R., & Njardvik, U. (2023). Usage and Daily Attrition of a Smartphone-Based Health Behavior Intervention: Randomized Controlled Trial. *JMIR mHealth and uHealth*, *11*(1), e45414.

III. Egilsson, E., Bjarnason, R., & Njardvik, U. (2024). Usage and daily attrition from a smartphone-based health behavior intervention among adolescents with anxiety and depression symptoms. Submitted for publication.

Declaration of Contribution

Paper I

The study was conceptualized by Egilsson, Bjarnason, and Njarðvík. Participant recruitment and treatment implementation were carried out by Egilsson, under Njarðvík's supervision. Data collection and analysis were conducted by Egilsson, who also prepared the initial manuscript draft. Both Njarðvík and Bjarnason provided critical revisions and oversight throughout the drafting process. The final manuscript received their collective approval for publication.

Papers II-III

Egilsson, Bjarnason, and Njarðvík designed Studies II and III. Egilsson was responsible for participant recruitment, implementing the interventions, data collection, and analysis, as well as the initial drafting of the research papers. This work was conducted under the supervision of Bjarnason and Njarðvík, who also provided critical revisions to the manuscripts, concluding in the final approval for the manuscripts' publications.

1 Introduction

1.1 History and current state of smartphones & mHealth applications

The history of smartphones is concise, spanning only three decades (Taplin, 2023). The IBM Simon, often recognized as the first commercially available smartphone, was launched in 1994 (Dainow, 2017). This pioneering device combined the features of a cell phone with those of a personal digital assistant (PDA), boasting a touchscreen and applications such as an address book, calendar, and notepad (Dainow, 2017; Wikipedia, 2023). Weighing approximately 0.5kg, its potential for commercial success was compromised by its bulky design, limited functionality, and a battery life that lasted only about an hour (Wikipedia, 2023). Technological advancements eventually addressed these early limitations, leading to the development of more powerful devices with longer-lasting batteries (Hynes, 2021). Additionally, the advent of faster digital mobile data networks and more mature software platforms facilitated further development (Hynes, 2021). Smartphone usage and ownership among adolescents were initially limited but began to increase significantly with the introduction of Apple's iPhone in 2007 (Grossman, 2007). The smartphone industry was revolutionized, offering user-friendly interfaces, capacitive touchscreens, and innovative approaches to software applications (Grossman, 2007). The subsequent launch of Apple's App Store and the Android Market, now known as Google Play Store, in 2008 transformed user interaction with mobile devices, beginning the app-centric era of smartphones (Dainow, 2017). This led to an explosion in development of mobile applications, which have become integral to daily life (Dainow, 2017; Hynes, 2021; Taplin, 2023). Over the past 15 years, smartphones have evolved to incorporate sophisticated features such as high-resolution cameras, biometric security, and artificial intelligence capabilities (Taplin, 2023). They have become indispensable tools for communication, entertainment, productivity, and accessing information, with millions of applications catering to the diverse needs of people worldwide (Perez-Pozuelo et al., 2021).

Adolescent cell phone use dramatically increased from the late 1990s through the 2000s (Lauricella et al., 2014). By 2009, two-thirds of U.S. adolescents owned a cell phone, with a marked preference for texting over voice calls (Lauricella et al., 2014; Rideout et al., 2010). The 2010s saw an uptick in smartphone ownership among adolescents, driven by need for social networking, entertainment, and communication (Pew Research Center, 2013; Brenner, 2015). The variety of models at different price points facilitated increased access across socio-economic statuses (SES), bringing smartphones into the lives of a diverse adolescent populations (Brenner, 2015). Use of smartphones among adolescents has continued to grow extensively. Currently, 96% of U.S. adolescents own or have access to a smartphone, a significant rise from 23% in 2011, marking a 73% increase over twelve years (Kunst, 2023; Pew Research Center, 2013; Pew Research Center, 2015; Pew Research Center, 2019). This trend is echoed in most developed economies, where adolescent smartphone access and ownership exceed 90% (Kliesener et al., 2022; Pew Research Center, 2019). Smartphones have become so entrenched in daily life that about 45% of adolescents are online for nearly all waking hours (Anderson & Jiang, 2018). Nonetheless, more conservative estimates suggest that many spend roughly four hours each day online (Ceci, 2023; Chaffey, 20016; Kliesener et al., 2022). Research examining adolescent usage patterns reveals evolving online trends, often directly linked to advancements in smartphone applications and hardware. Current trends for instance highlight YouTube as the top online platform among adolescents, with approximately 95% utilizing the app on their smartphones (Vogels, 2022). In contrast, the adolescent user base for Facebook has plummeted since 2015, with only 32% currently using the platform, down from 71% (Vogels, 2022). This decline suggests a shift towards other social media platforms, considering that 90% of adolescents are active on social media, with TikTok engaging about 67%, Instagram 62%, and Snapchat 59% (Vogels, 2022).

The evolution of mobile health (mHealth) applications, though brief, has been extraordinary. About 15 years ago, mHealth was synonymous with using short message service (SMS) to deliver basic health-related messages to patients (Badawy et al., 2017; McKinsey & Company, 2010). These early stages proved effective for reminders, education, and tracking disease outbreaks (McKinsey & Company, 2010; Vital Wave Consulting, 2009). As technology advanced, mHealth apps harnessed greater capabilities, initially focusing on wellness and fitness tracking, and soon branching into more nuanced health management tasks, including medication adherence, chronic disease monitoring, and mental health support (Dicianno et al., 2015; Grist et al., 2017; Lee et al., 2018; Peng et al., 2020; Wang et al., 2018). The integration of wearable technology marked a milestone in the relatively short history of mHealth applications. Fitness trackers and smartwatches, with sensors for monitoring heart rate, sleep patterns, and activity levels, have vastly broadened the functionalities of mHealth apps (Bayoumy et al., 2021; Liao et al., 2019; Muzny et al., 2020). These devices enable continuous health monitoring, providing essential real-time data for managing chronic conditions and facilitating preventative healthcare measures (Liao et al., 2019; Muzny et al., 2020). Further, the COVID-19 pandemic catalyzed the expansion of mHealth applications, particularly in online consultations (Taha et al., 2022). Remote consultations enabled by mHealth apps have substantially reduced the necessity for in-person visits, democratizing healthcare access across geographically diverse populations (Haleem et al., 2021). Recent advances in artificial intelligence (AI) and machine learning (ML) have further propelled mHealth applications into a new era of personalized care (Bhatt et al., 2022; Haque & Rubya, 2023; Sharma et al., 2023). AI-driven mental health apps, for instance, can offer tailored therapeutic interventions based on user input and behavioral patterns (Haque & Rubya, 2023). Today, mHealth applications range from simple information providers to complex platforms integrated within healthcare systems, enhancing patient empowerment, improving healthcare delivery and ultimately health outcomes (Messner et al., 2019). The growth in the number of mHealth applications has been meteoric in recent years with roughly 90.000 new applications introduced yearly (IQVIA, 2021). Currently, there are approximately 350,000 mHealth applications available on various platforms, reflecting the sector's rapid expansion (IQVIA, 2021). Despite this growth of mHealth applications, its adoption and utilization among adolescents remain limited (Maenhout et al., 2022; Wu et al., 2014; Yardley et al., 2016).

Mental health applications, in their emerging stages, were primarily designed to provide psychoeducational content and simple stress-relief exercises (Oliveira et al., 2021). With the technological advancements of smartphones, these applications evolved to include interactive features such as self-assessment tools, mood tracking, and enhanced stress management techniques (Miralles et al., 2020; Þórarinsdóttir et al., 2017). A pivotal development in the field was the incorporation of cognitive-behavioral therapy (CBT) methodologies into mental health applications (Huguet et al., 2016; Rathbone et al., 2017). This facilitated the delivery of evidence-based therapeutic strategies directly to users' devices, thereby making mental health care more accessible to a broader audience with less regard to SES status, location, or ethnicity (Huguet et al., 2016; Rathbone et al., 2017). Through the applications structured programs were offered and augmented by activities such as journaling, mindfulness exercises, and the monitoring of daily habits. Today, there is a vast number of mental health applications on the market, or roughly 22.750, and they represent a mixture of innovation and diversity (IQVIA, 2021; Torous & Roberts, 2017). The integration of advanced technologies like artificial intelligence (AI) and machine learning (ML) are being integrated to science-based interventions that offer individualized feedback on treatment progress and outcomes (Denecke et al., 2022; Meheli et al., 2022). The pandemic's onset in 2019 spurred a significant rise in the adoption of remote therapy sessions with mental health professionals, effectively transcending geographical limitations and making mental health support more accessible than ever. Despite these vast advancements, mental health apps face ongoing challenges. High attrition rates and data privacy remains a significant concern, as does the necessity to ensure the quality and efficacy of digital interventions match or surpass those of traditional therapeutic modalities (Litke et al., 2023; Lustgarten et al., 2020). These challenges necessitate an effort to ensure that mental mHealth interventions serve as a reliable and secure resource for individuals seeking support.

1.2 Emotional disorders in adolescent populations

Adolescence is marked by rapid physiological, psychological, and social transformations (Christie & Viner, 2005). These changes can precipitate or accompany significant emotional difficulties such as depression and anxiety (Beesdo et al., 2009; Thapar et al., 2012). Contributing factors to emotional disorders or sub-clinical emotional symptoms in adolescents are multifaceted, encompassing genetic predispositions, environmental stressors, and sociocultural influences (World Health Organization, 2019). The complexities of modern society, for instance, with its pervasive social media influences, and increased rates of virtual bullying, serve to further exacerbate matters (Estévez et al., 2020; Shannon et al., 2022; Sherman et al., 2016). Emotional disorders and sub-clinical emotional problems represent pervasive issues that exert a profound influence on approximately 10-20% of adolescents' well-being across the globe (World Health Organization, 2019). Anxiety disorders encompass among other a range of conditions, generalized anxiety disorder (GAD), social anxiety disorder (SAD), panic disorder, obsession-compulsive disorder (OCD) and specific phobias (Americal Psychology

Association, 2022). Depression is however marked by persistent and pervasive low mood accompanied by a loss of interest or pleasure in most activities and a range of cognitive and physical symptoms (American Psychology Association, 2022).

The COVID-19 pandemic cast a dark shadow over adolescents' mental health, exacerbating pre-existing mental health conditions in the population (Thorisdottir et al., 2023). The broad and adverse effects that the pandemic produced on the mental well-being of adolescents has been recognized through systematic reviews and among the most striking consequences are heightened prevalence of sleep disorders along with increased rates of depression and anxiety disorders (Jahrami et al., 2022; Jones et al., 2021; Kauhanen et al., 2023). The pandemic brought about unique sets of challenges for adolescents in the form of social isolation, disrupted routines, limited access to school-based health services, and incomplete socio-emotional development partially contributing to increased prevalence of emotional disorders (Samji et al., 2022; Thorisdottir et al., 2023). Recognizing the far-reaching consequences of anxiety and depression underscores the importance of early identification and intervention. Evidence-based interventions have been developed that help adolescents manage and overcome anxiety disorders and depression (Radomski et al., 2019; Richardson et al., 2010). As mentioned above, CBT is a widely recognized and effective approach for both disorder classes (Clarke et al., 2015; Richardson et al., 2010; Rooksby et al., 2015; Wergeland et al., 2021). CBT aids adolescents identify and challenge negative thought patterns and develop coping strategies (Seligman & Ollendick, 2011). Further, dialectical behavior therapy (DBT) is a science-based therapeutic approach frequently used targeting depression in adolescent populations (Kothgassner et al., 2021). Medication like selective serotonin reuptake inhibitors (SSRIs) may also be prescribed in severe cases or when science-based behavioral interventions alone are insufficient (Goodyer et al., 2007). Recent systematic reviews of global prevalence estimates of psychiatric disorders in children and adolescents align closely with the estimated rates provided by international health organizations, spanning from approximately 7% to considerably higher pooled rates reaching around 14% (Erskine et al., 2017; Hossain et al., 2022; Katzmarzyk et al., 2014; Polanczyk et al., 2015; Silva et al., 2020). According to the Centers for Disease Control and Prevention (CDC), 6% of adolescents aged twelve to seventeen in the United States are diagnosed with clinical depression while over 10% are diagnosed with anxiety disorders (CDC, 2019). Remarkably, anxiety and depression are so profound that these two conditions alone seem to account for nearly half of all mental disorders afflicting adolescent populations (Barker et al., 2019; Sacco et al., 2022; Shorey et al., 2022). In fact, the World Health Organization flags emotional disorders as among leading causes of illness and disability among adolescents (World Health Organization, 2019). These emotional problems ripple beyond the individual, significantly affecting academic performance, social relationships, and elevating the risk of substance abuse and self-harm, and suicide in adolescents (World Health Organization, 2019).

1.3 Gamification, motivational support, and altruistic rewards

Gamification in adolescent mHealth interventions is a growing field, enhancing engagement and effectiveness in health behavior change in the population (Xu et al., 2022). Applying game-design elements to non-game contexts, gamification can significantly improve mHealth interventions' efficacy (Deterding et al., 2011; Johnson et al., 2016; Xu et al., 2022). It aligns with adolescents' needs for achievement and social recognition, fostering deeper, lasting engagement. Unlike traditional health approaches, gamified mHealth interventions provide instant rewards and feedback, crucial for sustaining interest and motivation among adolescents, who often lack motivation from long-term health benefits (Alsawaier, 2017; Deterding et al., 2011; Xu et al., 2022). In gamified adolescent mHealth interventions, incentive schedules frequently start with continuous reinforcement, swiftly rewarding each in-app target behavior (Nuijten et al., 2021; Schmidt-Kraepelin et al., 2020). As interventions progress, they often transition to fixed-ratio or fixed-interval schedules, where rewards follow a set number of behaviors or time intervals, to encourage consistent effort (Nuijten et al., 2021). Variable-ratio schedules, which reward behaviors after unpredictable occurrences, and variable-interval schedules, offering rewards at varying intervals, are effective for sustaining long-term engagement and can hinder attrition (Nuijten et al., 2021). In adolescent mHealth interventions, variable-ratio and variable-interval schedules can be effectively implemented through diverse rewards, in-app lotteries, and social recognition such as badges. The most effective adolescent gamified approaches likely integrate these diverse extrinsic reinforcement schedules, initially aiming to increase health behaviors to desired levels and then maintaining them. Gamification of adolescent mHealth interventions could help bridge the gap between health behaviors and lasting outcomes (Alsawaier, 2017). Developmental social aspects such as peer influence seem critical motivators in adolescent populations (Albert & Steinberg, 2011; Angelini et al., 2024). Gamification in mHealth interventions leverages this by incorporating social networks within apps, encouraging socializing, competition, and cooperation (Alsawaier, 2017; Xu et al., 2022). Features like leaderboards and group challenges foster community and accountability, a likely key to adolescent health behavior change and adherence. Research has revealed lower attrition rates and increased activity in gamified intervention groups (Johnson et al., 2016). Personalization in gamification is of importance and tailoring challenges and rewards to individual preferences is likely to boost engagement (Johnson et al., 2016). However, gamification must be carefully implemented. Overemphasis on extrinsic rewards can undermine intrinsic motivation, so a balanced approach is essential for effective and engaging mHealth interventions for adolescents (Alsawaier, 2017; Johnson et al., 2016; Xu et al., 2022).

Self-Determination Theory (SDT) provides a comprehensive theoretical framework for designing motivational support in mHealth applications targeted at adolescents (Deci & Ryan, 2012). Motivation is here defined as the process that initiates, guides, and sustains goal-oriented behavior (Peters, 2015). SDT posits motivation's internalization along a continuum from non-self-determined to self-determined, where intrinsic motivation signifies the highest autonomy, competence and likelihood for enduring behavior change (Deci & Ryan, 2012). Moving through stages of extrinsic motivation (external, introjected, identified, and integrated) individuals can progress towards intrinsic motivational states (Deci & Ryan, 2012). SDT emphasizes that fulfilling the needs for competence, autonomy, and relatedness enhances intrinsic motivation (Deci & Ryan, 2012). Competence involves feeling capable in behavior execution while autonomy relates to perceived control over one's actions (Ng et al., 2012). Relatedness refers to feeling supported and socially connected. SDT as a model for behavioral change has been empirically supported, highlighting the pivotal role of motivation in initiating and maintaining health-related behavior in diverse populations (Hagger & Chatzisarantis, 2009; Ng et al., 2012; Sheeran et al., 2020; Vasconcellos et al., 2020). Promoting a sense of autonomy in mHealth applications targeted at adolescents could occur through personalizing their experience by selecting health goals and preferred health exercises, dietary plans, or mental health practices. Offering flexible options for engagement, including setting personal schedules and commitment contracts, could further empower adolescent mHealth users. Features that give users control over their progress, such as customizable challenges could aid building competence. Further, immediate and constructive feedback, and achievement badges, could highlight improvements and signify milestones, while in-app educational content could improve health literacy in marginalized adolescent populations (Nuijten et al., 2021; Stormacq et al., 2018). Integrating social features that allow users to connect with peers and participate in group challenges could ultimately create a sense of belonging and collective achievement. Visually highlighting intrinsic health benefits, such as improved mood, increased energy, and a sense of accomplishment, rather than focusing solely on external rewards, is likely to foster internal motivation in active mHealth adolescent user groups. Gradually minimizing extrinsic rewards as intrinsic motivation grows could support sustainability and avoid over justification effects, where external rewards effectively diminish intrinsic motivation (Cameron & Pierce, 1994). This introduces the intriguing concept of applying altruistic or prosocial rewards in adolescent mHealth interventions.

Adolescence represents dynamic shifts in socio-cognitive processes, such as perspective-taking and development of social goals (Crone et al., 2022). These changes partake in shaping how adolescents value rewards for themselves and others, leveraging similar neural systems (Crone et al., 2022). Social decision-making processes evolve from simple, equal-splits methods in earlier childhood to nuanced, context-dependent choices in adolescence (Crone et al., 2022). Adolescents' prosocial or altruistic behaviors are notably impacted by peer influences, underscoring their sensitivity to social contexts and peer feedback (Böckler et al., 2016; Crone et al., 2022). Both altruistic and prosocial behaviors benefit others (Böckler et al., 2016; Crone et al., 2022; Kahana et al., 2013). However, altruistic behavior is selfless, prioritizing others' welfare through effort, kindness and sacrifice while prosocial behavior includes any action that benefits others, which can involve self-interest or adherence to social norms (Böckler et al., 2016). Individual differences in prosocial and altruistic behavior are intricately shaped by personality traits like empathy, cooperation, and kindness. Nevertheless, such traits manifest in various ways depending on "situational affordances" or perceived openings for aiding others through actions (Reis, 2008; Thielmann et al., 2020). This underscores the differential impact of contextual cues on reasons for adolescent prosocial or altruistic behavior, indicating that health behavioral goal setting and subsequent altruistic or prosocial rewards are situation specific as well as socially influenced (Wentzel et al., 2007).

Altruistic rewards in mHealth interventions have the potential to drive adolescent motivation by tapping into their natural selflessness and desire for social connection despite scarce literature on the matter (Dubé et al., 2020; Mattis et al., 2009). This approach aligns with adolescents' developmental focus on identity formation and social values, offering them a chance to support causes beyond themselves, fostering purpose and social responsibility (Blakemore & Mills, 2014; Orben et al., 2020; Pfeifer & Berkman, 2018). In mHealth interventions with altruistic or prosocial incentives, adolescents would accordingly be motivated not just for personal gain but also by the impact of their actions on others. Altruism has been associated with positive mental health outcomes, such as higher life satisfaction and reduced depressive symptoms (Kahana et al., 2013). The integration of altruistic or prosocial rewards into mHealth interventions thus creates a cycle of reinforcement: adolescents help others and improve their mental well-being in the process. Such incentives are particularly potent for adolescents, where peer approval, social belonging, and adherence to perceived important social norms are strong behavioral drivers (Blakemore & Mills, 2014; Orben et al., 2020; Pfeifer & Berkman, 2018). Such incentive loops could ultimately increase engagement and adherence to mHealth interventions, as it goes beyond self-interest to a broader desire to contribute to the welfare of others, suggesting a possible integral role of altruistic rewards in sustaining participation.

Further, altruistic rewards in adolescent mHealth interventions can drive social change by fostering collective action among adolescents (Eisenberg et al., 2016). Such rewards promote health behaviors not just individually, but as part of a communal effort (Flores et al., 2018). For instance, altruistic incentives, such as donations triggered by users' actions, could spur adolescents to engage in mHealth interventions, thereby bolstering public health and social solidarity, even among those initially reluctant to participate. Effectiveness stemming from the brain's reward system, which releases dopamine during acts of giving, increasing the likelihood of continued engagement in promoted health behaviors (Bromberg-Martin et al., 2010; Flores et al., 2018). Altruistic incentives could also raise the perceived value of interventions, as adolescents view beneficial actions for others as meaningful. To ensure cultural relevance, adolescents should help choose the causes they support, increasing the interventions' motivational appeal (Wei et al., 2020). Care is necessary to balance altruistic and self-interested incentives to maintain intrinsic motivation to ultimately increase health behavior. Altruistic rewards should complement the satisfaction from health behaviors, aligning with adolescents' developmental needs for social contribution and meaning (Hornstein et al., 2023). If properly integrated, altruistic rewards could lower attrition, encourage lasting behavior change, and inspire collective action for social good in adolescent mHealth interventions.

1.4 Adolescent attrition from mHealth interventions

Mobile health interventions have demonstrated promising outcomes in increasing general well-being as well as reducing depression and anxiety symptoms in diverse adolescent populations (Ding et al., 2023; Litke et al., 2023). However, high attrition rates undermine their potential effectiveness (Adelman et al., 2014; Eysenbach, 2005; Maenhout et al., 2022; Meyerowitz-Katz et al., 2020; Mohr et al., 2013; Topooco et al., 2019). Attrition, here defined as discontinuing treatment before achieving the desired level of improvement or reaching intervention goals, presents a challenge to research due to its varying definitions as well as to intervention development to increase their effectiveness (Eysenbach, 2005). For instance, research on mHealth applications targeting emotional disorders in adolescents frequently lack comprehensive temporal data on attrition, as well as analyses of the underlying causes of attrition, although more recent studies have begun to address these gaps in the literature (Bear et al., 2022; Wei et al., 2020). Typically, attrition has been measured at two critical junctures in the intervention: Beginning and end of the intervention (Eysenbach, 2005). To enhance our understanding of attrition dynamics, continuous monitoring of usage patterns, paired with the collection of detailed usage data, may offer insights to ways that can lower or postpone attrition in future interventions. Research highlights seven key strategies to mitigate or delay attrition in development of adolescent mHealth interventions (Wei et al., 2020). Interventions should offer personalization, tailoring content to individual user preferences and needs to ensure relevance and sustained engagement (Hornstein et al., 2023). Second, incorporating elements of gamification and ensuring aesthetically appealing content that is easily navigated within applications can significantly enhance motivation and participation by making the experience more interactive and gratifying (Wei et al., 2020). Further, social support seems vital and can be facilitated by building peer communities within mHealth platforms (McColl et al., 2014). Actively involving adolescents in the developmental process of interventions can heighten their interest in usage and enhance perceived reinforcement from use and ultimately the effectiveness of the program (Wei et al., 2020). Lastly, it is essential to conduct ongoing evaluations to ensure credibility and pinpoint the specific reasons for attrition, thus enabling continuous improvement of the intervention (Bear et al., 2022; Wei et al., 2020). Such efforts could significantly enhance retention rates and overall impact of mHealth interventions among adolescent populations (Bear et al., 2022; Jeminiwa et al., 2019).

Traditional science-based interventions aimed at mental health problems exhibit attrition rates up to double those found in other health domains, where younger age has been identified among key attrition predictors in adult populations (Mitchell & Selmes, 2007). While the typical dropout rate for cognitive behavioral therapy (CBT) programs treating internalizing disorders in children and adolescents is approximately 12%, certain studies have observed significantly higher dropout rates, exceeding the 20th percentile (Wergeland et al., 2021). Mobile CBT interventions have proven effective for treating symptoms of anxiety and depression in adolescents even though attrition rates remain a significant concern (Clarke et al., 2015; Radomski et al., 2019; Richardson et al., 2010; Rooksby et al., 2015). Efforts to identify predictors of attrition in mental mHealth interventions for adolescents have yielded mixed results. Systematic reviews reveal wide variability in retention rates across studies on adolescent populations, ranging from nearly 16% to 100% (Liverpool et al., 2020). The diversity in retention rates may be attributable to the interventions' varied delivery methods and diverse definition of attrition, administrative approaches, and durations of interventions (Cohen & Schleider, 2022; Liverpool et al., 2020). Adolescent attrition rates in mental mHealth interventions therefore require further exploration and existing knowledge gaps need filling. For instance, there is scarce research on how demographic characteristics influence attrition rates. Studies have shown that adolescents from minority groups and lower SES backgrounds engage less with digital health interventions than peers, leading to underrepresentation of these groups (Bohnert & Gracia, 2023). There's a pressing need to tailor mental mHealth interventions for lower SES adolescents and minority groups, who generally experience worse health outcomes than their peers (Bohnert & Gracia, 2023; Reiss et al., 2019). Despite the widespread access to smartphones among all adolescents, mental mHealth tools are also underutilized by these groups of adolescents (Bohnert & Gracia, 2023). This discrepancy suggests that digital interventions may inadvertently exacerbate existing health disparities. Additionally, there is a gap in research on attrition concerning gender and sexual minority adolescents, who often face increased mental health vulnerabilities due to discrimination and stigma (Bauermeister et al., 2022; Patterson, Sepúlveda & White, 2021). The context in which mental mHealth interventions are accessed may also influence attrition rates. Adolescents seem, for instance, likelier to complete mobile health interventions in a school environment under supervision compared to those who independently partake through community setting (Neil et al., 2009). Additionally, the role of rewards in retaining participants warrants further examination since research findings suggest that incentives enhance participant motivation for usage (Milne-Ives et al., 2023). A nuanced understanding of the specific reasons for attrition among subgroups of adolescents, such as those experiencing anxiety or depression, is critical to reducing attrition rates from mHealth interventions designed for clinical emotional symptoms in these populations and should involve motivational factors that influence the engagement along with app customization, robust user support, the incorporation of gaming elements into health-related tasks, and immediate and visual feedback on user input.

2 Aims

2.1 Overall aim

The overarching goal of this project was to enhance understanding of attrition within adolescent mHealth interventions. The aim was to identify critical periods when adolescents are most vulnerable to disengagement, while also collecting comprehensive data on factors that could mitigate attrition, such as motivational support, altruistic incentives, and the gamification of health tasks. Given the significant prevalence of reported mental health issues among adolescents and the scarcity of cost-effective behavioral interventions tailored to this demographic, addressing this knowledge gap is imperative. There is an urgent need to understand attrition trends and the specific reasons for attrition in adolescent mHealth interventions to better design and implement effective health solutions for this age group.

2.2 Paper I

The first paper presents the pilot study wherein there are two main objectives. The first objective was to study the acceptability and usability of the mHealth application SidekickHealth among Icelandic adolescents in six-week long general mHealth intervention. The second objective of the study was to evaluate weekly attrition rates from intervention. This included examining how self-efficacy as well as emotional and physical health of the participants correlated with usage patterns and overall adherence to the intervention. The insights gained aimed to inform subsequent development of more effective mHealth interventions tailored to the needs of the adolescent population.

2.3 Paper II

Considering the substantial health challenges adolescents face and the limited availability of affordable behavioral treatments designed for them, comprehensively examining the attrition reasons in mHealth interventions for this age group is crucial. This study, the findings of which are detailed in Papers II and III, was designed to pursue a more profound comprehension of the patterns of continuous attrition rates from an adolescent mHealth intervention, SidekickHealth, particularly focusing on how motivational support influenced attrition rates. Additionally, the aim was to assess the effectiveness of the intervention in fostering daily mental, nutritional, and physical health behaviors among adolescents, aiming to contribute to the overall enhancement of their well-being.

2.4 Paper III

The third paper's objective was to determine daily attrition rates among adolescents experiencing clinical anxiety and/or depression engaged in the mHealth intervention through SidekickHealth. Concurrently, it aimed to discern the reasons behind attrition by analyzing time-based usage data, along with the frequency, duration, and extent of health behaviors across three domains: nutrition, physical activity, and mental health. Secondly, the aim was to evaluate the efficacy of intervention in improving the conditions of adolescents grappling with anxiety and depressive symptoms.

3 Materials and Methods

3.1 Research overview

This thesis is composed of three separate original manuscripts, stemming from two distinct data collection periods designed to meet specific research objectives. Table 1 presents a summary of the three studies, detailing their respective designs, participant demographics, primary study variables, control variables, and the data analysis methods employed.

Table 1. *Overview of papers I-III*

	I	II	III
Design	Randomized waitlist-control method 6-week pilot with parallel group randomization: control and intervention groups.	Randomized controlled 6-week trial with group randomization allocated the three participating schools into control, Treatment-As-Usual (TAU), and intervention groups.	Randomized controlled 6-week trial with group randomization allocated the three participating schools into control, Treatment-As-Usual (TAU), and intervention groups.
Participants	Icelandic elementary school students, n=41 m/f ratio=24/17, mean age 15.6 (SD = 0.26)	Icelandic elementary school students, n=304 m/f ratio=152/152 mean age 13.7 (SD=.83)	Depressed and anxious Icelandic elementary school students, n=121 m/f ratio=54/67 mean age 13.8 (SD=.87)
Measurements	App acceptability and functionality (SUS), in-app completion of health tasks, weekly attrition rates, psycho-social measures (GSE, CDI, MASC, BEARS), demographics (gender, age) and BMI-SDS.	Time of attrition, amount, time, and frequency of daily in-app health tasks, psycho-social measures (RCADS, GSE, BEARS).	Time of attrition, amount, time, and frequency of daily in-app health tasks, psycho-social measures (RCADS, GSE, BEARS).
Data analysis	Descriptive and mean measures tests (paired sample *t*-tests, repeated measures ANOVAs with Bonferroni adjusted alpha levels), bidirectional correlations, Kendall's tau and standard multiple regression analyses.	Pearson's correlation coefficient, independent samples *t*-tests, repeated measures ANOVAs with adjusted alpha levels, chi-square tests, Kaplan-Meier survival analysis plots and log-rank tests along with Cox proportional hazards regression models and multiple regression models.	Pearson's correlation coefficient, independent samples *t*-tests, repeated measures ANOVAs with adjusted alpha levels, chi-square tests, Kaplan-Meier survival analysis plots and log-rank tests along with Cox proportional hazards regression models and multiple regression models.

3.2 The mHealth application

The research project commenced in 2013, engaging Icelandic elementary school students and adolescents from the pediatric obesity clinic at Landspitali University Hospital in Iceland in a series of focus group studies. These studies provided valuable information that led to the design and development of the smartphone application SidekickHealth. The application was initially crafted into a social health game based on these insights, contribution from health and behavioral experts and guidance from design advisors. Its functionality emphasized goal setting and creating health-related tasks across three main categories: nutrition (e.g., daily intake of fruits, vegetables, and water), physical activity (e.g., body-weight exercises, logging sports activities, GPS-tracked biking, walking, or running), and mental health (e.g., improving sleep, managing stress, and practicing gratitude).

All health tasks were gamified in the sense that by completing health tasks and engaging in friendly competitions, the adolescents earned badges, advanced to higher levels within the game, and accumulated points ("kicks"), which translated into altruistic rewards. For instance, users could donate liters of clean water or send polio vaccinations to children in need through UNICEF. Further, the application provided a visual representation of the user's performance and a storyline that tracked their progress, ensuring that the interface remained engaging, entertaining, and user-friendly. The application was compatible with both Android and iOS platforms and aimed to educate and enable users through the benefits of physical activity, relaxation exercises, and a balanced diet, including portion sizes and appetite awareness training (AAT). AAT, a behavioral tool used in obesity treatment, was visually integrated into Sidekick Health's nutrition category to encourage users to eat based on internal appetite cues (Bloom et al., 2013; Gunnarsdottir et al., 2012).

Throughout the studies, usage within the application was focused on overall health promotion in groups and individually. Participants in the intervention arms were assigned to health teams of six to eight persons, collectively and individually competing to accumulate points through in-app health tasks. Winners received confirmation of UNICEF's distribution of polio vaccinations in their honor. Additionally, participants' completion of in-app health exercises resulted in the donation of liters of water to children in need through UNICEF. The altruistic rewards, funded by this author, ranged from around 40-56 US cents per participant throughout each study.

Each week of the 6-week trials commenced with in-app messages outlining the weekly competitions and tasks, which included both group and individual challenges, accompanied by altruistic rewards. From the second to the sixth week, participants were also rewarded for their previous week's efforts that were separate from the competitions, with these rewards taking the form of altruistic contributions. Winners of the competitions were acknowledged with confirmation that UNICEF had dispatched Polio vaccinations to children in need on their behalf. Additionally, by completing specific in-app health exercises, participants could contribute liters of water to children in need, also through UNICEF.

3.3 Paper I

3.3.1 Participants

The study comprised 41 participants: 17 girls and 24 boys, all aged between 15 and 16 years, from an elementary school in the greater capital area of Iceland. The average age at the start of the study was 15.6 years (SD = 0.26). Eligible participants were all children born in 2001 and attending a participating public elementary school within the capital area of Iceland. Each participant was a native Icelandic speaker and owned a smartphone at the beginning of the study, with 56% using iOS and 44% on Android platforms. Exclusion criteria specified that individuals with obesity due to recognized medical conditions, mental retardation, or any physical, developmental, or mental illness that significantly restricted diet or physical activity were ineligible, as were those without access to an Android or iOS device. However, no potential participants were excluded based on these criteria. Parents and legal guardians of all eligible participants were informed about the research specifications and the mobile application via emails sent by school officials, which included a link to a confirmative survey and detailed information regarding the potential exclusion criteria. Completion and submission of the online survey were constituted consent to participate in the study. The research protocol was approved by the National Bioethics Committee (license number: VSNb2015060065/03-01).

3.3.2 Measurements

The primary outcome measure focused on app acceptability and functionality, which was assessed using the System Usability Scale (SUS). The SUS is an extensively used 10-item questionnaire that rates app usability on a scale from 0 to 100, with scores above 70 indicating satisfactory usability and user acceptance (Bangor et al., 2008; Lewis & Sauro, 2009). The Cronbach's alpha for the current sample was .73, suggesting acceptable internal consistency.

Self-efficacy was measured using the General Self-Efficacy Scale (GSE), a 10-item self-report questionnaire with total scores ranging from 10 to 40, where higher scores indicate increased self-efficacy. The GSE has demonstrated acceptable psychometric properties in various studies and is widely used among global youth populations (Luszczynska et al., 2004; Schwarzer & Jerusalem, 1995). In this study, the GSE scored a Cronbach's alpha of .94, indicating high reliability.

Secondary outcome measures included the standardized body mass index (BMI-SDS), which is adjusted for age and sex using reference values for Swedish children. Participants' weight was measured in kilograms using a Marel type C2 digital scale, and height in centimeters with a Seca stadiometer. Both measures were obtained with participants in light clothing and without shoes.

Depressive symptoms were assessed using the Children's Depression Inventory (CDI), a widely validated self-report tool for children and youth. A T-score above 70 indicates a potential clinical concern. The CDI has shown reliable psychometric strength in both U.S. and Icelandic pediatric populations, with a Cronbach's alpha of .82 for this sample (Arnarson et al., 1994; Craighead et al., 1998).

Anxiety symptoms were evaluated with the Multidimensional Anxiety Scale for Children (MASC), which includes a clinical cut-off T-score above 64 and encompasses subscales for physical symptoms, harm avoidance, social anxiety, and separation anxiety. The MASC has been recognized for its acceptable psychometric properties, including in the

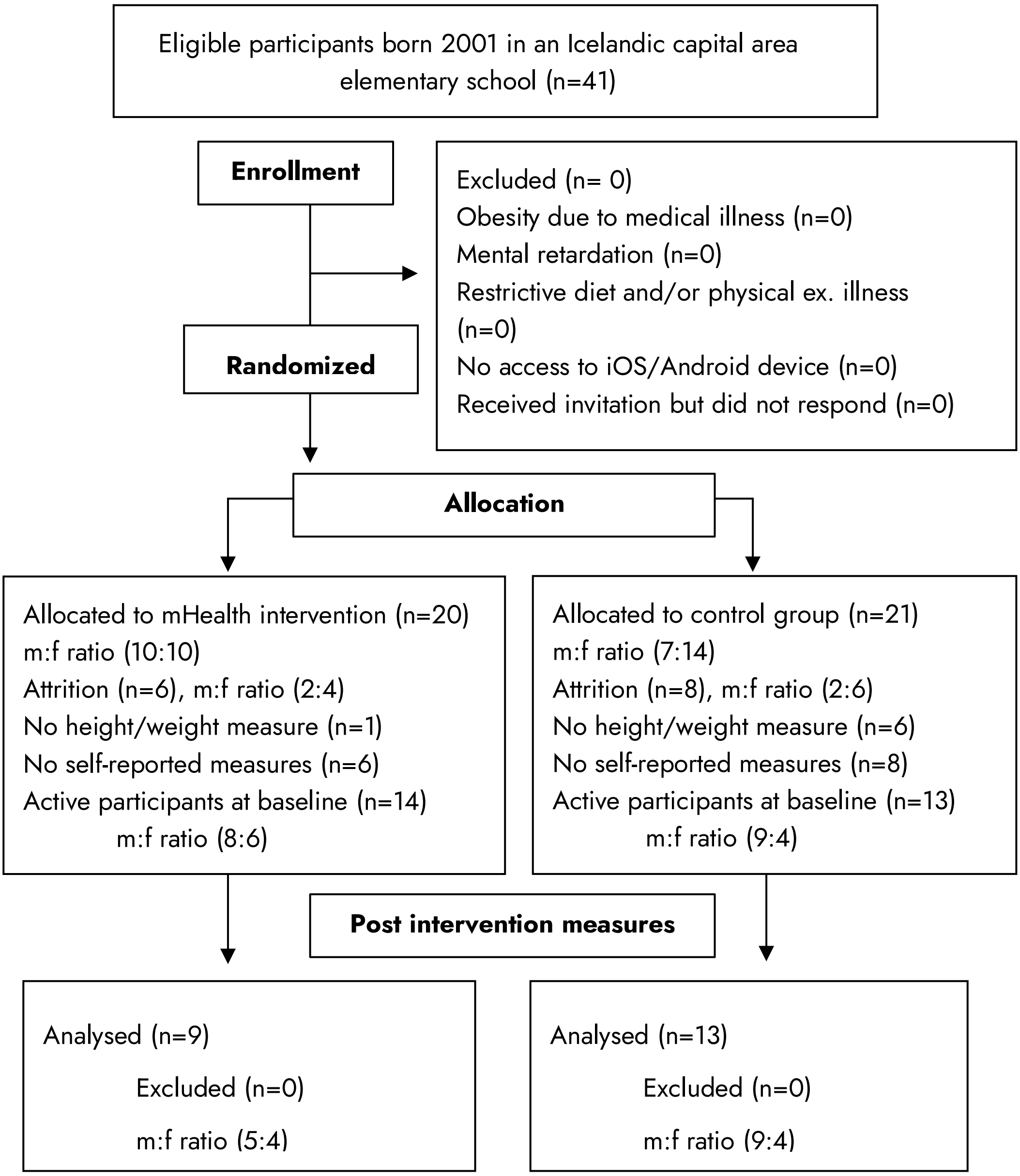
Icelandic population, and had a Cronbach's alpha of .90 in this study (March et al., 1997; Thor Olason et al., 2004)

Sleep issues were screened using the BEARS sleep screening algorithm, designed for children aged 2 to 18 years, covering five domains: bedtime problems, excessive daytime sleepiness, awakenings during the night, regularity and duration of sleep, and snoring. The Cronbach's alpha for the BEARS in this study was .71, suggesting acceptable reliability for the pilot study sample (Owens & Dalzell, 2005)

3.3.3 Procedures

The study was conducted as a randomized controlled pilot study featuring blind raters. A waitlist-control method with parallel group randomization distinguished between control and intervention groups. Research specifications and an introduction to download the mobile application were sent via email to the parents and legal caretakers of all eligible participants through school officials, accompanied by a survey link. Completion of the survey served as confirmation for study participation. Assessments were made at baseline and then again 6 weeks later at the end of the study. Anthropometric measurements were obtained by four research assistants, all undergraduate students nearing completion of their degrees at the Psychology Department of the University of Iceland. These assistants were unaware of the participants' group randomization. Each participant received an approximately five-minute introduction to the study specifications. The control group had no further contact, did not receive an invitation to download or use the mHealth application or receive additional information until the end-of-study measures. The treatment group was provided with a ten-minute introduction to the mobile application and its functions. Participants were randomly allocated into teams of six by a coin toss. These teams then collectively and individually engaged in collecting points by completing health tasks within the app. Active participation in the intervention arm was defined as downloading the SidekickHealth app and completing at least three health exercises within it. Weekly retention was determined by the completion of health exercises in the app during each week of the intervention period, thus allowing for the assessment of attrition rates on a weekly basis. The process was depicted in a flow chart presented in figure 1.

Figure 1. *Flow of participants through pilot study process*



3.3.4 Statistical analysis

The collected data was described using means, standard deviations, and the frequency of observed behaviors. Paired sample *t*-tests and repeated measures ANOVAs, with alpha levels adjusted through Bonferroni corrections, were utilized to assess mean treatment effects, such as app usage, frequency of in-app exercises, and changes in BMI-SDS and health behavior variables from baseline to post-treatment. The pilot study primarily employed descriptive statistical analysis. Categorical differences between population groups (such as gender, research group, and mobile operating system), the frequency of health behaviors (including the intake of fruits and vegetables, water consumption, and physical activity), daily screen time, and hours of sleep, along with clinical cut-off rates of psychometric measures (such as CDI and MASC) at baseline, were assessed using chi-square tests. Bidirectional correlations were evaluated between predictive variables (gender, research groups, weight category); scores in the clinical range or above cut-off for concern on psychological measures (CDI, MASC, BEARS, GSE); and the frequency of in-app categorical health exercises. These correlations were then related to outcome variables such as treatment adherence, in-app exercises, and BMI-SDS changes from baseline to post-treatment. Kendall's tau was employed to assess the relationship between app usage time categories and completion group. The variables of in-app frequency of different health category exercises (nutrition, mental health, and physical activity) were used to predict BMI-SDS change from pre-treatment to post-treatment along with treatment adherence through standard multiple regression analyses. Data were analyzed using IBM SPSS Statistics, Release Version 26.00 (SPSS, Inc., 2009, Chicago, IL, USA).

3.4 Paper II & III

3.4.1 Participants

The study included 304 individuals (152 girls and 152 boys) aged 13 to 15 years attending one of three public schools for children and adolescents in the greater capital area of Iceland that participated in the study. The mean age at baseline was 13.70 (SD 0.83) years. All children attending the highest 3 grades (8th to 10th grade) in the 3 participating public elementary schools in Iceland were eligible to participate (n=661; male-to-female ratio of 313:348). These adolescents were eligible participants in paper 2. In paper 3 however, data analysis consisted of 121 participants from the larger sample, with a distribution of 67 girls and 54 boys that showed significant anxiety and/or depressive symptoms. The mean age at baseline was 13.88 years (SD 0.87). All children in partaking elementary schools in the municipality are equipped with an iPad from 10 years of age. Exclusion criteria was the diagnosis of a severe disorder of intellectual development or a physical, developmental, or mental illness significantly restricting the ability to use mobile apps. No participant was excluded from the study based on this exclusion criterion. Research specifications and an introduction to the app were sent via email to the parents and legal caretakers of all eligible participants through school officials, along with a confirmative survey link. Parents or legal guardians provided informed consent by replying to the survey link. Adolescents with informed consent from parents or legal guardians were invited to take part in the study through a confirmative survey link. The study was approved by the National Bioethics Committee (license number: VSNb2015060065/03-01) and registered as a randomized controlled trial (Clinical Trials ID: NCT05912439).

3.4.2 Measurements

The primary outcome measures were the amount, time, and frequency of daily health activities, which were assessed through the completion of in-app exercises in SidekickHealth. Additionally, quality of sleep, energy levels, self-reported stress levels, and gratitude levels were evaluated. For all self-reported health tasks within the app, the Cronbach's alpha for the sample was .920.

Anxiety and depressive symptoms were measured using the Revised Children's Anxiety and Depression Scale (RCADS), a self-report tool for children and adolescents. This scale includes a 4-point Likert scale, contains 47 items, and is categorized into six subscales: separation anxiety symptoms, general anxiety symptoms, obsessive-compulsion symptoms, social anxiety symptoms, panic symptoms, and depression symptoms. A T-score exceeding 65 was considered the clinical cut-off point. The scale's psychometrics have been validated with satisfactory results in both U.S. and Icelandic pediatric populations (Chorpita et al., 2000; Gisladottir, 2014). For paper two, the Cronbach's alpha was .958 and .948 for paper three.

Self-efficacy levels were gauged using the General Self-Efficacy Scale (GSE), a 10-item self-report questionnaire with total scores ranging from 10 to 40, where a higher score suggested elevated self-efficacy. This scale has demonstrated acceptable psychometric validity and has been used internationally in youth populations (Luszczynska et al., 2004;

Schwarzer & Jerusalem, 1995). The Cronbach's alpha for the larger sample was .937 and .916 for paper three.

The BEARS sleep screening algorithm was employed to ascertain participants' sleep-related issues. This screening tool is applicable to children aged 2 to 18 years and investigates five sleep domains: bedtime problems, excessive daytime sleepiness, awakenings during the night, regularity and duration of sleep, and snoring. The algorithm has shown reliable psychometric properties in pediatric populations (Owens & Dalzell, 2005). For the larger sample, the Cronbach's alpha was .769 and .732 for data analysis of anxious/depressed sample.

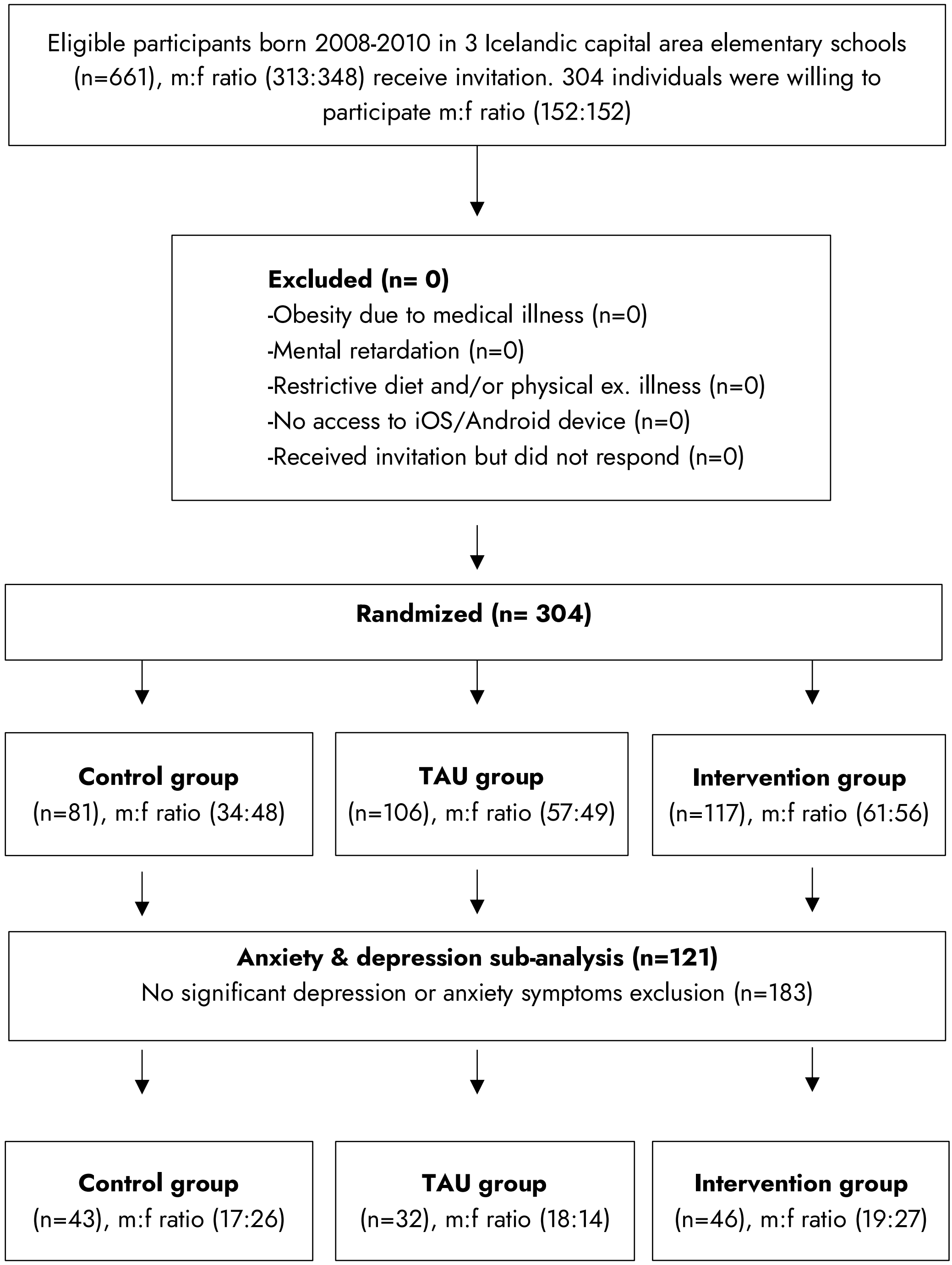
3.4.3 Procedures

The study was conducted as a randomized controlled trial. Group randomization allocated the three participating schools into control, treatment-as-usual (TAU), and intervention groups leading to diverse group sizes. Assessments were carried out at baseline and again after 42 days. Participants in the TAU and intervention groups were given an introduction of approximately 10 minutes on the study specifications and the app. The control group did not receive any further contact, access to the app, or information until the end-of-study questionnaire measures were taken. In the intervention group, participants were randomly placed into teams of eight. These teams collectively and individually competed to accrue points by completing health tasks in the app. Inclusion in the TAU and intervention groups required downloading the SidekickHealth app and finishing at least three health exercises within it. Exercise time was recorded at the moment of completion for any exercise within the app's three categories (physical activity, nutrition, and mental health). Exercise frequency was the count of times a participant completed a specific exercise. Attrition time was noted as the timestamp of the last health exercise completed within the SidekickHealth app during the intervention period. The main and key procedural difference between the TAU and intervention groups lay in the provision of motivational support and gamification of health tasks. The intervention group received weekly motivational in-app support, including individual and group feedback on app usage, participation in health task competitions, and weekly altruistic rewards for app engagement. The TAU group participants utilized the app individually throughout the trial without any added motivational support. The procedural flowchart is displayed in figure 2.

3.4.4 Statistical analysis

Descriptive characteristics of participating adolescents and reasons for attrition were reported. Mean differences from baseline to the trial's end between and within research groups for primary and secondary outcome measures were calculated using Pearson's correlation coefficient, independent samples t-tests, repeated measures ANOVAs with adjusted alpha levels, and chi-square tests. The timing of attrition and potential significant differences between and within research groups were assessed using Kaplan-Meier survival analysis plots and log-rank tests. The defined beginning of the trial was defined at the point of the first in-app health exercise completion, with a duration of six weeks, or 42 days, from that date. Attrition, or the event of interest, was marked by the exact time of a participant's last completed health exercise in the SidekickHealth app. Cases were considered censored if participants were still active in the app 42 days post-study initiation. Cox proportional hazards regression models, incorporating interacting covariables and using research groups as clusters, were employed to investigate attrition predictions based on the usage of in-app health exercises. This included the timing, type, and frequency of exercises, along with sociodemographic variables such as age and gender. Multiple regression models were utilized to identify predictor variables for the primary mean change from baseline to the trial's end in anxiety and depressive symptoms, selecting significant correlations to avoid overfitting the regression models. The threshold for significance was set at $p < .05$. Data analysis was conducted using IBM SPSS statistics, release version 29.0.1.0.

Figure 2. *Procedural flowchart of participants*



4 Results

4.1 Paper I

After a 6-week intervention, attrition stood at 35% among those who initiated the intervention, with a male-to-female ratio of 5:4. No significant gender difference in attrition rates was observed; X^2 (2, 14) = 0.83, p =.36. Attrition started in the trial's 3rd week and a significant decrease of 76% was noted in the total number of in-app health exercises from the first to the second week. However, from the second week to the end of the study, there was a 22% increase in the total number of exercises completed. Average usage levelled off at roughly 15 weekly in-app exercises throughout the intervention period and is detailed in table 2 while weekly individual in-app health exercises along with attrition rates are depicted in figure 3 and 4, respectively. Daily time of usage seemed to play a contributing role to attrition. Participants who discontinued the intervention were significantly likelier to use the app between midnight and midday compared to those who completed the intervention; R_t = 0.43, p <.05. Those who completed intervention were both more likely to use the app from midday to midnight as well as doing more in-app exercises on average than those who dropped out.

Table 2. *Weekly comparison of usage & attrition*

Week	In-app health ex. (m:f)	Indiv. ex. mean (SD)	Attrition (%)
1	859 (337:552)	55.25 (10.96)	0
2	209 (60:149)	13.63 (2.94)*	0
3	280 (142:138)	17.5 (5.33)*	35
4	272 (193:77)	17 (6.35)*	35
5	157 (109:48)	9.81 (4.07)*	35
6	267 (143:124)	16.69 (8.37)*	35

*Significant difference at p<0.05 from 1st week

Figure 3. *Weekly completion of individual in-app exercises*

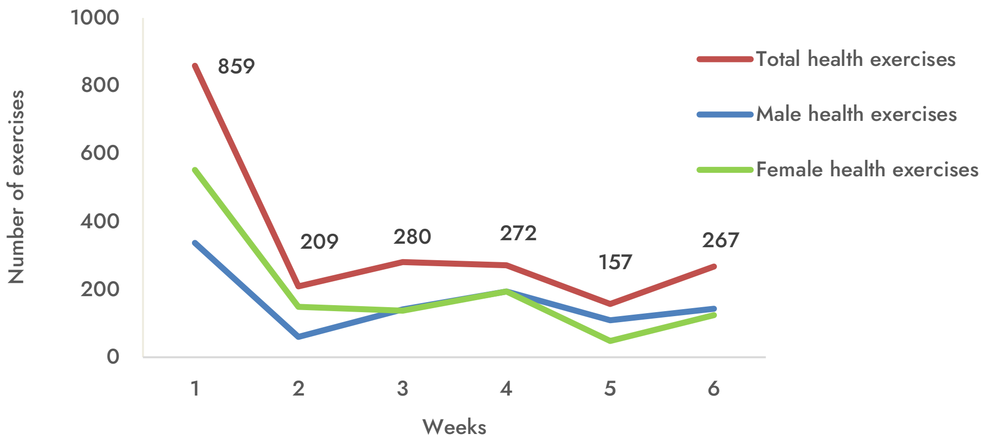
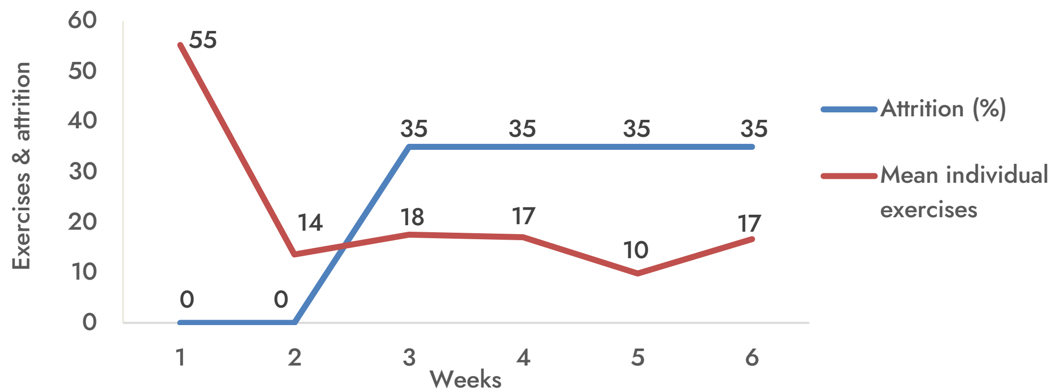


Figure 4. *Weekly mean completion of individual in-app exercises & attrition percentage*



Participants provided feedback on the app's usability, indicating they found it adequate and showed a willingness to engage with the health exercises. On average, they completed over 21 in-app exercises weekly during the intervention. Additionally, the mean total score on SUS was satisfactory, standing at 78.09 (SD = 9.82). On average however, female participants exhibited higher frequency of app usage across all health behavior categories. Table 3 details the time periods during which participants engaged with the SidekickHealth app and the types of health exercises they completed. Approximately 39% of the participants had not previously used an mHealth solution, but all were familiar with app usage as all of them had downloaded and utilized social media apps on their smartphones. When participants classified as underweight were removed from the analysis, the decrease in BMI-SDS from baseline to the study's end was significantly more pronounced in the intervention group (mean=.48, *SD*=.36) compared to the control group (mean=.08, *SD*=.44); $t(17) = -2.14$, $p < .05$.

Table 3. *Time of exercise categories in frequency & percentage*

Time of Usage	Food Ex. (%)	Physical Ex.(%)	Mental Health Ex. (%)	Total (%)
12 to 5:59 AM	42 (5%)	40 (4%)	24 (8%)	106 (5%)
6 to 11:59 AM	149 (19%)	105 (11%)	34 (11%)	288 (14%)
12 to 5:59 PM	303 (38%)	289 (32%)	93 (30%)	685 (34%)
6 to 11:59 PM	294 (37%)	482 (53%	156 (51%)	932 (46%)
Total	788 (100%)	916 (100%)	307 (100%)	2011 (100%)

The perceived amount of physical exercise in the intervention group saw a near 20% increase from baseline to the end of the study, while the control group experienced a 26% decrease. Although total anxiety scores were not significantly different between groups at the start, by the end of the study, the intervention group exhibited an 8% reduction, as opposed to a 4% increase observed in the control group, as detailed in table 4. Symptoms of depression, more pronounced in the SidekickHealth group at baseline, were no longer apparent by the study's conclusion. Additionally, the significant disparity in negative self-esteem between the intervention and control groups obtained at baseline had dissipated following the intervention, as shown in table 4. Lastly, an analysis of sleeping habits at baseline and at the study's conclusion revealed that the intervention group initially experienced significantly more issues with daytime sleepiness compared to the control group ($\chi^2(5, 20) = 11.29$, $p < .05$). However, this difference was not observed at the end of the study ($\chi^2(5, 23) = 2.35$, $p > .05$). At baseline, participants in the intervention group experienced significantly more disruptive nighttime wake-ups compared to those in the control group ($\chi^2(5, 20) = 11.87$, $p < .05$). However, these differences were not present at the end of the study. Additionally, the mean hours of sleep did not differ significantly between the intervention group (M = 6.90, SD = 1.29) and the control group (M = 7.15, SD = 0.69); $t(21) = 0.47$, $p > .05$.

Table 4. *Anxiety, depression, and self-efficacy between research groups*

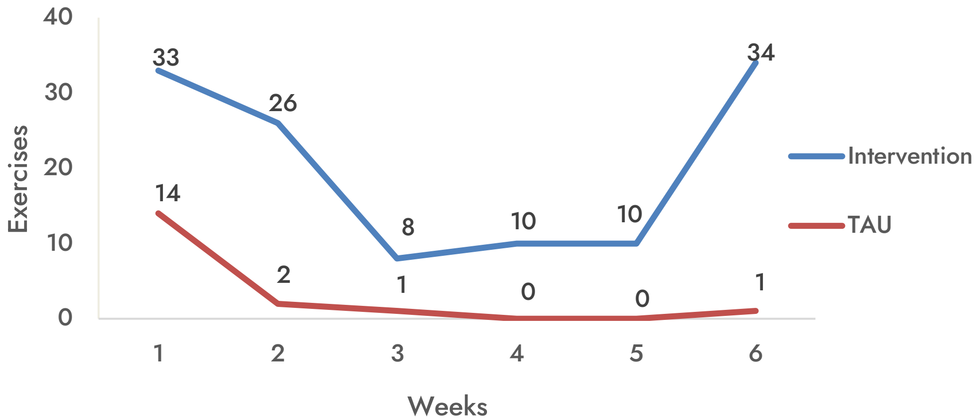
	Data Point	Control m(SD)	Intervention m(SD)	Sig.
Physical anxiety symptoms	Baseline	49.73 (15.93)	60.40 (10.93)	*t*(19)=-1.77
	End	56.08 (13.81)	59 (13.27)	*t*(20)=-0.51
Anxiety harm avoidance	Baseline	48.73 (10.07)	52 (11.12)	*t*(19)=-0,71
	End	48.77 (11.55)	51.30 (9.50)	*t*(21)=-0.56
Social anxiety	Baseline	44.73 (13.73)	55.90 (10.45)	*t*(19)=-2.08
	End	43.85 (10.03)	51.70 (13.74)	*t*(20)=-1.59
Separation anxiety & panic score	Baseline	54.73 (16.29)	58.50 (13.52)	*t*(19)=-0,57
	End	52.92 (14.41)	55.90 (9.72)	*t*(21)=-0,56
Total anxiety score	Baseline	48.18 (15.72)	60.60 (14.15)	*t*(19)=-1.90
	End	50.23 (13.36)	55.50 (13.10)	*t*(21)=-0,95
General self-efficacy	Baseline	34 (4,29)	29 (6,90)	*t*(18)=1,95
	End	33 (5,00)	31,60 (5,54)	*t*(21)=0,64
Depressive negative mood	Baseline	75.82 (4.14)	70.70 (6.88)	*t*(19)=2.09
	End	76.15 (7.77)	76.40 (5.21)	*t*(21)=-0.86
Depressive interpers. problems	Baseline	62.00 (6.80)	66.40 (8.30)	*t*(19)=-1.33
	End	64.23 (8.06)	66.90 (8.62)	*t*(21)=-0.76
Depressive ineffectiveness	Baseline	62.00 (6.80)	66.40 (8.30)	*t*(19)=1.27
	End	64.23 (8.06)	66.90 (8.62)	*t*(21)=1.03
Anhedonia	Baseline	55.18 (6.03)	59.90 (5.32)	*t*(20)=-1.89
	End	59.80 (6.88)	65.80 (5.94)	*t*(21)=-2.21*
Negative self esteem	Baseline	73.27 (5.33)	73.00 (8.11)	*t*(19)=0.92
	End	73.69 (6.47)	74.90 (10.18)	*t*(21)=-0,35
Total depression score	Baseline	69.82 (3.03)	70.40 (5.91)	*t*(19)=-0.29
	End	71.85 (7.45)	73.40 (7.03)	*t*(21)=-0.58

*Significant at $p < .05$

Paper II

Out of the 451 individuals who were invited and had received parental or caretaker consent, 304 (67.41%) participated. Analysis of the logged data highlighted significant differences in app usage among participants (figure 5). Specifically, individuals in the intervention group completed an average of 120.869 exercises (SD = 32.434), which is approximately six times more than those in the TAU group, who averaged 18.341 exercises (SD = 31.802) throughout the study (t_{221}=−3.00; p <.001). Additionally, an analysis of the health exercises logged on the first day of the study revealed a less pronounced but still significant difference between the intervention group (mean = 16.835, SD = 21.820) and the TAU group (mean = 8.100, SD = 7.237); t_{221}=−2.12; p <.05.

Figure 5. *Average weekly individual in-app health task completion*



There were pronounced disparities in completion rates between the intervention group (55.6%) and the treatment-as-usual (TAU) group (5.7%), as determined by log-rank tests ($\chi^2(1)$=61.220; p <.001) (figure 6). The average survival time for participants in the TAU group was 6.286 days (95% CI: 4.304-8.277), in contrast to the intervention group, which had an average of 24.975 days (95% CI: 21.452-28.518). Further, log-rank tests indicated significant differences in completion rates based on gender within the intervention group ($\chi^2(1)$=6.574; p <.001), with male participants showing a mean survival time of 29.155 days (95% CI: 24.519-33.812) and female participants 20.433 days (95% CI: 15.301-25.558). These gender-based differences were not observed in the TAU group ($\chi^2(1)$=1.570; p =.21). Gender-specific attrition rates for both the TAU and intervention groups are illustrated in Kaplan-Meier plots in Figure 7.

Figure 6. *Comletion rates between research groups*

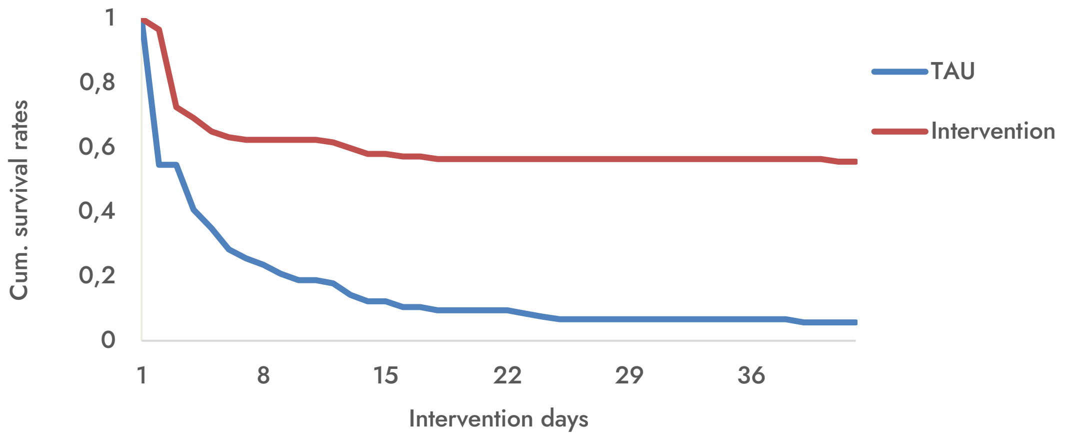
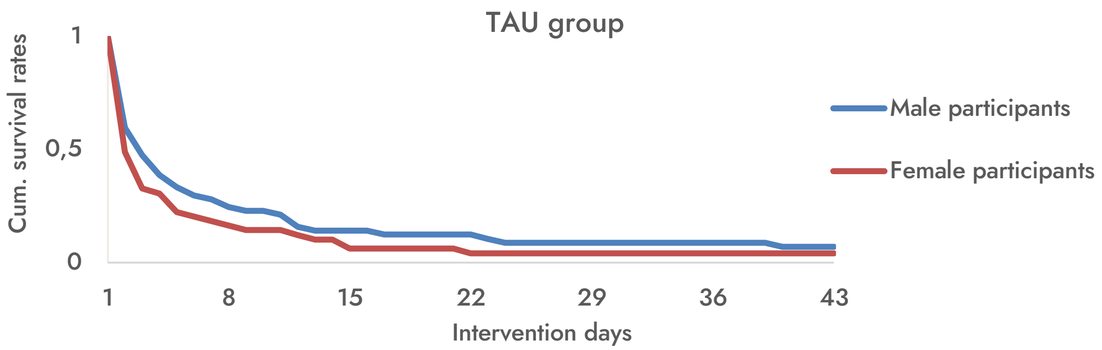
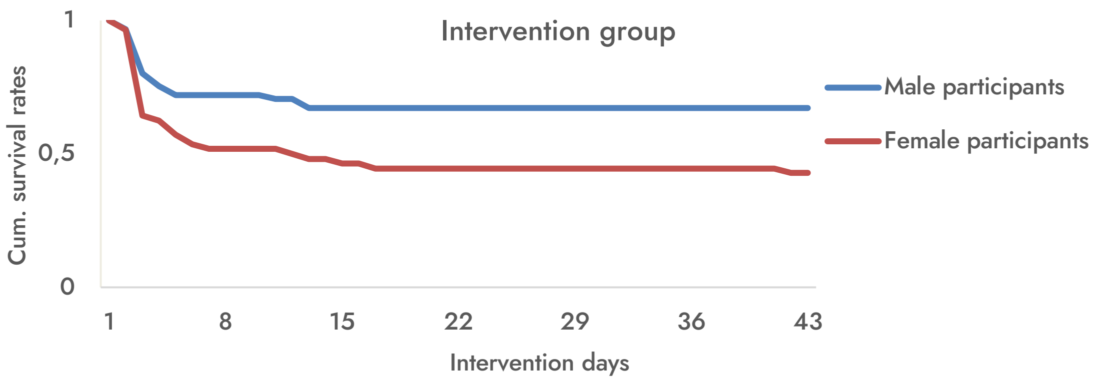


Figure 7. *Gender-based completion rates in research groups*





In the study, a significant difference was observed between the two groups regarding the average number of in-app health exercises completed each week. Notably, participants in the TAU group showed a significant decline in usage from the first to the second week, with an average decrease of 12.347 exercises (SD = 13.803) (t_{105}=9.208; p <.001) (table 5). In the intervention group, usage also declined between the first and second weeks of the trial (mean = 6.798, SD = 37.481), but this change was statistically insignificant (t_{105}=1.959; p =.06). However, a substantial increase (mean = 22.904, SD = 71.721) in the average number of in-app health exercises was recorded for the intervention group between the fifth and the final sixth week of the trial (t_{105}=3.446; p <.001), a pattern not mirrored in the TAU group.

Table 5. *Weekly comparison of usage and attrition*

Week	In-app health exercises completed, n			TAU group usage, mean (SD)	Intervention group usage, mean (SD)	*p* value
	Overall	Male	Female			
1	5369	3531	1838	14.20 (17.34)	33.03 (72.38)	<.001
2	3265	2514	751	1.85 (8.71)	26.23 (90.61)	<.001
3	1016	548	468	0.84 (5.38)	7.92 (26.71)	<.001
4	1192	803	389	0.24 (1.28)	9.97 (34.08)	<.001
5	1223	891	332	0.00 (0.00)	10.45 (60.09)	<.001
6	4029	2889	1140	1.20 (6.99)	33.35 (110.99)	<.001
Overall	16,094	11,176	4918	18.32 (27.44)	120.96 (350.09)	<.001

No significant gender differences were found in the average weekly in-app exercise frequency within research groups (table 6).

Table 6. *Weekly average in-app health exercise frequency by gender*

Week and group	Male, mean (SD)	Female, mean (SD)	*p* value
Week 1			
TAU	16.19 (19.36)	11.88 (14.50)	.20
Intervention	42.75 (97.75)	22.43 (20.12)	.13
Week 2			
TAU	3.02 (11.71)	0.49 (1.56)	.14
Intervention	38.89 (72.64)	12.98 (23.79)	.13
Week 3			
TAU	0.07 (0.42)	1.73 (7.84)	.11
Intervention	8.92 (22.29)	6.84 (30.99)	.68
Week 4			
TAU	0.37 (1.70)	0.08 (0.45)	.25
Intervention	12.84 (30.06)	6.88 (26.09)	.35
Week 5			
TAU	0.00 (0.00)	0.00 (0.00)	N/A[a]
Intervention	14.61 (62.43)	5.93 (12.73)	.44
Week 6			
TAU	1.02 (4.66)	1.41 (9.02)	.78
Intervention	46.41 (77.42)	19.13 (43.32)	.19
All weeks			
TAU	20.67 (33.60)	15.59 (17.85)	.35
Intervention	163.90 (271.22)	74.18 (109.50)	.08

[a]N/A: not applicable.

Upon analyzing the relationship between exercise time and the type of exercise, the data demonstrated substantial differences within both groups (table 7). Specifically, in the intervention group, there was a highly significant variation across exercise categories (χ^2_6=2162.559; p <.001). A similar pattern of significant differences was observed in the TAU group (χ^2_6=69.372; p <.001).

Table 7. *Frequency of exercise categories at different daily times*

Group and exercise category	0:01 to 6:00, n (%)	6:01 to 12:00, n (%)	12:01 to 18:00, n (%)	18:01 to 0.00, n (%)
TAU group	32 (100)	644 (100)	833 (100)	435 (100)
Physical health	1 (3.13)	116 (18.01)	210 (25.21)	119 (27.36)
Mental health	12 (37.50)	329 (51.09)	294 (35.29)	130 (29.89)
Nutrition	19 (59.38)	199 (30.90)	329 (39.50)	186 (42.76)
Intervention group	2575 (100)	3446 (100)	5113 (100)	3008 (100)
Physical health	2407 (93.48)	1275 (37.00)	2970 (58.09)	1576 (52.39)
Mental health	90 (3.50)	1248 (36.22)	912 (17.84)	599 (19.91)
Nutrition	78 (3.03)	923 (26.78)	1231 (24.08)	833 (27.69)
Overall	2607 (100)	4090 (100)	5946 (100)	3443 (100)
Physical health	2408 (92.37)	1391 (34.01)	3180 (53.48)	1695 (49.23)
Mental health	102 (3.91)	1577 (38.56)	1206 (20.28)	729 (21.17)
Nutrition	97 (3.72)	1122 (27.43)	1560 (26.24)	1019 (29.60)

A robust association was found between group assignment and attrition, with participants assigned to a certain group (hazard ratio 0.308, 95% CI 0.222-0.420) demonstrating significant attrition (*p* <.001). This was also true for the number of mental health and nutrition exercises completed in the app (*p* <.001 for both) across both research groups (table 8). For the TAU group, there was a notable correlation between completing an in-app health exercise between days two and six and the likelihood of completing the trial (hazard ratio 0.387, 95% CI 0.201-0.748), although this finding was not statistically significant (*p* =.29). In contrast, no such significant relationship was observed in the intervention group. Furthermore, the completion of health exercises in the first, second, and last weeks of the trial was significantly related to higher survival rates in the TAU group (*p* <.001 for all), a pattern not replicated in the intervention group. Additionally, all types of health exercises completed were significantly related to attrition in the TAU group, a trend not seen in the intervention group.

Table 8. *Regression models between groups, demographics, and application usage*

	Coefficient	HR (95% CI)	*p* value	Coefficient	HR (95% CI)	*p* value
Research Group	0,18	.31 (.22 - .42)	0,000			
Exercise Type						
Physical Health	0,24	.96 (.92-.1.00)	0,067			
Mental Health	0,20	.93 (.90-.97)	0,000			
Nutrition	0,02	.95 (.92-.98)	0,000			
		TAU Group			Intervention	
Sociodemographics						
Gender	0,23	.92 (0.58-1.46)	0,728	0,33	1.66 (.87-3.15)	0,118
Age	0,21	.97 (.64-1.46)	0,882	0,24	1.40 (0.87-2.26)	0,157
Exercise frequency						
Exercised W1*	0,34	.39 (.20-.75)	0,009	0,43	.57 (.25-1.33)	0,191
Exercises Week1	0,52	5.69 (2.06-15.71)	0,000	0,13	1.15 (.89-1.49)	0,284
Exercises Week2	0,51	4.44 (1.63-12.11)	0,000	0,16	1.16 (.84-1.58)	0,367
Exercises Week3	0,02	1.00 (.95-1.04)	0,821	0,04	1.00 (.94-1.08)	0,921
Exercises Week4	0,96	2.94 (0.45-19.20)	0,258	0,13	.98 (.76-1.28)	0,904
Exercises Week5				0,44	1.10 (.46-2.62)	0,839
Exercises Week6	5,68	.00 (.00-.02)	0,000	0,28	.81 (.46-1.41)	0,445
Exercise Type						
Physical Health	0,57	.13 (.04-.41)	0,000	0,16	.93 (.69-1.26)	0,641
Mental Health	0,53	.16 (.06-.44)	0,000	0,14	.83 (.63-1.10)	0,193
Nutrition Exercises	0,53	.17 (.06-.47)	0,000	0,15	.88 (.66-1.18)	0,396
Time of Exercise						
0:01 to 6:00	0,26	.71 (.43-1.19)	0,201	0,15	.92 (.68-1.23)	0,566
6:01 to 12:00	0,07	1.08 (.93-1.24)	0,309	0,06	.94 (.84-1.06)	0,288
12:01 to 18:00	0,07	1.14 (.99-1.31)	0,064	0,07	.96 (.84-1.09)	0,291
Interaction with Usage Days						
Physical Health & Usage Days	0,02	1.08 (1.04-1.13)	0,000	0,01	.99 (.98-1.01)	0,571
Mental Health & Usage Days	0,02	1.02 (.99-1.06)	0,173	0,01	.99 (.98-1.01)	0,709

Nutrition Exercises & Usage Days	0,01	1.01 (.99-1.04)	0,256	0,01	.99 (.98-1.01)	0,567
0:01 to 6:00 & Usage Days	0,05	1.07 (.97-1.18)	0,161	0,01	1.01 (.98-1.03)	0,733
6:01 to 12:00 & Usage Days	0,01	.98 (.96-1.01)	0,245	0,01	1.00 (.99-1.02)	0,526
12:01 to 18:00 & Usage Days	0,01	.97 (.95-1.00)	0,043	0,01	1.01 (.98-1.03)	0,621

*After 1st day of trial

4.2 Paper III

Participants' baseline characteristics are portrayed in table 9. The results highlighted a significant difference in the quantity of logged health exercises between the research groups. Participants in the intervention group logged a significantly higher number of health exercises (M = 245.790, SD = 211.845) compared to the TAU group (M = 17.630, SD = 17.848) throughout the study ($t(58)$= -1,930, p <.05). Further analysis of the health exercises logged in the app across all exercise categories showed a notable difference between the intervention group (M = 23.07, SD = 35.21) and TAU group (M = 7.94, SD = 6.92); $t(221)$=-1,31, p <.05.

Table 9. *Baseline Participants Characteristics*

Characteristic	Control (n=43)	TAU (n=32)	Intervention (n=46)	*p* value
Age (years), mean (SD)	13.77 (.43)	13.19 (.59)	13.52 (.62)	
Male:female ratio	17:26	18:14	19:27	
Native Icelandic Speakers, n(%)	43 (100)	32 (100)	46 (100)	
Sleep Impairment, n(%)	22 (51.16)	10 (31.25)	16 (33.33)	.004**
Anxiety Symptoms				
OCD Symptoms, n(%)	20 (46.51)	11 (34.38)	19 (43.30)	.706
Social Anxiety Symptoms, n(%)	21 (48.84)	14 (43.75)	17 (36.95)	.524
Panic Symptoms, n(%)	6 (13.95)	0 (0)	6 (13.04)	.090
Generalized Anxiety Symptoms, n(%)	23 (53.49)	13 (40.63)	25 (54.35)	.433
Seperation Anxiety Symptoms, n(%)	14 (32.56)	9 (28.13)	13 (28.26)	.175
Depression symptoms, n(%)	12 (27.91)	5 (15.63)	7 (15.22)	.447
RCADS Total Score, mean (SD)	59.67 (12.77)	57.81 (8.04)	58.61 (13.12)	.867
General Self-Efficacy, mean (SD)	16.26 (4.07)	15.16 (6.37)	14.85 (6.68)	.501

**Significant at $p < .01$

Attrition rates during the 6-week trial are illustrated in figure 8. The log-rank tests indicate a significant difference in completion rates, with 63% in the intervention group compared to 6.3% in the treatment-as-usual (TAU) group ($\chi^2(1) = 27.11$, p <.01). The average survival time among participants was 6.31 days (95% CI: 2.90-9.73) for the TAU group, whereas it was substantially longer for the intervention group at 29.96 days (95% CI: 22.58-37.34).

Figure 8. *Days of Attrition Between Research Groups*

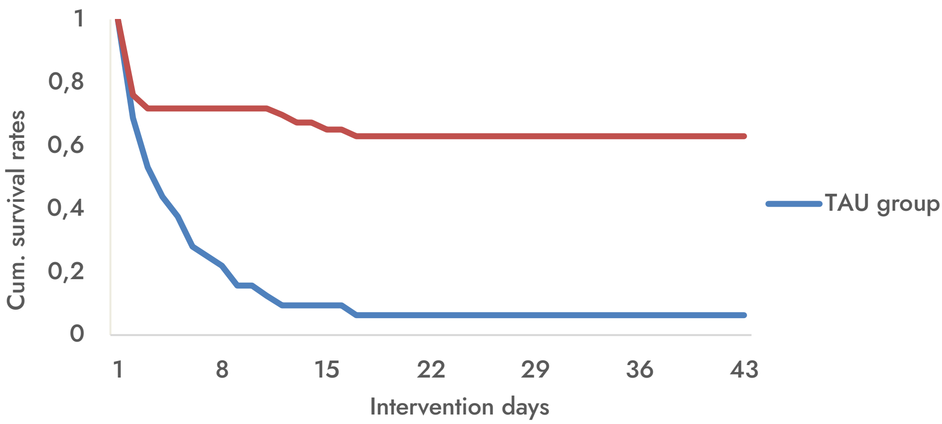


Table 10 illustrates that there was a consistent and significant difference in the mean number of in-app health exercises completed between the intervention and TAU groups throughout the trial. On average, participants in the intervention group completed ten times more health exercises than those in the TAU group. Specifically, a significant decrease in exercise completion was noted in the TAU group, with a mean reduction of 13.469 (SD = 15.486) from the first to the second week of the trial ($t(31) = 4.920$, $p < .01$). This reduction was not mirrored in the intervention group, which showed a slight, though statistically insignificant, increase of 7.954% in exercise completion from the first to the second week. Furthermore, in the last week of the trial, the intervention group's mean number of completed health exercises was significantly greater than in the fifth week (M = 35.261, SD = 72.013; $t(45) = 2.344$, $p < .05$), an uptick not seen in the TAU group.

Table 10. *Weekly comparison of usage and attrition*

Week	In-app health exercises completed, n (M:F)	TAU Group M (SD)[1]	Intervention Group M (SD)[1]	*p* value
1	2627 (1768:859)	15.28 (15.625)	46.48 (49.126)	.030*
2	2373 (1818:555)	1.81 (5.012)	50.33 (67.453)	.003**
3	770 (371:399)	1.88 (8.816)	15.43 (40.164)	.005**
4	865 (540:325)	.31 (1.768)	18.59 (32.495)	.001**
5	951 (768:183)	.00 (.00)	20.67 (44.608)	.001**
6	2601 (1882:719)	.88 (4.434)	55.93 (96.439)	.002**
Total	10187 (7147:3040)	20.16 (19.869)	207.43 (331.316)	.006**

[1]Average frequency of weekly exercise completion, ** Significant at $p < .01$, *Significant at $p < .05$

The relationship between the duration of exercise and the type of in-app health exercise is demonstrated for participants experiencing anxiety and depression in table 11.

Table 11. *Correlations between exercise time and category in anxious/depressed participants*

Exercise Category	0:01 to 6:00	6:01 to 12:00	12:01 to 18:00	18:01 to 0.00
Anxious participants				
Physical Health	.833**	.346**	.864**	.846**
Mental Health	.043	.705**	.137	.160
Nutrition	-.041	.480**	.130	.225*
Depressed participants				
Physical Health	.960**	.877**	.245	.540*
Mental Health	.429	.841**	.664**	.648**
Nutrition	0.017	.204	.122	.814**

**Significant at $p < .01$, *Significant at $p < .05$

Multiple linear regression analyses were conducted to identify significant predictors for changes in anxiety symptoms, depressive symptoms, and total RCADS scores from beginning to the end of the intervention. The data, presented in table 12, show that the number of days participants actively used the app was a significant predictor of improvements in the RCADS total score (β = -0.252, *p* <.01), anxiety symptoms (β = -0.334, *p* <.05), and depressive symptoms (β = -0.307, *p* <.05). Additionally, the volume of mental health exercises completed by participants was significantly predictive of the same pre- and post-intervention measures on the RCADS total score (β = 0.215, *p* <.01), anxiety symptoms (β = -0.382, p <.01), and depressive symptoms (β = -0.271, *p* <.04).

Table 12. *Multiple regression models on emotional symptoms and application usage*

Pre- Post Measure Differences	β (SE)	*B* (95% CI)	*t value*	*p* value
RCADS Total Score				
Predictor Variables				
Usage Days	-.252 (.088)	-.410 (-.428-.076)	-2.858	<.001
Gender	4.161 (2.440)	.179 (-.709-9.030)	1.705	.093
Total Exercise Amount	-.232 (.107)	-8.285 (-.447-.018)	-2.162	<.05
Mental Health Exercises	.215 (.072)	-.638 (.071-.359)	2.978	<.01
Nutrition Exercises	-.080 (.078)	-.212 (-.075-.235)	1.026	.308
0:01 to 6:00 Exercises	.263 (.106)	4.410 (.052-.475)	-2.481	<.05
6:01 to 12:00 Exercises	.051 (.135)	.209 (-.219-.320)	.374	.710
12:01 to 18:00 Exercises	.302 (.104)	4.338 (0.94-.510)	2.895	<.01
18:01 to 0:00 Exercises	-.089 (.133)	.796 (-.176-.353)	.669	.506
G-Self Difference	-.283 (.137)	.231 (.010-.557)	2.066	<.01
R^2=.327, *F*(10,77)= 3.255, *p*<.01				
Anxiety Symptoms				
Predictor Variables				
Usage Days	-.334 (.150)	-.337 (.034-.634)	-2.225	<.05
Gender	-3.063 (4.156)	-.082 (-11.355-5.230)	-.737	.464
Total Exercise Amount	-.248 (.183)	5.482 (-.117-.613)	1.356	.180
Mental Health Exercises	.382 (.123)	-.702 (-.627-.136)	-3.106	<.01
Nutrition Exercises	-.093 (.132)	-.153 (-.357-.171)	-.701	.485
0:01 to 6:00 Exercises	-.281 (.181)	-2.910 (-.641-.080)	-1.551	.125
6:01 to 12:00 Exercises	.047 (.230)	.120 (-.412-.506)	.203	.840
12:01 to 18:00 Exercises	.302 (.104)	4.338 (0.94-.510)	2.897	<.01
18:01 to 0:00 Exercises	-.335 (.178)	-2.978 (-.689-.020)	-1.884	.064
G-Self Difference	-.530 (.232)	.268 (-.993-.068)	-2.289	<.01

R^2=.284, F(10,77)= 2.363, p<.05				
Depression Symptoms				
Predictor Variables				
Usage Days	-.307 (.140)	-.344 (.028-.586)	2.199	<.05
Gender	-2.718 (3.866)	-.080 (-10.431-4.996)	-.703	.484
Total Exercise Amount	.195 (.170)	4.780 (-.145-.535)	1.146	.256
Mental Health Exercises	-.271 (.114)	-.552 (-.499-.043)	-2.368	<.05
Nutrition Exercises	-.037 (.123)	-.068 (-.283-.209)	-.303	.763
0:01 to 6:00 Exercises	-.223 (.168)	-2.566 (-.559-.113)	-1.326	.189
6:01 to 12:00 Exercises	.007 (.214)	.019 (-.420-.434)	.032	.975
12:01 to 18:00 Exercises	-.261 (.165)	-2.574 (-.591-.069)	-1.578	.119
18:01 to 0.00 Exercises	-.070 (.210)	-.433 (-.489-.349)	-.334	.739
G-Self Difference	-.813 (.201)	-.455 (-1.214-.413)	-4.053	<.001
R^2=.319, F(10,77)= 3.138, p <.01				

The results from Cox proportional hazard regression models presented in table 13 indicate significant associations with attrition rates. Specifically, the research group assignment was significantly negatively related to attrition, with participants in one group showing a hazard ratio of 0.299 (95% CI .208-.429, p <.01), suggesting they were less likely to drop out. Moreover, the total number of exercises completed was inversely related to attrition timing in both the TAU group (HR 0.959, 95% CI .930-.989) and the intervention group (HR 0.960, 95% CI .922-.999). A notable observation was that the frequency of in-app exercise completion from 6AM to noon significantly decreased the risk of attrition in both the TAU group (HR 1.209, 95% CI 1.008-1.451) and the intervention group (HR 0.924, 95% CI .858-.996). However, this pattern was not seen with exercises completed during other time periods in the TAU group. In contrast, there was a significant association between the number of exercises completed between noon and 6PM and attrition timing in the intervention group (HR 0.931, 95% CI .872-.993). Additionally, the amount of nutrition exercises completed showed a significant negative relationship with attrition in the intervention group (HR 0.926, 95% CI .858-1.000). There was also a significant interaction effect between the number of mental health exercises and usage days on attrition rates (HR 0.891, 95% CI .801-.991).

Table 13. *Cox proportional hazard regression models*

	Coefficient (SE)	HR (95% CI)	*p* value	Coefficient (SE)	HR (95% CI)	*p* value
Group	-1.208 (.185)	.299 (.208 - .429)	.001			
		TAU Group			Intervention	
Sociodemographics						
Gender	.603 (.402)	1.827 (.831-4.020)	.134	.573 (.542)	1.773 (.613-5.132)	.291
Age	-.196 (.331)	.822 (.430-1.572)	.553	-.047 (.420)	.954 (.419-2.173)	.910
Exercise Type						
Physical Health	-.909 (3.028)	.403 (.083-.152.311)	.764	-.073 (.085)	.930 (.787-1.098)	.392
Mental Health	-.512 (3.047)	.599 (.002-.235.06)	.867	-.094 (.066)	.910 (.799-1.037)	.157
Nutrition	-.464 (3.025)	-.629 (.002-235.964)	.878	-.077 (.039)	.926 (.858-1.000)	<.05
Exercise Frequency						
Exercised W1*	-1.062 (.727)	.346 (.83-.1.438)	.144	.648 (.884)	1.911 (.338-10.799)	.464
Week1	.425 (3.035)	1.529 (.004-586.18)	.889	-.007 (.026)	.993 (.944-1.045)	.798
Week2	.071 (3.035)	1.074 (.003-411.028)	.981	-.183 (.144)	.832 (.627-1.105)	.204
Week3	.007 (.027)	1.007 (.956-1.061)	.794	-.338 (.232)	.713 (.453-1.123)	.145
Week4	-.978 (5.193)	.376 (.00-9898.76)	.851	-.011 (.117)	.989 (.786-1.244)	.924
Week5	-	-	-	.277 (.580)	1.320 (.423-4.114)	.633
Week6	-.263 (2.671)	.789 (.004-144.497)	.922	-2.006 (1.151)	.134 (.014-1.283)	.081
Total Exercises	-.042 (.016)	.959 (.930-.989)	<.01	-.041 (.020)	.960 (.922-.999)	<.05
Time of Exercise						
0:01 to 6:00	.025 (.421)	1.025 (.449-2.340)	.954	-.377 (1.309)	.686 (.053-8.921)	.773
6:01 to 12:00	-.190 (.093)	1.209 (1.008-1.451)	<.05	-.079 (.038)	.924 (.858-.996)	<.05
12:01 to 6:00	.160 (.117)	1.174 (.934-1.475)	.170	-.072 (.033)	.931 (.872-.993)	<.05
6:01 to 12:00	-	-	-	-.077 (.043)	.926 (.851-1.008)	.076
Psychometrics Pre-Post						
General Self Efficacy	.001 (.033)	1.001 (.939-1.067)	.987	-.011 (.052)	.989 (.893-1.095)	.834
Total Score RCADS	-.102 (307)	.903 (495-1.647)	.739	.052 (.089)	1.053 (.885-1.254)	.558
Social Anxiety	.038 (0.37)	1.039 (.864-1.250)	.683	-.011 (.052)	.989 (.893-1.095)	.834
Separation Anxiety	.000 (.037)	1.000 (.929-1.076)	.998	.003 (.029)	1.003 (.947-1.062)	.931
General Anxiety	.007 (.064)	1.007 (.888-1.141)	.918	-.014 (.033)	.986 (.924-1.052)	.667
Panic Symptoms	.029 (.071)	1.030 (.897-1.183)	.676	-.069 (.042)	.933 (.859-1.014)	.105
OCD Symptoms	.019 (.051)	1.019 (.922-1.127)	.708	.015 (.021)	1.015 (.973-1.059)	.486
Depression	.009 (.081)	1.009 (.861-1.184)	.908	-.008 (.035)	.992 (.927-1.063)	.828
Interaction with Usage Days (UD)						

12:01 to 18:00*UD	-.074 (.027)	.929 (.880-.980)	<.01	-.111 (.035)	.895 (.835-.959)	<.01
18:01 to 0:00 *UD	-	-	-	-.098 (.047)	.907 (.828-.993)	<.05
Nutrition*UD	.02	1.02 (.99-1.06)	.17	-.077 (.033)	.926 (.869-.987)	<.05
Mental Health *UD	.01	1.01 (.99-1.04)	.26	-.115 (.054)	.891 (.801-.991)	<.05

* After 1st day of trial

5 Discussion

5.1 Generalizability

The evolution of mHealth interventions over the past decade has been both rapid and expansive, with a surge to approximately 325,000 applications available, including 22,750 dedicated to mental health (IQVIA, 2021). This proliferation speaks volumes about the potential mHealth interventions hold for transforming healthcare delivery, particularly in engaging adolescent populations. Yet, the effectiveness of these interventions has been tainted by remarkably low actual usage by adolescents and high attrition rates, a challenge that this research projects has pursued to examine (Adelman et al., 2014; Eysenbach, 2005; Maenhout et al., 2022; Meyerowitz-Katz et al., 2020; Mohr et al., 2013; Topooco et al., 2019). This research project aimed to delve into the underlying motivations and behaviors associated with mHealth usage in adolescents by analyzing in-app activities, including the frequency and time of engagement with nutritional, physical, and mental health exercises. The project's primary contribution to literature's current state is a granulated analysis of continuous attrition, perhaps marking a departure from the conventional binary measurement of adolescents' mHealth attrition where they either completed the programs or not. By examining continuous usage and attrition rates, the research project identified critical periods in the days after the commencement of mHealth interventions that appear particularly prone to participant withdrawal. Understanding the nuances of these sensitive periods could pave the way for interventions that are more finely tuned to the needs of diverse groups of adolescents at various stages of intervention.

This approach to measuring attrition is further enriched by the project's attention to the daily patterns of app usage. The findings suggest that not all in-app mHealth usage is equal; the time of day when participants engage with the app for instance correlates with their likelihood of completing the program. Findings also highlighted the different patterns of app usage between adolescents with anxiety and those with depressive symptoms, showing variations in the time of day when health exercises were completed. This finding points to the need for tailored intervention strategies that consider the unique behaviors and preferences of these subgroups. The observation that participants who engaged with the app in the afternoons and evenings were less likely to drop out points to the potential of adapting mHealth interventions to fit the daily rhythms of adolescents' lives. This adjustment could include optimizing the timing of notifications and interventions to periods when users are more receptive. These findings and subsequent insight underscore the need for a nuanced understanding of how adolescents interact with mHealth tools and the potential benefits of tailoring app engagement strategies to fit these patterns. However, while initial engagement among participants is high, a significant drop-off occurs after the first week of intervention. This dip suggests a dissonance between initial willingness to engage and sustained usage, highlighting an area ripe for further investigation. Despite the high prevalence of smartphone usage and familiarity with social media apps among adolescents, mHealth usage remains comparatively low (Maenhout et al., 2022; Vogels, 2022; Yardley et al., 2016). This discrepancy raises questions about the factors influencing the adoption and sustained use of health-related apps by adolescents. It therefore seems urgent to explore whether these factors are related to the perceived relevance, user experience, or other barriers to engagement.

The outcomes from the research project suggest that the intervention supports positive health behavior modifications, such as self-reported increases in physical activity. Further, the intervention seems to have merit regardless of the presence of clinical emotional symptoms, such as depression and/or anxiety. In the larger-scale studies, attrition rates within intervention groups were recorded at 44.4%, while it stood at 37% among participants suffering from anxiety and/or depression. The intervention therefore demonstrates potential in engaging both anxious and/or depressed adolescents as well as those without these conditions. The potential of mHealth interventions to not only track but also influence health behaviors is an exciting frontier, but it necessitates a robust approach to measurement that combines self-reporting with objective data collection.

The project's main findings evolve around the importance of motivational support in adolescent mHealth interventions. Motivational support—such as weekly feedback, individual and group-based health task competitions, and altruistic rewards—on app usage and attrition are particularly noteworthy. They hint at the complex interplay between the app's features and the adolescents' engagement. While the rewards were modest and importantly altruistic, their impact on usage and retention was quite significant, suggesting that even small philanthropical incentives can have an extensive effect on behavior and lower attrition rates substantially. The findings indicated that adolescents in the intervention group completed a significantly higher number of health tasks across various categories, indicating the potential efficacy of supportive and motivational program elements. Notably, there was a distinct decrease in usage after the first week in the TAU group, which was not observed in the intervention group. Furthermore, the intervention group showed increased activity towards the end of the trial, underscoring the importance of sustained support motivational support. Hence, this research project highlights the critical role of motivational support in mHealth interventions for adolescents both with and without anxiety and/or depressive symptoms. The research project took significant strides in addressing the nuanced patterns of attrition through an adolescent mHealth intervention. The insights gleaned point to the potential for tailored, time-sensitive strategies that align with the rhythms and preferences of adolescents. Yet, the path forward demands a concerted effort to expand the scope of research, deepen our understanding of motivational factors, and, ultimately, harness the full potential of mHealth interventions to support adolescent well-being.

5.2 Low mHealth utilization rates among adolescents

Despite the ubiquity of smartphones and the significant number of mHealth applications available on the market, there remains a disproportionately low utilization rate among adolescents. There exists a digital divide based on SES status among adolescents regardless of smartphone access and usage and it seems to play a critical role in disproportional mHealth uptake among adolescents (Bohnert & Gracia, 2023). Limitations on data plans, suitable environments or daily time-periods for engaging with mHealth applications, lack of digital- or health literacy, which can impede the ability of adolescents to navigate and utilize these applications effectively are all significant factors that increase the division among diverse groups of adolescents and hinder mHealth usage (Bear et al., 2022; Bohnert & Gracia, 2023; Wei et al., 2020). Secondly, the design and appeal of mHealth applications are crucial determinants of their use (Wei et al., 2020). Many apps fail to engage adolescents due to a mismatch between the app's functionality and the user's expectations or needs (Wei et al., 2020). Adolescents have unique preferences and needs that are often not addressed by mHealth applications, which are typically designed by adults for either adults or pediatric user bases. The lack of design involving adolescents results in apps that may not resonate with their daily life, interests, or the way they consume digital content. It is for instance interesting that adolescents seem to choose other social media platforms, such as TikTok (67%), Instagram (62%) and Snapchat (59%) rather than Facebook (32%), which is not the case among adults where approximately 69% use Facebook (Vogels, 2022). Moreover, privacy concerns regarding sensitive health information, can deter adolescents from using mHealth applications though the perceived relevance and credibility of the content within mHealth applications appear to be more significant factors (Litke et al., 2023; Lustgarten et al., 2020). Adolescents are more likely to engage with applications that they perceive to be directly beneficial and credible.

When considering mHealth usage among adolescents or lack thereof, the influence of social factors cannot be underestimated (McColl et al., 2014). Adolescence is a developmental period marked by strong peer influence. If mHealth application usage is not seen as a norm or endorsed within social circles, individuals are less inclined to adopt it (McColl et al., 2014). Furthermore, the fragmented nature of the mHealth market contributes to the problem of low usage among adolescents. With an overwhelming number of applications available, adolescents may find it challenging to identify which ones are suitable for their needs or what needs they seek to fulfill. The lack of standardization and quality control in the mHealth app market can lead to confusion and distrust, ultimately discouraging consistent use. Further, developmental, and psychological factors likely play a part in the underuse of mHealth applications. The desire for immediate gratification, a characteristic commonly associated with childhood and adolescence, may lead to impatience with health task completion if quick results or perceived positive feedback on behavior is not provided. This need for quick feedback is often unmet by mHealth apps, which are inherently designed for gradual improvement and long-term health behavior change (Wei et al., 2020). The underutilization of mHealth applications by adolescents is a complex issue rooted in technological, design, psycho-social, and developmental factors. To increase usage, there must be efforts to bridge the digital divide, enhance the appeal and relevance of app design for adolescents, ensure the credibility of content, address social influences, simplify the market, and strengthen the role of social support among healthcare providers in advocating for these digital tools.

5.3 Effects of gamification, altruistic rewards, and health care feedback

Gamification of adolescent mHealth interventions is an expanding and integral field to enhance engagement and outcomes in health-related behaviors. Gamification, or the application of game-design elements in non-game contexts, seems to significantly boost the efficacy of mHealth interventions (Alsawaier, 2017; Wei et al., 2020; Xu et al., 2022). The competitive elements, progress tracking, and reward systems inherent in gamification align with adolescents' developmental needs for achievement and social recognition, thereby fostering a more profound and sustained engagement with mHealth applications. Gamification addresses the challenge of sustaining adolescents' interest and motivation (Wei et al., 2020). Unlike traditional health interventions, gamified mHealth applications offer immediate rewards and feedback, satisfying the adolescent need for instant gratification (Xu et al., 2022). This is crucial in forming and maintaining completion of in-app health tasks, as the delayed gratification associated with long-term health benefits often fails to motivate this age group and contributes to high attrition rates. By providing a continuous loop of challenges and rewards, gamification can bridge the temporal gap between health behaviors and their outcomes (Alsawaier, 2017; Johnson et al., 2016; Xu et al., 2022). Secondly, the social dynamics of gaming mirror the peer influences that are pivotal during adolescence. Gamification can tap into social networks, allowing users to socialize, compete, or cooperate within the app. This can normalize health behaviors, reduce stigma, and create a supportive community that encourages usage of mHealth application (Orben et al., 2020; Wei et al., 2020). For instance, leaderboards, group challenges, and social sharing features can foster a sense of community and accountability, which are influential factors in adolescent behavior change. The results align with these notions, since participants in intervention arms of trials were both significantly unlikelier to dropout and were both more active and longer in terms of in-app health task completion. Further, the customization and personalization that gamification allows are important. By tailoring challenges, goals, and rewards to individual preferences and progress, gamified mHealth interventions can cater to the diverse needs and interests of adolescents (Wei et al., 2020). This was evident from early developmental project stages were adolescents seemed particularly motivated to partake if children in need received aid based on their efforts. The altruistic reward system, that was integrated into the intervention design was therefore tremendously important in terms of motivating gamification elements. Additionally, the data generated from gamified apps offer invaluable insights into adolescent health behaviors. The tracking of in-game behaviors and achievements can provide a detailed understanding of an individual's health journey, allowing for real-time feedback and adjustments to the intervention. This data-driven approach enables continuous improvement of applications based on actual user engagement, leading to more effective and user-centric mHealth solutions (Wei et al., 2020). However, the implementation of gamification in mHealth interventions for adolescents must be approached with caution. Poorly designed gamification can lead to overemphasis on rewards, potentially undermining intrinsic motivation.

Altruistic rewards, which are benefits given to others as a result of one's actions, could be a compelling motivational strategy in adolescent interventions, especially within the realm of mHealth applications. Incorporating altruistic incentives into mHealth interventions can substantially enhance their effectiveness by leveraging the natural inclination of adolescents towards altruism and their developmental stage that is characterized by a search for meaning and social connectedness (Blakemore & Mills, 2014; Dubé et al., 2020; Mattis et al., 2009; Orben et al., 2020; Pfeifer & Berkman, 2018). The adolescent stage of development is marked by a heightened focus on identity formation and the development of social and moral values (Orben et al., 2020; Pfeifer & Berkman, 2018). Altruistic rewards align with these developmental tasks by providing adolescents with opportunities to contribute to causes larger than themselves, thereby hopefully fostering a sense of purpose and social responsibility. When adolescents engage in health interventions that offer altruistic rewards, such as was the case in this research project, they are not only incentivized by personal gain but also by the positive impact their actions have on others. This dual incentive structure can potentiate engagement and adherence to intervention protocols, as it transcends self-interest and taps into the desire to help others. Research has shown that altruism is linked to positive mental health outcomes, including increased life satisfaction and decrease in clinical depressive symptoms (Kahana et al., 2013). By integrating altruistic rewards into adolescent mHealth interventions, the research project harnessed these benefits in order to create a reinforcement cycle: as adolescents engage with the intervention and earn rewards for others, they simultaneously enhance their own mental well-being. This may be particularly effective for adolescents, who are at a stage where peer approval and social integration are highly significant (Blakemore & Mills, 2014; Orben et al., 2020). It is for instance interesting to note that all those individuals that won a health task and received an official recognition that they had sent polio vaccinations or water purification tablets to children in need through UNICEF, finished the interventions. Whether it is was because they were so engaged beforehand or due to the rewards nevertheless remains uncertain.

Altruistic rewards can serve as a catalyst for social change by encouraging a collective action mindset among adolescents. In the context of mHealth interventions, this means that health behaviors can be promoted not only at the individual level but also as part of a larger community effort (Eisenberg et al., 2016; Flores et al., 2018). For instance, when applications donate a certain amount of polio vaccinations to children in need through UNICEF it can motivate diverse groups of adolescents to become active, promoting public health through a more significant social support among adolescents that otherwise would be unlikely to engage or be active in mHealth interventions. This was clearly the case among a some of the participants in the research project. They actively tried to finish as many health tasks as possible because their actions translated into real help for children in need. When asked, these participants were not particularly health oriented but were nevertheless quite active in the intervention and motivated to complete health-tasks to selflessly help others. The effectiveness of altruistic rewards in mHealth interventions can be attributed to several factors. Firstly, it leverages the reward system of the brain, which releases dopamine not only when we receive rewards but also when we give to others (Bromberg-Martin et al., 2010; Flores et al., 2018). This neurochemical response can increase the likelihood of repeated engagement with the health behavior promoted by the mHealth intervention. Secondly, altruistic rewards can enhance the perceived value of the intervention, as adolescents may perceive actions that benefit others as more significant and worthwhile. This is perhaps why financial expense for the altruistic rewards was between 40 and 56 pence per participant in the project. However, the implementation of altruistic rewards in mHealth interventions requires careful consideration to ensure that the rewards are meaningful and culturally relevant to the target adolescent population (Wei et al., 2020). This might involve engaging adolescents in the selection of the altruistic causes they wish to support, thereby increasing the personal relevance and motivational pull of the intervention. Additionally, it is crucial to balance altruistic and self-interested incentives to preserve and hopefully increase intrinsic motivation during trials. Altruistic rewards should perhaps be framed and presented in a way that complements, rather than replaces, the inherent satisfaction derived from engaging in health behaviors. By aligning with adolescents' developmental needs for social contribution and perceived meaning of their actions, altruistic rewards can bolster engagement, promote sustained behavior change, and foster a sense of social connectedness and responsibility. As such, the integration of altruistic rewards into mHealth interventions represents an innovative strategy to engage adolescents in health behaviors, with positive implications for public health, social psychology, and design of adolescent mHealth interventions. When done thoughtfully, altruistic rewards have the potential not only to improve individual health outcomes in mHealth interventions but also to inspire collective action and contribute to broader social good.

The integration of feedback from healthcare professionals into adolescent mHealth interventions is an essential element for the success and efficacy of these digital health solutions (Wei et al., 2020). The feedback can take various forms, including personalized advice, encouragement, monitoring of health behaviors, and adjustment of health goals. It is however the personalized interaction that seems crucial as it offers adolescents a sense of validation and support that is often missing in purely automated systems (Wei et al., 2020). Direct involvement of healthcare professionals in mHealth interventions provides a reliable source of accurate and tailored health guidance. Adolescents are in a stage where they are establishing lifelong health behaviors, and the guidance from professionals ensures that the information they receive is not only correct but also appropriate for their specific health needs and concerns. Such personalized feedback can lead to better health literacy, empowering adolescents to make informed decisions about their health. Moreover, healthcare professional feedback seems to significantly impact adherence to mHealth interventions. Adolescents may be more motivated to follow through with prescribed activities or recommendations if they know that their progress is being monitored and evaluated by a professional (Wei et al., 2020). This sense of accountability can be a powerful motivator, encouraging consistency and persistence in engaging with the intervention. The emotional and psychological support provided by healthcare professional feedback should not be underestimated. Adolescents are navigating complex social and emotional landscapes, and personalized feedback can offer support and reassurance, reducing feelings of isolation or uncertainty regarding health concerns. This is particularly important for interventions targeting mental health conditions, where ongoing support and encouragement can be critical to the user's well-being. Furthermore, feedback from healthcare professionals can facilitate a collaborative approach to health management, involving adolescents in the process of setting realistic and achievable health goals. This collaborative goal setting can lead to increased self-efficacy among adolescents, as they feel more in control of their health outcomes and more capable of achieving their objectives.

Despite its benefits, integrating healthcare professional feedback into mHealth interventions presents challenges, including ensuring privacy and confidentiality, maintaining engagement over time, and providing feedback that is both empathetic and effective. Moreover, it requires a significant commitment of time and resources from healthcare professionals, which may not always be available and designing realistic ways for the frequency, amount, and timing of healthcare feedback into mHealth interventions should perhaps be an integral part of interventions' design. In this research project, weekly feedback on user's health task completion statistics, announcement of competition winners and coming week's competition focus served as a sustainable, yet sufficient, way to effectively include healthcare feedback into the intervention. In conclusion, healthcare professional feedback is one of the cornerstones of effective adolescent mHealth interventions. By providing accurate health information, enhancing adherence, offering support, and facilitating collaborative goal setting, professional feedback can significantly improve the quality and impact of mHealth solutions for adolescents. As the field of mHealth continues to grow, the integration of healthcare professional feedback will be crucial in designing interventions that are not only technologically advanced but also deeply attuned to the complex needs of the adolescent population.

5.4 Methodological strengths and limitations

Findings from the research project offer valuable insights, but its generalizability is constrained by a focus on Icelandic elementary school students, limiting its application across the broader adolescent demographic. These constraints illustrate a somewhat common dilemma in mHealth research, the search for balance between the rich understanding gleaned from small-scale studies and the need for broad applicability of results. The first limitation of the research is the randomization at the level of elementary schools rather than individuals, a strategy employed to mitigate contamination effects. This choice, while methodologically sound, introduces a potential bias, as it does not account for the individual variability in app usage that might arise from personal preferences or behaviors. The limited six-week data collection period also poses a constraint, suggesting that a more extended research duration and follow-up would provide a deeper understanding of long-term usage and the enduring impact of motivational features. The generalizability of results is further limited by the potential variability in how different cultural settings might perceive and engage with altruistic reward schemes and competitive features. It is, for instance, uncertain whether altruistic rewards in the form of polio vaccinations or water purification tablets to children in need through UNICEF would function as effectively in different cultural settings or among adolescents with dissimilar SES heritage. This underlines the importance of contextualizing mHealth interventions within cultural frameworks to ensure relevance and effectiveness. Despite these limitations, the study significantly contributes to the sparse research on attrition rates and patterns within adolescent mHealth interventions. Methodologically, the study's strengths are notable, particularly the continuous data collection throughout the larger trial period, the systematic and detailed description of time-based attrition rates through survival analysis, and the use of a relatively large sample sizes in the larger trials. These strengths underscore the potential replicability of its methodology in future research. By addressing these limitations and building on the strengths, future research can expand on these findings to develop more generalized and culturally sensitive mHealth strategies. These strategies must align with the rhythms and preferences of adolescents, ultimately improving the reach and efficacy of mHealth interventions in fostering adolescent well-being.

5.4.1 Paper I

The study's scope was confined to one research location in an Icelandic elementary school, and the findings were derived from a small, convenience-based sample. This presents a significant constraint in terms of statistical robustness and the ability to generalize the research findings to a broader population. The design of the study is further limited by its small sample size. The structure of the research design, comprising only the intervention group and a wait-list control group, without a treatment-as-usual (TAU) group for comparison, complicates the ability to draw definitive conclusions about in-app behavior, attrition rates, and the effectiveness of motivational support mechanisms within the app. Despite these limitations, the study has noteworthy strengths. It employs a collection of comprehensive measures, including anthropometric data, demographic information, and psycho-social variables. These, coupled with detailed data on in-app usage, provide a substantial basis for analyzing the impact of the mHealth pilot. The inclusion of these varied and robust measures offered a multidimensional view of the pilot's effects, which was a valuable contribution to subsequent trials.

5.4.2 Paper II & III

The trials faced certain methodological constraints, notably with their randomization approach, which was conducted across participating elementary schools rather than at the individual level—a decision aimed at mitigating contamination effects but potentially affecting the internal validity of the findings. The six-week timeframe for data collection, while providing initial insights, was limited in scope. Future research should extend this period to better assess the longevity of the intervention's impact, incorporating a more nuanced randomization approach to equilibrate app usage across groups. A subsequent three-month follow-up would be invaluable in evaluating persistent usage and the enduring effects of motivational support mechanisms. A notable limitation was that not all measures employed were validated for an Icelandic adolescent population, pointing to a broader issue of the lack of validated psychosocial measures for Icelandic children and adolescent populations. Additionally, the study's reliance on self-reported data, rather than objective measures of health behavior, may impact the validity of the findings concerning in-app health task completion. However, the results indicate that completion rates positively correlate with overall well-being in participants and reducing the likelihood of attrition, which is a valuable insight despite the noted constraints. Future studies would benefit from the inclusion of psychometrically validated tools tailored for the target population and objective in-app metrics to quantify health behaviors more accurately. The generalizability of findings from adolescent mHealth studies to broader populations is inherently challenging due to the variability in how different cultural contexts may perceive and engage with elements such as altruistic rewards and competitive features. This study, although insightful, is not immune to these generalizability concerns. Nevertheless, this research enriches the field with data on attrition rates and behavioral patterns in adolescent mHealth interventions—a domain where research is notably scarce. Methodologically, the study stands out for its continuous data collection during the trial, application of survival analysis to chart time-specific attrition rates, and the engagement of a considerable number of participants.

6 Conclusions

Over the past decade, mHealth interventions have rapidly expanded to around 325,000 applications, 22,750 of which are focused on mental health. This growth indicates the significant potential of mHealth to transform healthcare delivery, particularly for engaging adolescents. However, the effectiveness of these interventions is undermined by low usage rates and high attrition among adolescents. This research project aimed to explore the motivations and behaviors behind adolescent mHealth usage by analyzing in-app activities, such as the frequency and duration of engagement with nutritional, physical, and mental health exercises. A significant contribution of the project is the detailed analysis of continuous attrition, moving away from the binary perspective of program completion to recognize critical periods prone to participant withdrawal after starting mHealth interventions. This insight allows for the development of more finely tuned interventions to meet the varied needs of adolescents.

The study also considered daily app usage patterns, discovering that the time of day affects the likelihood of program completion. It highlighted differences in app usage between adolescents with anxiety compared to those with depressive symptoms, indicating the need for customized intervention strategies. Observations suggest that those who used the app in the afternoons and evenings were less likely to drop out, pointing to the advantage of aligning mHealth interventions with adolescents' daily schedules, possibly by optimizing notification and intervention timings. Despite high initial engagement, there is a significant decrease in usage after the first days. This trend suggests a gap between the initial willingness to engage and the maintenance of sustained usage, an area that warrants further research. The contrast between the widespread use of smartphones and social media apps and the comparatively low mHealth usage among adolescents raises questions about the factors that affect the adoption and ongoing use of health-related apps. This underscores the urgency to investigate whether these factors relate to the perceived relevance, user experience, or other engagement barriers. In conclusion, the research provides insights into the importance of understanding adolescent interactions with mHealth tools and the benefits of customizing app engagement strategies to their daily patterns and preferences. There is a clear need for continued exploration into the motivational aspects and design of mHealth interventions to maximize their potential in supporting adolescent well-being.

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Original Publications

I. Egilsson, E., Bjarnason, R., & Njardvik, U. (2021). Usage and weekly attrition in a smartphone-based health behavior intervention for adolescents: pilot randomized controlled trial. JMIR formative research, 5(2), e21432.

II. Egilsson, E., Bjarnason, R., & Njardvik, U. (2023). Usage and Daily Attrition of a Smartphone-Based Health Behavior Intervention: Randomized Controlled Trial. JMIR mHealth and uHealth, 11(1), e45414.

III. Egilsson, E., Bjarnason, R., & Njardvik, U. (2024). Usage and daily attrition from a smartphone-based health behavior intervention among adolescents with anxiety and depression symptoms. Submitted for publication.

Paper I

Paper I

Original Paper

Usage and Weekly Attrition in a Smartphone-Based Health Behavior Intervention for Adolescents: Pilot Randomized Controlled Trial

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Abstract

Background: The majority of adolescents own smartphones, although only 8% of them use health apps. Attrition rates from adolescent mobile health (mHealth) interventions for treating mental health problems such as anxiety and depression are an issue with a high degree of variation. Attrition in mHealth interventions targeting adolescent populations is frequently presented in a two-point fashion, from initiation of the intervention to the end of treatment, lacking more time-specific information on usage and times of attrition. Self-efficacy could provide an avenue to lower attrition rates, although a better understanding of the relationship between mental health factors and time-specific attrition rates is needed.

Objective: The aims of this study were to obtain time-specific attrition rates among adolescents in an mHealth intervention, and to describe the intervention's usage and feasibility in relation to adolescent self-efficacy levels, and emotional and physical health.

Methods: A single-center randomized controlled public school pilot trial was undertaken with 41 adolescents. Outcome measures were assessed at baseline and after 6 weeks, while in-app activity and attrition rates were continually assessed throughout the intervention period. The primary outcome was attrition based on time and type of in-app health behavior usage, and feasibility of the mHealth app. Secondary outcome measures were self-efficacy levels, depressive and anxiety symptoms, as well as standardized BMI and sleep. Analyses of group mean variances with adjusted α levels through Bonferroni corrections were used to assess main outcome effects.

Results: The attrition from initiation of the intervention to 6-week follow up was 35%. Attrition started in the third week of the intervention and was related to daily time of app usage (R_t=0.43, P<.001). The number of average weekly in-app health exercises completed decreased significantly from the first week of the intervention (mean 55.25, SD 10.96) to the next week (mean 13.63, SD 2.94). However, usage increased by 22% between week 2 and the last week of the intervention (mean 16.69, SD 8.37). Usability measures revealed satisfactory scores (mean 78.09, SD 9.82) without gender differences (P=.85). Self-reported daily physical activity increased by 19.61% in the intervention group but dropped by 26.21% among controls. Self-efficacy levels increased by 8.23% in the invention arm compared to a 3.03% decrease in the control group.

Conclusions: This pilot study demonstrated the feasibility and usability of an mHealth intervention among adolescent participants. Indications were toward beneficial effects on physical and mental health that warrant further research. Focus on time-specific attrition measures alongside daily times of usage and ways to increase participants' self-efficacy levels appear to be a promising avenue for research on mHealth interventions for adolescent populations with the aim to ultimately lower attrition rates.

(JMIR Form Res 2021;5(2):e21432) doi: 10.2196/21432

KEYWORDS

mHealth; intervention; adolescent; attrition; self-efficacy; mental health; physical activity; young adult; behavior

Introduction

Recent systematic reviews on the global prevalence of psychiatric disorders in children and adolescents have produced varying results ranging from 6.8% to a notably higher pooled rate of 13.4% [1,2]. Emotional disorders as well as significantly distressing subthreshold emotional problems are among the most common psychiatric problems reported in adolescent populations [1-3]. According to the Centers for Disease Control and Prevention, over 6% of US children between 12 and 17 years old have been diagnosed with depression and over 10% have been diagnosed with anxiety disorders [4]. Globally, it is estimated that 10% to 20% of youth experience mental health problems [5-7].

Smartphone ownership is growing fast worldwide. In the United States, smartphone ownership or access among adolescents was estimated at 95% in 2018, representing an increase from 73% in 2015 [8,9]. Similar development is evident elsewhere, with youth smartphone ownership surpassing the 90th percentile in the majority of developed economies [9]. Not only are smartphones widely distributed but people also tend to carry their phones with them, spending an estimated 170 minutes per day using smartphone apps [10]. Some studies indicate that daily smartphone usage among adolescents is often more than 270 minutes [11]. The number of mobile health (mHealth) interventions available has risen steeply in a steady fashion since first appearing roughly a decade ago, with an estimated 325,000 apps available on the market in 2017 [12]. However, only 8% of adolescents use health apps and relatively few studies have documented how they specifically function in adolescent populations [13]. Although mental health problems disproportionally burden minority and lower socioeconomic status groups in terms of receiving evidence-based interventions, smartphones may be used as a tool to diminish such disparities [14,15]. For example, in the United States, adolescent smartphone ownership is not related to gender, race, parental educational levels, or socioeconomic status [9].

Smartphones offer possibilities of a uniquely personalized platform to tailor the many aspects of treatment to individual patients. Patient treatment through support by smartphones or other mobile devices such as tablets, patient monitoring devices, and personal digital assistants have been collectively labeled "mHealth" [16]. mHealth interventions have shown promising cost-effective outcomes related to lowered anxiety and depression symptoms in youth populations despite recurring issues of high attrition rates [15,17-22]. Attrition is here defined as leaving treatment before obtaining a required level of improvement or completion of intervention goals [23,24]. Treatment attrition is common, costly, and important, although varying definitions of the term have challenged research on the matter [17,24].

Studies on mHealth interventions targeting emotional disorders or subthreshold emotional problems in adolescent populations have frequently lacked time-specific data alongside a lack of accurate definitions and analysis of treatment attrition [15,25]. Usability data in mHealth studies targeting adolescent populations are frequently presented with attrition rates from the initiation of intervention, either at the time of recruitment or launch of the intervention's first section. For instance, average weighted attrition rates prior to commencing online treatment and after treatment have been reported to be 21%, whereas the rate was 8% from treatment completion to follow up [23].

Attrition in mental health care interventions has been shown to be up to twice as common compared to that in other medical fields [24]. For example, attrition from cognitive behavioral therapy (CBT) was reported to range from 20% to up to nearly 44%, although some indications are toward lower attrition in CBT at the group level [26]. Recent research has found that online CBT programs are effective in treating adolescent mental health problems such as anxiety and depression [5,15,25,27]. However, attrition from these programs remains an issue, with a high degree of variation and attrition rates reaching up to 50% [15,28]. To ultimately lower attrition in adolescent mental mHealth interventions, a better understanding of what factors explain mHealth usage in different adolescent subgroups and time-specific attrition is direly needed.

Adolescents with significant emotional problems (ie, anxiety and depression) were reported to have lower general self-efficacy than their peers and were more likely to either not seek treatment or drop out [3,29,30]. Originating from social cognitive theory, self-efficacy is defined as an individual's belief that ability is sufficient to succeed or accomplish a task and has been used extensively to guide a theoretical framework for interventions targeting health behaviors [3,29-31]. Individuals with higher levels of self-efficacy are more likely to seek treatment and persist longer in their efforts to change behavior [32]. A partial reason for this appears to be effective use of self-regulatory skills such as planning, problem-solving, and self-incentives [32]. Research has shown a positive relationship between higher levels of self-efficacy and successful health behavior change in terms of weight management and exercise behavior [33]. Studies have also revealed a mediating relationship between higher levels of self-efficacy and treatment adherence in diverse chronic illnesses [34]. Attrition rates in adolescent mHealth interventions could perhaps be better accounted for by an increased understanding of the relationship between self-efficacy levels and detailed descriptions of time- and content-based usage. The purpose of this study was to assess time-specific attrition rates in an adolescent mHealth intervention, as well as to describe usage and the intervention's feasibility in relation to self-efficacy levels and participants' emotional and physical health.

Methods

Participants

Participants were 41 individuals, including 17 girls and 24 boys, between 15 and 16 years of age attending a public school in the greater capital area of Iceland. The average age at baseline was 15.6 years (SD 0.26). All children born in 2001 attending a participating public school in Iceland's capital area were eligible participants. All participants were native Icelandic speakers and owned smartphones at baseline; 56% (n=23) of participants had smartphones operating on iOS and 44% (n=18) had those operating on Android devices. Exclusion criteria were obesity rooted in recognizable medical illness; mental retardation; physical, developmental, and mental illness significantly restricting diet or physical exercise; and not having access to an Android or iOS operating device. No participant was excluded from the study based on these criteria. Research specifications and mobile app introduction were sent to parents and legal guardians of all eligible participants through school officials by email, including a confirmative survey link along with parental information about possible exclusion criteria. Participation in the online survey was regarded as consent. The study was approved by the National Bioethics Committee (license number VSNb2015060065/03-01).

Measurements

The primary outcome measure was app acceptability and functionality, assessed with the Systematic Usability Scale (SUS), a widely used and relatively well-studied 10-item questionnaire on app usability where the scores range from 0 to 100, and a total score over 70 indicates satisfactory usability and user acceptance [35,36]. Further primary measures were the amount, frequency, and time of daily physical activity measured through in-app activity; self-reported stress levels; and quality of sleep and energy levels, measured through levels of health app usage and completion of in-app health tasks. Cronbach α for the current sample was .73.

Self-efficacy was assessed with the General Self Efficacy Scale (GSE), a 10-item self-report questionnaire with scores ranging from 10 to 40, with a higher score yielding increases in self-efficacy [37]. GSE has shown acceptable psychometric properties in studies, and was used in global youth populations [38]. Cronbach α for the current sample was .94.

Secondary outcome measures included the standardized BMI (BMI-SDS) based on BMI index reference values for Swedish children adjusted for age and sex. Participants were weighed in kilograms in light clothing without shoes using a digital scale (Marel type C2; Marel, Reykjavik, Iceland). Height was measured in centimeters using a wall-mounted stadiometer (Seca stadiometer; Seca, Hamburg, Germany).

Participants' depressive symptoms were assessed with Children's Depression Inventory (CDI), a self-report assessment tool for children and youth. A T-score over 70 was used as the clinical cut-off point. The CDI's psychometrics have been studied with acceptable findings in both US and Icelandic pediatric populations [39,40]. Cronbach α for the current sample was .82.

The Multidimensional Anxiety Scale (MASC) was used to measure anxiety symptoms. The MASC is a self-report scale with a clinical cut-off T-score over 64 and the following subscales: physical symptoms, harm avoidance, social anxiety, and separation anxiety. Acceptable psychometric properties of the MASC have been documented overall as well as in the Icelandic population [41,42]. Cronbach α for the current sample was .90.

The BEARS sleep screening algorithm was used to assess sleep problems among participants. BEARS is a screening instrument for children from 2 to 18 years old, divided into five sleep domains: bedtime problems, excessive daytime sleepiness, awakenings during the night, regularity and duration of sleep, and snoring [43]. Cronbach α for the current sample was .71.

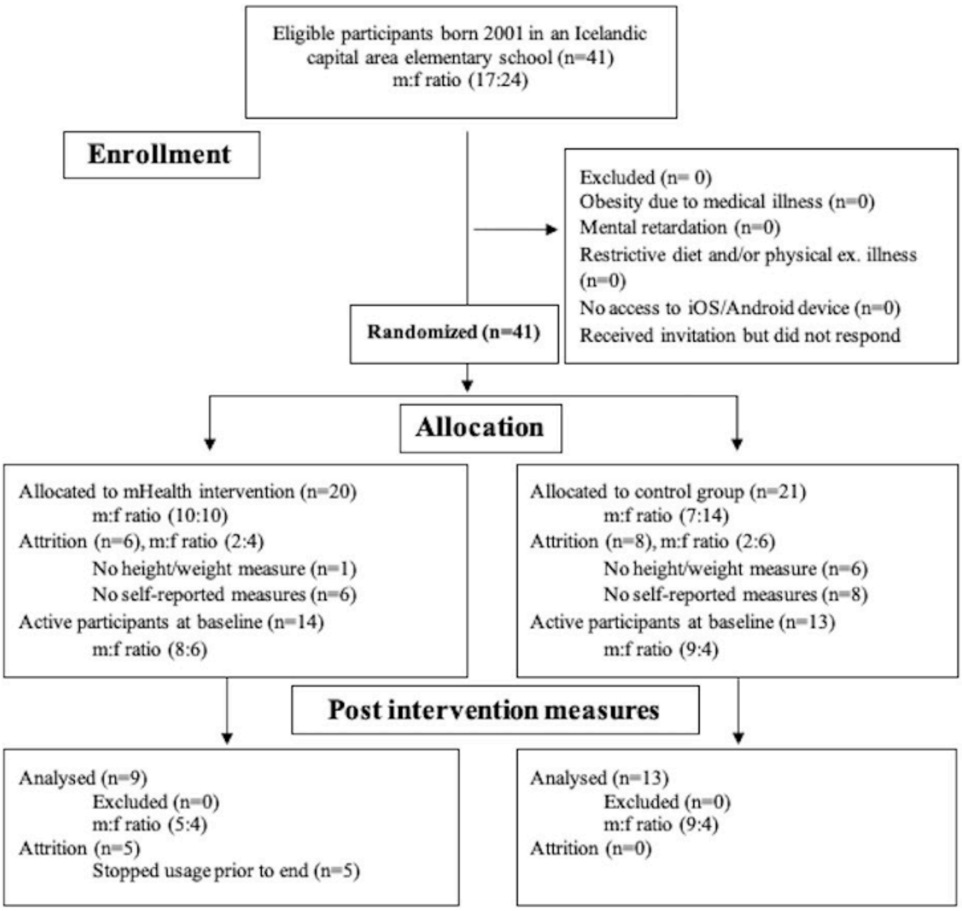
mHealth App

Multiple focus group studies were performed among both Icelandic public school students and adolescents in the obesity clinic at Landspitali University Hospital in Iceland to design and implement the smartphone app named SidekickHealth. Based on results from focus group studies and design advisors, the app took the form of a social health game (see Multimedia Appendix 1). Functionality is centered on helping the user set goals and create health-related missions (gamification of tasks) in three main categories: food and drink (eg, daily fruits, vegetable and water intake), physical activity (eg, body weight exercises, minutes of sports activity, GPS-based biking, walking, or running), and mental health (eg, improving sleep, reducing stress, and exercising gratitude). By completing missions and friendly competitions, the user accumulates badges, moves to higher levels, and aggregates points (called "kicks") providing altruistic rewards (liters of water or polio vaccinations that are sent in their name to children in need through UNICEF). A visual representation of user performance in different categories is provided along with a storyline highlighting progress. Emphasis is on keeping the app fun, entertaining, and easy to use. The smartphone app operates on the Android and iOS platforms. The app's function focuses on education and enablement through essentials of the benefits of physical activity and relaxation exercises, as well as a healthy diet, portion sizes, and appetite awareness training (AAT). AAT is a behavior tool that is used in obesity treatment, which encourages overweight/obese children and teenagers to eat in response to internal appetite cues, and has shown promise for the treatment of overweight and obese children and teenagers [44,45]; thus, AAT was visually developed as an individual mission in the app's nutrition category. Throughout this study, mHealth usage was focused on overall health promotion in groups and individually. In weeks 2 to 4, the in-app focus was on individual mental health promotion, dietary habits, and physical exercise, respectively. Participants were randomly ascribed to health teams consisting of 6 individuals that collectively and individually competed in point collection through completion of in-app health tasks. Winners of competitions, groups and individuals, received confirmation that UNICEF had sent polio vaccinations to children in need. Further, through completion of in-app health exercises, participants collected liters of water that were sent in their name to children in need through UNICEF. The total cost for the altruistic rewards, paid for by the first author, for all in-app rewards throughout the treatment period was roughly US $16 or US $0.40 per participant.

Procedure

The study was a randomized controlled pilot study with blind raters. The waitlist-control method with simple parallel group randomization was used to distinguish control and intervention groups. Research specifications and mobile app introduction were sent via email to the parents and legal caretakers of all eligible participants through school officials along with a confirmative survey link, which if answered yielded confirmation for participation. Measures were taken at baseline and 6 weeks later at the study end. All participants received an approximately 5-minute-long introduction regarding the study specifications. The control group received no further contact or information until study-end measures. Anthropometric measures were performed by four research assistants, all of whom were senior undergraduate students at the Psychology Department of University of Iceland. The research assistants were blinded to group assignment. The treatment group received a 10-minute introduction about the mobile app and its functions. Participants were randomly assigned with the coin toss method to teams consisting of 6 individuals that collectively and individually competed in point collection through completion of in-app health tasks. Participation in the intervention arm was defined as downloading the SidekickHealth app and completing at least 3 health exercises within the app. Weekly retention was defined as completing health exercises in the app during each week of the intervention period. Attrition rates were therefore assessed on a weekly basis. A flow chart of the study is provided in Figure 1.

Figure 1. Pilot intervention flow chart. mHealth: mobile health; m: male; f: female.



Statistical Analysis

Data are presented as means (SD) and frequency of observed behaviors. Paired-sampled *t* tests and repeated-measures analysis of variance with adjusted α levels through Bonferroni corrections were used for assessing mean treatment effects (ie, app usage, frequency of in-app exercises, and changes in BMI-SDS and health behavior variables) from baseline to post-treatment. Statistical analysis for the pilot study is mainly

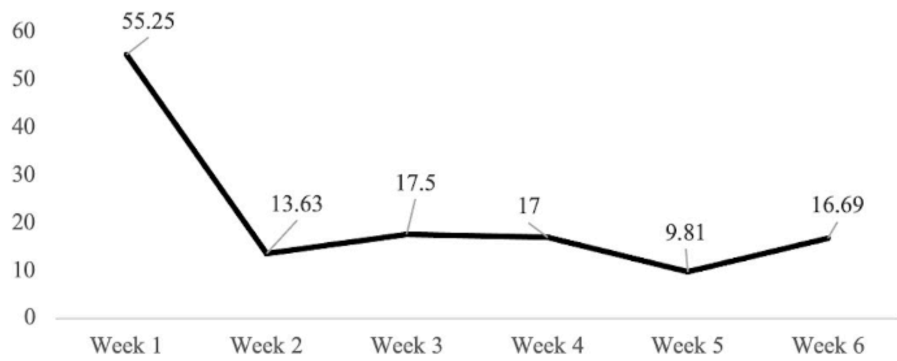
Table 2. Weekly comparison of usage and attrition.

Week	In-app health exercises completed, n (M:F)	Attrition (%)	Active in app (%)	Individual exercises completed, mean (SD)	*P* values
1	859 (337:552)	0	100	55.25 (10.96)	N/A[a]
2	209 (60:149)	0	100	13.63 (2.94)	<.001
3	280 (142:138)	35	65	17.5 (5.33)	<.001
4	272 (193:77)	35	79	17 (6.35)	<.001
5	157 (109:48)	35	73	9.81 (4.07)	<.001
6	267 (143:124)	35	65	16.69 (8.37)	.02

[a]N/A: not applicable; all weeks were compared to week 1.

There was a significant 76% decrease in the total number of in-app health exercises from week 1 to week 2. However, from week 2 to study end, there was a 22% increase in the total number of exercises. The weekly individual mean number of in-app exercises is shown in Figure 2 and the average usage throughout the intervention is summarized in Table 2.

Figure 2. Weekly mean frequency of individual in-app exercises.



Participants who dropped out of the intervention were significantly more likely to use the app between midnight and midday than those who completed the intervention (R_r=0.43, *P*<.001). Details of when the participants used the app and the types of health exercises they completed are shown in Table 3.

Table 3. Times of day spent on each exercise category.

Time of usage	Food, n (%)	Physical, n (%)	Mental health, n (%)	All categories, n (%)
12 AM to 5:59 AM	42 (5.3)	40 (4.4)	24 (7.8)	106 (5.3)
6 AM to 11:59 AM	149 (18.9)	105 (11.5)	34 (11.1)	288 (14.3)
12 PM to 5:59 PM	303 (38.5)	289 (31.6)	93 (30.3)	685 (34.1)
6 PM to 11:59 PM	294 (37.3)	482 (52.6)	156 (50.8)	932 (46.3)
Total, N	788	916	307	2011

Among the 23 participants who answered the baseline questionnaire, 13 (57%) participants were either interested or very interested in using the app to increase health behavior. Four participants (17%) had never downloaded a health app prior to the intervention. However, 9 participants (39%) had never used health apps, which indicates that 5 (22%) participants had downloaded a health app that they never used. All participants had downloaded and used social media apps. Daily active screen time did not significantly differ between the intervention and control groups or between genders at baseline and at study end ($\chi^2_{1,23}$=3.73, *P*=.16). At baseline, the intervention group had more problems with daytime sleepiness than the control group ($\chi^2_{5,20}$=11.29, *P*=.04) but this difference was no longer detected at study end ($\chi^2_{5,23}$= 2.35, *P*=.80). There were significantly greater problems with disruptive wake-ups during night sleep for participants in the intervention group than for participants in the control arm ($\chi^2_{5,20}$=11.87, *P*=.04) at baseline, although no such difference was evident at study end. Mean hours of sleep did not differ significantly between the intervention group (6.90, SD 1.29) and the control group (7.15, SD 0.69; t_{21}=0.4, *P*=.64) at study end.

There were no significant differences in daily portions of vegetables or fruits and berries between the intervention and control groups. There were also no differences regarding the frequency and amount of sugary or sugar-free soft drinks at pre and post measures, as well as for the consumption of salted chips, French fries, or popcorn and candy or sweets. In addition, there were no differences between the intervention and control groups in terms of the consumption of energy drinks at baseline or at study end. The perceived amount of physical exercise was increased by nearly 20% in the intervention group between baseline and study end but decreased by 26% in the control group. Total anxiety scores did not differ significantly between groups at baseline; however, an 8% decrease was found for the intervention group compared to a 4% increase in the control group (Multimedia Appendix 2). Symptoms of depression were also more evident in the SidekickHealth app intervention group at baseline. However, these differences were not apparent at study end. There was also a significant difference between the intervention group and control group in terms of negative self-esteem at baseline, which was not evident after the intervention (Multimedia Appendix 2). The total score on the GSE scale revealed a roughly 8% increase in self-efficacy scores in the intervention group compared to a 3% decrease in the control group from baseline to study end.

Correlations were found between the count of app exercises during the intervention period and weight difference from baseline to intervention end. However, none of the correlations found was statistically significant due to the small sample size. When underweight participants were excluded from the calculations, the decrease in BMI-SDS from baseline to study end appeared to be significantly more apparent in the intervention group (mean 0.48, SD 0.36) compared to that of the control group (mean 0.08, SD 0.44; t_{17}=–2.14, *P*=.04).

Discussion

There has been a steep and steady increase in mHealth interventions since their appearance roughly a decade ago, with an estimated 325,000 mHealth apps available on the market in 2017 [12]. The purpose of this study was to report attrition rates in a pilot study of an adolescent mHealth intervention and to begin to depict different attrition periods. Time-specific data alongside accurate definitions and analysis of attrition in adolescent mHealth interventions (ie, online CBT programs) targeting emotional disorders or subthreshold emotional problems in adolescent populations are lacking in the literature [15]. Studies on attrition in mHealth interventions targeting adolescent populations frequently present attrition rates in a two-point fashion, from initiation of the intervention to the end of treatment. This study offers some insight into mHealth usage among adolescents in this regard with an observed 35% attrition rate from program initiation to termination, which is similar to reported rates in previous online youth CBT programs [5]. However, as this study focused on usage and attrition rates on a weekly basis throughout the intervention, some interesting findings emerged regarding usage of the app. There was a 22% increase in usage between the second week of the intervention and termination, suggesting a sensitive attrition period shortly after instigation of mHealth interventions treating adolescents that warrants further examination. A better understanding of the timeline from treatment instigation to attrition in adolescent mHealth interventions and how emotional disorders or subthreshold emotional problems are connected to that timeline would be a reasonable next step.

Daily time of usage seemed to play a contributing role to gaining an increased understanding of attrition rates. Participants who dropped out of the intervention were significantly more likely to use the app between midnight and midday than those who completed the intervention. Those who completed the intervention were both more likely to use the app from midday to midnight as well as to complete more in-app exercises on average than those who dropped out. The latter finding may seem somewhat rudimentary but is of importance, since this indicates that participants who dropped out are not less motivated to use the app at initiation of treatment. These findings do perhaps highlight the importance of examining time of usage through survival analysis in subsequent studies assessing the factors contributing to attrition from interventions.

An integral measuring factor in the development and implementation of mHealth interventions for adolescent populations is assessing the intervention's feasibility and usability for the desired research population. Participants reported on the app's adequate usability on the SUS and seemed willing to engage in health exercises, completing over 21 in-app exercises on a weekly basis throughout the intervention. A significant decrease in average exercises performed between the first week of the intervention and subsequent intervention weeks was evident, although average usage leveled off at roughly 15 weekly in-app exercises throughout the intervention period. Interestingly, roughly 39% of the participants had never used an mHealth solution prior to this study, although all participants were accustomed to apps since all had downloaded and used social media apps on their smartphones. These findings reveal higher usage rates among participants as previous studies have shown that merely 8% of adolescents use health apps [13].

This study also highlights noteworthy health behavior changes based on app usage. Indications were toward a positive impact on reported sleep problems, in disruptive night sleep wake-ups, and problematic daytime sleepiness, although these findings need to be studied and documented in a more thorough manner. Reported daily physical exercise was increased by nearly 20% in the intervention group, whereas these numbers dropped by roughly 26% in the control arm. These findings could either point to the fact that in-app usage may heighten perceived levels of physical exercise or simply increase how much the adolescents are physically exercising through the intervention. This could be assessed in a more detailed manner in subsequent studies by comparing the self-reporting and frequency of actual exercise simultaneously. Both factors could aid in increasing health behavior since a perceived increase in behavior can increase self-efficacy levels among adolescents in general mHealth interventions or online CBT interventions targeting emotional problems [30]. These findings are related to the fact that self-efficacy levels increased by 8% among adolescents in the intervention arm while decreasing by 3% among controls.

In conclusion, this pilot study was designed to assess time-specific attrition rates in an adolescent mHealth intervention, as well as the usage and feasibility in relation to self-efficacy levels and participants' emotional and physical health. The study was limited to a single research site and the results are based on a small convenience sample, which limits the ability to generalize the findings and determine the intervention's overall efficacy. However, the results revealed interesting findings regarding sensitive attrition periods that warrant further examination. The obtained attrition rates point to a sensitive period during the first week, and indicate that adolescents who use the app in the afternoons and evenings are less likely to drop out. More research in this area seems called for as this could be studied in relation to app features such as the timing and frequency of notifications and instructions.

Acknowledgments

The authors wish to thank the officials of the participating public school. The study was partially funded by a research grant from the Icelandic Research Fund (IRF 141381051).

Conflicts of Interest

EE is a minority shareholder and former employee of SidekickHealth AB. The other authors have no conflicts of interest to declare.

Multimedia Appendix 1

App function.
[PNG File , 904 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Anxiety, depression and self-efficacy measures between research groups.
[PDF File (Adobe PDF File), 77 KB-Multimedia Appendix 2]

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Abbreviations

AAT: appetite awareness training
BMI-SDS: standardized body mass index
CBT: cognitive behavioral therapy
CDI: Children's Depression Inventory
GSE: General Self Efficacy Scale
MASC: Multidimensional Anxiety Scale
mHealth: mobile health
SUS: Systematic Usability Scale

Edited by G Eysenbach; submitted 27.09.20; peer-reviewed by T Schwinn; comments to author 21.10.20; revised version received 28.11.20; accepted 17.01.21; published 17.02.21

Please cite as:
Egilsson E, Bjarnason R, Njardvik U
Usage and Weekly Attrition in a Smartphone-Based Health Behavior Intervention for Adolescents: Pilot Randomized Controlled Trial
JMIR Form Res 2021;5(2):e21432
URL: http://formative.jmir.org/2021/2/e21432/
doi: 10.2196/21432
PMID: 33481750

Paper II

Paper II

Original Paper

Usage and Daily Attrition of a Smartphone-Based Health Behavior Intervention: Randomized Controlled Trial

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Abstract

Background: Although most adolescents have access to smartphones, few of them use mobile health (mHealth) apps for health improvement, highlighting the apparent lack of interest in mHealth apps among adolescents. Adolescent mHealth interventions have been burdened with high attrition rates. Research on these interventions among adolescents has frequently lacked detailed time-related attrition data alongside analysis of attrition reasons through usage.

Objective: The objective was to obtain daily attrition rates among adolescents in an mHealth intervention to gain a deeper understanding of attrition patterns, including the role of motivational support, such as altruistic rewards, through analysis of app usage data.

Methods: A randomized controlled trial was conducted with 304 adolescent participants (152 boys and 152 girls) aged 13-15 years. Based on 3 participating schools, participants were randomly assigned to control, treatment as usual (TAU), and intervention groups. Measures were obtained at baseline, continuously throughout the 42-day trial period (research groups), and at the trial end. The mHealth app is called SidekickHealth and is a social health game with the following 3 main categories: nutrition, mental health, and physical health. Primary measures were attrition based on time from launch, and the type, frequency, and time of health behavior exercise usage. Outcome differences were obtained through comparison tests, while regression models and survival analyses were used for attrition measures.

Results: Attrition differed significantly between the intervention and TAU groups (44.4% vs 94.3%; χ^2_1=61.220; *P*<.001). The mean usage duration was 6.286 days in the TAU group and 24.975 days in the intervention group. In the intervention group, male participants were active significantly longer than female participants (29.155 vs 20.433 days; χ^2_1=6.574; *P*<.001). Participants in the intervention group completed a larger number of health exercises in all trial weeks, and a significant decrease in usage was observed from the first to second week in the TAU group (t_{105}=9.208; *P*<.001) but not in the intervention group. There was a significant increase in health exercises in the intervention group from the fifth to sixth week (t_{105}=3.446; *P*<.001). Such a significant increase in usage was not evident in the TAU group. The research group was significantly related to attrition time (hazard ratio 0.308, 95% CI 0.222-0.420), as well as the numbers of mental health exercises (*P*<.001) and nutrition exercises (*P*<.001).

Conclusions: Differences in attrition rates and usage between groups of adolescents were identified. Motivational support is a significant factor for lowering attrition in adolescent mHealth interventions. The results point to sensitivity periods in the completion of diverse health tasks, and emphasis on time-specific attrition, along with the type, frequency, and time of health behavior exercise usage, is likely a fruitful avenue for further research on mHealth interventions for adolescent populations, in which attrition rates remain excessive.

Trial Registration: ClinicalTrials.gov NCT05912439; https://clinicaltrials.gov/study/NCT05912439

(JMIR Mhealth Uhealth 2023;11:e45414) doi: 10.2196/45414

KEYWORDS

mHealth intervention; mobile health; adolescent; attrition; mental health; physical activity

Introduction

Throughout the past decade, ownership of and access to smartphones and mobile devices have grown profoundly among adolescents and youth worldwide [1,2]. The growth has been such that smartphone ownership or access among US adolescents was 95% 4 years ago and had increased by 23% in the 4 years prior [1,2]. A similar development was observed in the majority of developed economies where adolescent smartphone access and ownership is above the 90th percentile [2]. Smartphones are so widely distributed and used that approximately 45% of adolescents spend nearly all waking hours online [3]. However, modest projections of daily usage indicate that many spend way less time online each day, though it is usually more than 4 hours [4-6].

Widespread smartphone usage in adolescent and youth populations has been extensively covered, but a more positive side to mobile usage is that a significant proportion of adolescents seek health information and clinical help online through their mobile devices, providing ample opportunities to reach at-risk adolescents with science-based methods focusing on health improvement [7-9]. Health problems (ie, mental health and lifestyle diseases) disproportionally burden lower socioeconomic status groups as well as diverse minority groups, and smartphones could become a vital tool for eliminating such disparities since smartphone access and ownership are not related to socioeconomic status, gender, or race in diverse economies [2,10,11]. The mobile health (mHealth) market is steadily becoming saturated with apps, and the yearly increase in the number of apps available has skyrocketed in recent years, with an estimated 350,000 mHealth apps currently on the market [12]. However, only 8% of adolescents seem to use health apps to improve their health, highlighting the apparent gap between easy access, extensive daily usage, and lack of interest in mHealth apps among adolescents [13].

Lack of physical activity has been labeled a global pandemic and has been reported as the fourth leading global cause of death [14]. Physical inactivity increases the risk of lifestyle diseases, such as heart disease, type 2 diabetes, and cancer, resulting in over 5 million annual global deaths [15]. Further, the estimated annual financial burden of physical inactivity is nearly USD 54 billion in health care costs around the world [16]. There seems to be a drop in physical activity in adolescence, and a large number of adolescents are under the recommended physical activity levels provided by the World Health Organization (WHO) [17-19]. Lack of sufficient physical activity tends to continue into adulthood, and research suggests that the majority of adolescents in the European Union do not even reach 30% of the recommended daily physical activity [19-21]. Further, adolescents seem to have the unhealthiest diet of all age groups, and they are particularly susceptible to weight gain [22]. Research has repeatedly revealed a significant relationship between nutritional behavior and physical activity in terms of weight management [23]. A tremendous increase in global adolescent obesity has been witnessed in the past decades, and the prevalence, for instance, has tripled since 1975 [24]. Cost-effective interventions to increase physical activity and improve nutritional behaviors in adolescent populations are therefore urgently needed.

Physical inactivity and inadequate nutritional habits are often interrelated to disabling emotional problems, and integrated strategies should include all 3 pillars to improve physical as well as mental well-being in adolescent populations. mHealth interventions targeting disabling emotional problems in adolescent populations have revealed encouraging outcomes, despite the fact that attrition rates in these interventions are generally high [11,25-30]. Varying definitions of attrition have complicated research on this topic, but attrition is defined as leaving treatment before obtaining a required level of improvement or completing intervention goals [31-33]. Research on mental mHealth interventions among adolescents has frequently lacked detailed time-related attrition data alongside accurate definitions and analysis of attrition reasons, though recent studies show promise in that regard [11,30,34]. Attrition is regularly reported at 2 distinct points of time, that is, intervention start and intervention end. A continuous measure of usage versus nonusage in mHealth interventions for adolescents while simultaneously obtaining detailed usage data to prevent or delay exact times of attrition in future interventions, would perhaps be an improved representation of attrition [35].

Increased knowledge on the actual attrition factors and patterns associated with mHealth interventions in adolescent populations is urgently needed. Obtaining a better understanding of how motivational support motivates adolescents to use mHealth apps and why adolescents maintain or lose interest in using these apps to improve their health is of vital importance. Motivational support in mHealth interventions, defined as strategies to enhance motivation and counter attrition to overcome behavior change barriers, often includes goal-setting, feedback, social support, and rewards [36,37]. Systematic reviews examining possible drivers behind usage point to group and task customization, localization, functional user support, gamification of health tasks, and immediate visual but simplified feedback on user action, while gender-related motivational support features could be contributing factors [36-38]. The timing of tailored motivational support, through just-in-time adaptive interventions, should be considered as well when implementing adolescent mHealth interventions, since time-based individualization could counter high attrition rates [35,39]. Given the magnitude of reported health problems among adolescents and lack of cost-effective health behavior interventions specifically developed for adolescent populations, the need for a better understanding of attrition reasons in adolescent mHealth interventions is large. The study aimed to (1) seek a richer understanding of continuous attrition rates for an mHealth intervention in an adolescent population and the effects motivational support has on attrition rates, and (2) examine the effectiveness of the intervention with the aim to increase daily mental, nutritional, and physical health behaviors.

Methods

Participants

The study included 304 individuals (152 girls and 152 boys) aged 13 to 15 years attending 1 of 3 public schools for children and adolescents in the greater capital area of Iceland. The mean age at baseline measurement was 13.70 (SD 0.83) years. All children attending the highest 3 classes (8th to 10th classes) in the 3 participating public elementary schools in Iceland were eligible to participate (n=661; male-to-female ratio of 313:348). All children in public schools in the municipality are equipped with an iPad from 10 years of age. The exclusion criterion was the diagnosis of a severe disorder of intellectual development or a physical, developmental, or mental illness significantly restricting the ability to use mobile apps. No participant was excluded from the study based on this exclusion criterion. Research specifications and an introduction to the app were sent via email to the parents and legal caretakers of all eligible participants through school officials, along with a confirmative survey link. If the link was answered, it provided confirmation for informed consent. Adolescents with informed consent from parents or legal caretakers were invited to take part in the study through a confirmative survey link.

Ethics Approval

The study was approved by the National Bioethics Committee of Iceland (license number: VSNb2015060065/03-01).

Measurements

The amount, time, and frequency of daily health activities measured through completion of in-app exercises, quality of sleep and energy levels, self-reported stress levels, and gratitude levels were primary outcome measures. The Cronbach α for the current sample was .920 for all self-reported health tasks within the app.

Anxiety and depressive symptoms were assessed using the Revised Children's Anxiety and Depression Scale (RCADS), a self-report assessment tool for children and youth. The scale involves a 4-point Likert scale, spans 47 questions, and is divided into 6 subscales (separation anxiety symptoms, general anxiety symptoms, obsessive-compulsion symptoms, social anxiety symptoms, panic symptoms, and depression symptoms). A *T*-score over 65 marks the clinical cutoff point. The inventory's psychometrics have been studied with acceptable findings in both US and Icelandic pediatric populations [40,41]. The Cronbach α for the current sample was .958.

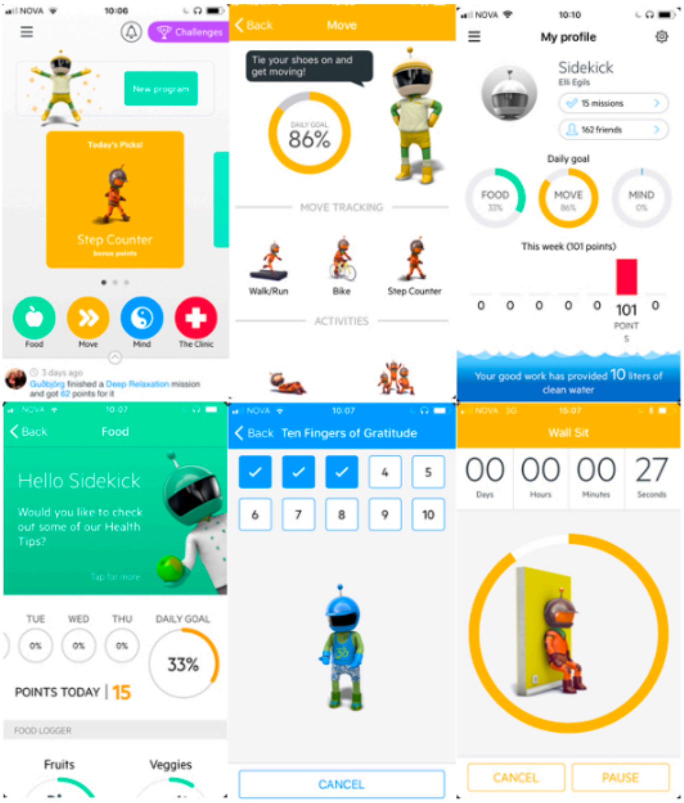
The General Self-Efficacy Scale (GSE), a 10-item self-report questionnaire with the total score ranging from 10 to 40, was used to measure self-efficacy levels, with a higher score indicating higher self-efficacy [42]. Acceptable psychometric properties for the questionnaire have been obtained, and it has been used globally in youth populations [43]. The Cronbach α for the current sample was .937.

The *BEARS* sleep screening algorithm was used to evaluate participants' sleep problems. It is a sleep screening instrument for children from 2 to 18 years old, and is divided into 5 sleep domains (bedtime problems, excessive daytime sleepiness, awakenings during night, regularity and duration of sleep, and snoring) [44]. The algorithm's psychometrics have been studied with acceptable findings in pediatric populations [45]. The Cronbach α for the current sample was .769.

mHealth App

The app is called SidekickHealth and has been described in the research group's previous work [35]. SidekickHealth was initially developed through multiple focus group studies among both Icelandic elementary school students and adolescents in the obesity clinic at the Landspitali University Hospital in Iceland to incorporate the target groups' needs and opinions. Based on results from focus group studies and design advisors, the app took the form of a social health game (Figure 1). Functionality of the app evolves around motivational support to help the user set goals and complete health tasks (gamification of tasks) in the following 3 main categories: food and drink (eg, vegetable and water intake, consumption of fruits, and avoiding sugary soda or energy drinks), physical activity (eg, body weight exercises, logged minutes of sports activity, GPS-based biking, walking, and running), and mental health exercises (eg, reducing stress, exercising gratitude, and improving sleep habits). By completing health tasks that are labeled missions and participating in friendly competitions with peers, users earn points (called "kicks") and badges providing altruistic rewards (eg, liters of water for children in need or polio vaccines that are sent in their name to children in need through UNICEF). A visual representation of the user's performance is provided in different categories. Keeping the app fun, entertaining, and easy to use is of integral importance and was a strong focus point throughout the developmental phases (Multimedia Appendix 1). The smartphone app operates on the Android and iOS platforms. The app's function focuses on education and simple health behavior changes through the benefits of increased physical activity and mental health exercises, as well as a healthy diet, portion sizing, and appetite awareness training. Appetite awareness training is a behavior modification tool that has, for instance, been used in obesity treatment and encourages overweight/obese children and youth to consume food and drink in response to internal appetite cues. It has shown promise for the treatment of overweight and obese children and teenagers, and has been visually developed as an individual mission in the app's nutrition category [46,47]. Participants in the intervention arm were randomly assigned to groups consisting of 8 individuals that collectively and individually competed in point collection through completion of in-app health tasks. In the beginning of each of the trial's 6 weeks, the intervention group received in-app messages where a new weekly competition (both individual and group levels) with altruistic rewards was introduced. In weeks 2 to 6, altruistic rewards for the past week's efforts were also handed out. Winners of competitions received confirmation that UNICEF had sent polio vaccines to children in need. Further, through completion of in-app health exercises, participants collected liters of water that were sent in their name to children in need through UNICEF. The total cost for the altruistic rewards, paid for by the first author, throughout the treatment period was roughly US $68 (56 US cents per participant).

Figure 1. Overview of app functions and categories.



Procedure

This study was a randomized controlled study. Group randomization was used to divide the 3 participating schools into control, treatment as usual (TAU), and intervention groups. Measures were obtained at baseline and 42 days later. Participants in both the TAU and intervention groups received an approximately 10-minute-long introduction regarding the study specifications and the app. The control group received no further contact, access to the app, or information until study-end questionnaire measures. Participants in the intervention group were randomly assigned to teams consisting of 8 individuals that collectively and individually competed in point collection through completion of in-app health tasks. Participation in the TAU and intervention groups was defined as downloading the SidekickHealth app and completing at least 3 health exercises within it. Exercise time was defined as the timestamp on completion of the exercise within any of the 3 types of exercise categories (physical activity, nutrition, and mental health) in the app. Exercise frequency referred to how often a given exercise was completed by a participant. Attrition time was defined as the timestamp of the last completed health exercise within the SidekickHealth app throughout the intervention period. The procedural difference between the TAU and intervention groups is related to motivational support. The intervention group received motivational support in the form of weekly individual and group feedback on usage, participation in friendly health task competitions, and weekly altruistic rewards for usage. Participants in the TAU group used the app individually throughout the trial period without any motivational support. A flowchart of participation is displayed in Multimedia Appendix 2.

Statistical Analysis

The descriptive characteristics of participants along with attrition reasons are reported. Pearson correlation coefficients, independent samples *t*-tests, repeated measures ANOVA with adjusted alpha levels, and χ^2 tests were used to measure mean differences in primary and secondary outcome measures from baseline to the trial end within and between research groups. Kaplan-Meier survival analysis plots and log-rank tests were used to assess the attrition time and possible significant differences between and within research groups [48,49]. The trial start was defined as the time of the first in-app health exercise completion, and the trial period was 6 weeks (42 days) from that moment. Attrition, or the event, was defined as the time of the participant's last completed health exercise in the SidekickHealth app. Participant cases were evaluated as censored when the app was still being used 42 days after the study start. Cox proportional hazard regression models with interacting covariables using research groups as clusters were used to examine attrition prediction based on usage of in-app health exercises for the time, type, and frequency of exercises, as well as sociodemographic variables (age and gender) [50]. Significance was defined as a P value <.05. Data were analyzed using IBM SPSS Statistics, Release Version 29 (IBM Corp).

Results

Among all invited participants with parental or caretaker consent to participate (N=451), 304 (67.41%) individuals took part in the study. Participants who did not answer questionnaires at the study end were excluded. Participant characteristics are presented in Table 1. Logged data revealed broad differences in app usage among participants as shown in Figure 2. There was a significant difference in the mean number of health exercises completed by participants, where individuals in the intervention group (mean 120.869, SD 32.434) completed on average roughly 6 times as many exercises as individuals in the TAU group (mean 18.341, SD 31.802) over the study period (t_{221}=–3.00; P<.001). When logged health exercises on the first day of the study period were examined, the results showed that the difference between the intervention group (mean 16.835, SD 21.820) and TAU group (mean 8.100, SD 7.237) was less extensive but still significant (t_{221}=–2.12; P=.04).

Forms of attrition over the 42-day study period are shown in Figure 3. Significant differences in completion rates were evident in log-rank tests between the intervention group and TAU group (χ^2_1=61.220; P<.001). Among participants in the TAU group, the mean survival time was 6.286 days (95% CI 4.304-8.277), while among participants in the intervention group, the mean survival time was 24.975 days (95% CI 21.452-28.518). Log-rank tests revealed significant differences in completion rates between male and female participants in the intervention group (χ^2_1=6.574; P<.001). In the intervention group, the mean survival time among male participants was 29.155 days (95% CI 24.519-33.812) and among female participants was 20.433 days (95% CI 15.301-25.558). Such differences were not evident in log-rank tests in the TAU group (χ^2_1=1.570; P=.21). Figure 4 presents Kaplan-Meier plots for gender-based attrition in the TAU and intervention groups.

There was a significant difference between groups in the average number of in-app health exercises in all weeks (Table 2). There was a significant mean drop (mean 12.347, SD 13.803) in usage in the TAU group from the first week to the second week (t_{105}=9.208; P<.001). Even though there was a drop in usage in the intervention group between the first and second weeks of the trial (mean 6.798, SD 37.481), the difference was not significant (t_{105}=1.959; P=.06). There was however a significant increase (mean 22.904, SD 71.721) in the average individual in-app health exercises completed by the intervention group from the fifth week to the sixth and last week of the trial (t_{105}=3.446; P<.001). Such a significant increase in usage was not evident in the TAU group.

No significant gender differences were found in the average weekly in-app exercise frequency within research groups (Table 3).

When exercise time was compared with the exercise category, the results revealed significant differences within both the intervention group (χ^2_6=2162.559; P<.001) and the TAU group (χ^2_6=69.372; P<.001). Differences in usage based on exercise time and exercise type are presented in Table 4 and Figure 5.

Results from the Cox proportional hazard regression models are shown in Multimedia Appendix 3. The research group that participants were assigned to (hazard ratio 0.308, 95% CI 0.222-0.420) was significantly related to attrition (P<.001), as well as the numbers of mental health exercises (P<.001) and nutrition exercises (P<.001) completed in the app by participants in both research groups. Participants in the TAU group (hazard ratio 0.387, 95% CI 0.201-0.748) who completed an in-app health exercise between day 2 and day 6 of the trial were found to be significantly more likely to finish (P=.03). Such significant differences were not found in the intervention group. Further, the numbers of health exercises completed in the app in the first week (P<.001), second week (P<.001), and last week (P<.001) of the trial were significantly related to survival rates in the TAU group. Similar significant differences were not evident in the intervention group. All types of health exercises completed in the app were also significantly related to attrition in the TAU group, although such differences were not found among intervention group members. Anxiety, depression, and self-efficacy measures between research groups are shown in Multimedia Appendix 4.

Table 1. Baseline participant characteristics.

Characteristic	Control group (n=81)	TAU[a] group (n=106)	Intervention group (n=117)
Age (years), mean (SD)	13.72 (0.45)	13.14 (0.51)	13.50 (0.63)
Male:female ratio	34:47	57:49	61:56
Disabling sleep problems, n (%)	32 (39.5)	23 (21.7)	38 (32.5)
Clinical anxiety symptoms, n (%)	18 (22.2)	10 (9.4)	14 (12.0)
Clinical depression symptoms, n (%)	12 (14.8)	7 (6.6)	7 (6.0)
General self-efficacy score, mean (SD)	17.90 (5.89)	16.17 (5.71)	18.14 (5.04)

[a]TAU: treatment as usual.

Figure 2. Mean weekly in-app exercises. TAU: treatment as usual.

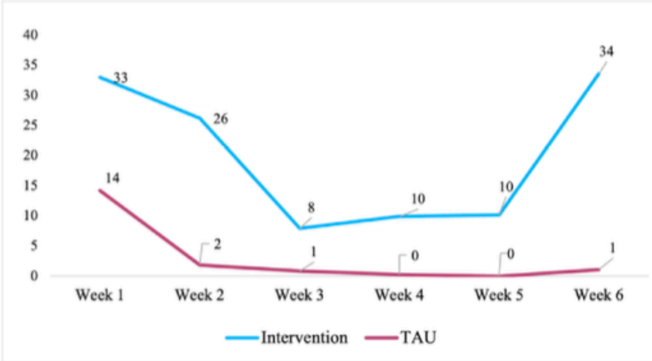


Figure 3. Forms of attrition. TAU: treatment as usual.

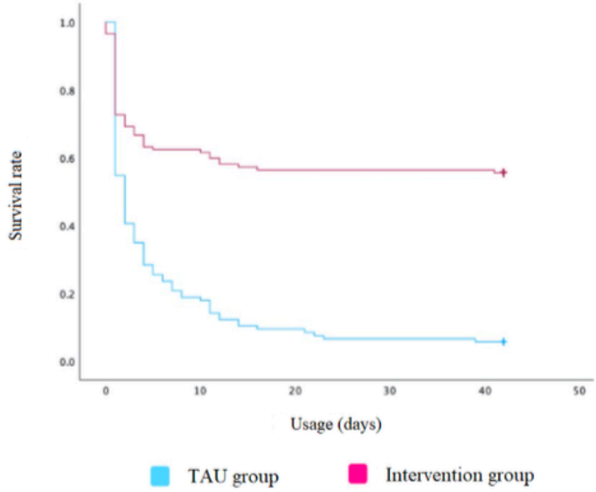


Figure 4. Gender-based attrition in the TAU and intervention groups. TAU: treatment as usual.

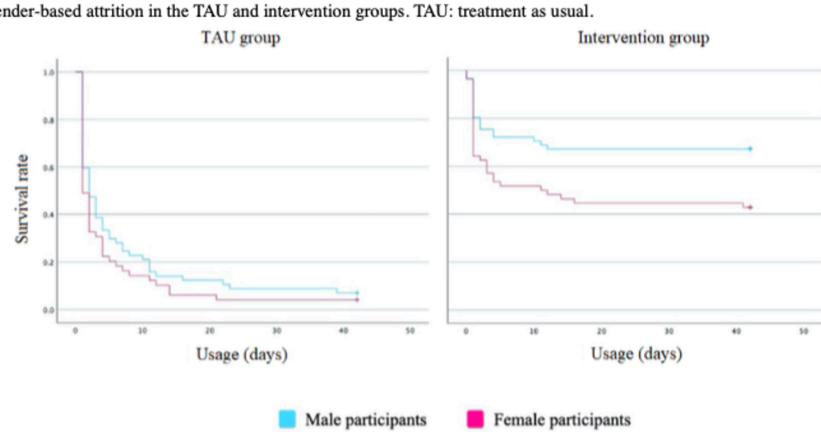


Table 2. Weekly comparison of usage and attrition.

Week	In-app health exercises completed, n			TAU[a] group usage, mean (SD)	Intervention group usage, mean (SD)	*P* value
	Overall	Male	Female			
1	5369	3531	1838	14.20 (17.34)	33.03 (72.38)	<.001
2	3265	2514	751	1.85 (8.71)	26.23 (90.61)	<.001
3	1016	548	468	0.84 (5.38)	7.92 (26.71)	<.001
4	1192	803	389	0.24 (1.28)	9.97 (34.08)	<.001
5	1223	891	332	0.00 (0.00)	10.45 (60.09)	<.001
6	4029	2889	1140	1.20 (6.99)	33.35 (110.99)	<.001
Overall	16,094	11,176	4918	18.32 (27.44)	120.96 (350.09)	<.001

[a]TAU: treatment as usual.

Table 3. Weekly average in-app health exercise frequency by gender.

Week and group	Male, mean (SD)	Female, mean (SD)	*P* value
Week 1			
TAU[a]	16.19 (19.36)	11.88 (14.50)	.20
Intervention	42.75 (97.75)	22.43 (20.12)	.13
Week 2			
TAU	3.02 (11.71)	0.49 (1.56)	.14
Intervention	38.89 (72.64)	12.98 (23.79)	.13
Week 3			
TAU	0.07 (0.42)	1.73 (7.84)	.11
Intervention	8.92 (22.29)	6.84 (30.99)	.68
Week 4			
TAU	0.37 (1.70)	0.08 (0.45)	.25
Intervention	12.84 (30.06)	6.88 (26.09)	.35
Week 5			
TAU	0.00 (0.00)	0.00 (0.00)	N/A[b]
Intervention	14.61 (62.43)	5.93 (12.73)	.44
Week 6			
TAU	1.02 (4.66)	1.41 (9.02)	.78
Intervention	46.41 (77.42)	19.13 (43.32)	.19
All weeks			
TAU	20.67 (33.60)	15.59 (17.85)	.35
Intervention	163.90 (271.22)	74.18 (109.50)	.08

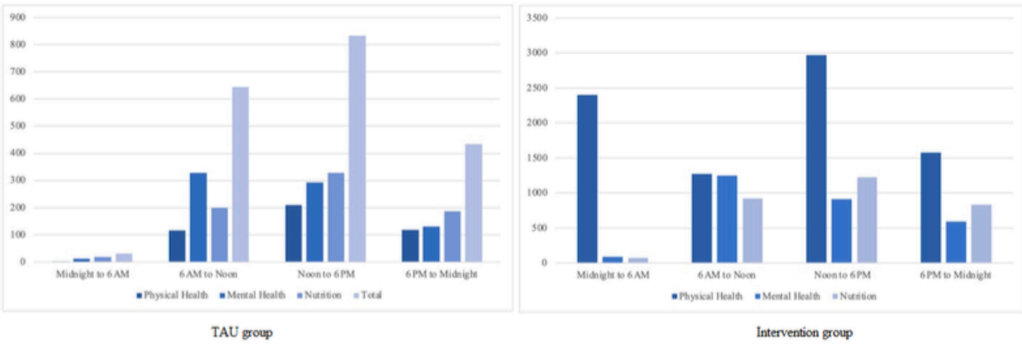
[a]TAU: treatment as usual.
[b]N/A: not applicable.

Table 4. Frequency of exercise categories at different daily times.

Group and exercise category	Midnight to 6 AM, n (%)	6 AM to noon, n (%)	Noon to 6 PM, n (%)	6 PM to midnight, n (%)
TAU[a] group	32 (100)	644 (100)	833 (100)	435 (100)
Physical health	1 (3.1)	116 (18.0)	210 (25.2)	119 (27.4)
Mental health	12 (37.5)	329 (51.1)	294 (35.3)	130 (29.9)
Nutrition	19 (59.4)	199 (30.9)	329 (39.5)	186 (42.7)
Intervention group	2575 (100)	3446 (100)	5113 (100)	3008 (100)
Physical health	2407 (93.5)	1275 (37.0)	2970 (58.1)	1576 (52.4)
Mental health	90 (3.5)	1248 (36.2)	912 (17.8)	599 (19.9)
Nutrition	78 (3.0)	923 (26.8)	1231 (24.1)	833 (27.7)
Overall	2607 (100)	4090 (100)	5946 (100)	3443 (100)
Physical health	2408 (92.4)	1391 (34.0)	3180 (53.5)	1695 (49.2)
Mental health	102 (3.9)	1577 (38.6)	1206 (20.3)	729 (21.2)
Nutrition	97 (3.7)	1122 (27.4)	1560 (26.2)	1019 (29.6)

[a]TAU: treatment as usual.

Figure 5. Time-based exercise categories in the TAU and intervention groups. TAU: treatment as usual.



Discussion

The focus of this study was on time-specific attrition in an adolescent mHealth intervention. We hoped to build on previous work while focusing on the type, frequency, and time of usage in order to better understand why adolescent attrition from mHealth interventions is generally as excessive as it is, with a market saturated with roughly 350,000 mHealth apps adolescents seem reluctant to engage in [12,35]. The results showed that research groups are related to time of attrition (hazard ratio 0.308, 95% CI 0.222-0.420), and attrition differed between the TAU group (94.3%) and intervention group (44.4%). Attrition was somewhat higher than in our previous study, where attrition was in the 35th percentile. The difference in attrition rates between research groups was however vast, and the only distinction in program setup was motivational support in the form of weekly feedback on individual progress through the app, friendly health task competitions at the individual and group levels, and small altruistic rewards for completion of health tasks or active participation in competitions. The app was the same, but support through program setup differed. It is interesting that the altruistic reward cost per participant was only 56 US cents but still seemed to contribute strongly to increased usage and participation.

Completion rates differed greatly between research groups as did days of active usage since the number of usage days in the intervention group was nearly 25 (95% CI 21.452-28.518) and that in the TAU group was approximately 6 (95% CI 4.304-8.277). Differences in completion rates were therefore evident between the intervention group (55.6%) and TAU group (5.7%), and gender differences in completion rates were also observed in the intervention group but not in the TAU group. Male participants (95% CI 24.519-33.812) completed in-app health tasks longer than female participants (95% CI 15.301-25.558). This gender difference was not evident in our prior research but has been observed in adult populations and should be examined in future research hoping to explain attrition factors in adolescent mHealth interventions [38]. A deeper gender-based exploration into motivational support could be a promising avenue for further research on the matter, particularly how altruistic rewards and competitive intervention features facilitate motivational support between genders.

Broad differences in the completion of health exercises were evident between groups since the intervention group completed on average roughly 6 times as many health exercises as the TAU group throughout the trial period. It is somewhat interesting that this difference was only 2-fold on the first day of the trial, suggesting that participants in the TAU group did not lack usage motivation at the beginning of the trial but were simply not supported to keep on using the app. This was more evident when average weekly health exercise frequency was examined since there was a decrease in usage between the first and second weeks among participants in the TAU group, while such a difference was not evident among participants in the intervention group. In fact, intervention group members completed on average more health exercises in all 6 weeks of the trial than their peers in the TAU group. An interesting finding is that usage increased from the fifth week of the trial to the last one among intervention group members but not among TAU group members, which is thought to be related to motivational support features as well as the altruistic reward setup at the end of the trial's sixth week, and warrants further research.

There seemed to be different daily sensitivity periods for increased frequency of health task completion in different health categories. Adolescents in both research groups completed most of the physical activity exercises within the app from noon to 6 PM. The same applied to nutrition exercises in both groups. However, when it came to the frequency of mental health exercises, adolescents in both groups tended to do them from 6 AM to noon. Further, results from regression models indicated that the frequency of mental health exercises as well as nutrition exercises completed in the app by participants in both groups was related to delayed attrition. Physical activity exercises did not show such effects, possibly because those participants who did few exercises and were likely to drop out mainly used the physical activity category. Adolescents in the TAU group who completed an in-app health exercise between day 2 and day 6 of the trial were also found to be more likely to finish. This was not evident in the intervention group. These results imply that there are sensitivity usage periods that differ between the types of health behaviors adopted by adolescents in mHealth interventions and highlights the need for the development of just-in-time adaptive interventions in the future to hamper attrition and hopefully increase the frequency of health behavior exercises.

Taken together, the aim of this study was to examine time-specific attrition rates in an mHealth intervention for adolescents and hopefully increase our understanding of attrition in this group through a focus on the type, frequency, and time of health behavior exercise usage. Attrition between research groups was vastly different, and motivational support seems to be of vital importance to lower attrition in future mHealth interventions, specifically for adolescents in different age groups. Further research on how specific motivational support features in adolescent mHealth interventions function to lower attrition rates and how they affect usage patterns is evidently needed.

The limitations of this research include randomization factors, since randomization was between elementary schools rather than on an individual level to prevent contamination effects. Another limitation was related to the initial difference in usage between research groups. The data collection period was 6 weeks, and further research on the matter should include a prolonged research period with added randomization efforts to level usage between research groups, along with a 3-month follow-up to track usage and sustained gains from motivational support features. The generalizability of findings in adolescent mHealth studies to wider populations can be questionable, and this study is no exception (for instance, the function of altruistic reward schemes and competitive features in diverse cultural settings). The study's foremost strength lies in added knowledge to limited research on attrition rates and patterns in adolescent mHealth interventions. Additional strong points are related to the methodological approach. Continuous data collection throughout the trial period, efforts to accurately describe time-based attrition rates through survival analysis, and use of a relatively large sample size (n=304) are regarded as strengths.

Acknowledgments

The authors wish to thank the elementary school officials who helped in the study. The authors also wish to thank Icelandic Research Fund (IRF 141381051) for partially funding the study through a research grant.

Conflicts of Interest

EE is a minority shareholder in SidekickHealth AB and a former employee. The other authors have no conflicts to declare.

Editorial Notice

This randomized study was only retrospectively registered. The authors explained that the trial was originally registered in domestic registries through the University of Iceland and the Icelandic bioethics committee. The editor granted an exception from ICMJE rules mandating prospective registration of randomized trials because the risk of bias appears low and the study was considered formative, guiding the development of the application [or other reasons for the exception, as argued by the authors]. However, readers are advised to carefully assess the validity of any potential explicit or implicit claims related to primary outcomes or effectiveness, as retrospective registration does not prevent authors from changing their outcome measures retrospectively.

Multimedia Appendix 1

App function.
[PNG File , 445 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Study flowchart.
[PDF File (Adobe PDF File), 112 KB-Multimedia Appendix 2]

Multimedia Appendix 3

Regression model.
[PDF File (Adobe PDF File), 124 KB-Multimedia Appendix 3]

Multimedia Appendix 4

Anxiety, depression, and self-efficacy measures between research groups.
[PDF File (Adobe PDF File), 76 KB-Multimedia Appendix 4]

Multimedia Appendix 5

CONSORT-EHEALTH checklist.
[PDF File (Adobe PDF File), 1604 KB-Multimedia Appendix 5]

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Abbreviations

mHealth: mobile health
TAU: treatment as usual

Edited by L Buis; submitted 29.12.22; peer-reviewed by L Maenhout, H Bear, B Chaudhry, OR Patil; comments to author 18.01.23; revised version received 03.03.23; accepted 24.04.23; published 26.06.23

Please cite as:
Egilsson E, Bjarnason R, Njardvik U
Usage and Daily Attrition of a Smartphone-Based Health Behavior Intervention: Randomized Controlled Trial
JMIR Mhealth Uhealth 2023;11:e45414
URL: https://mhealth.jmir.org/2023/1/e45414
doi: 10.2196/45414
PMID:

Paper III

Paper III

Usage and daily attrition from a smartphone-based health behaviour intervention among adolescents with anxiety and depression symptoms: Randomized controlled trial

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Abstract

Most adolescents own smartphones and are frequently online, yet few use health apps for mental health. Around one-tenth are diagnosed with an emotional disorder, and many face significant emotional problems during adolescence. There's a gap between smartphone usage and interest in mHealth apps among them. Attrition rates in mHealth interventions for anxious/depressed adolescents are high, and detailed time-related attrition data and analysis of attrition reasons are lacking. The objective was to obtain continuous attrition rates and usage trends in nutrition, physical activity, and mental health over six weeks in a randomized controlled trial with 121 adolescents with clinical anxiety or depression symptoms across control, treatment-as-usual, and intervention groups receiving motivational support and altruistic incentives. Significant differences in attrition and usage days were found between groups and results indicated usage trends along with sensitivity periods based on motivational support and altruistic incentives, warranting further research.

Keywords

mHealth intervention; adolescent; attrition; mental health; physical activity, anxiety, depression

Trial Registration

ClinicalTrials.gov ID: NCT05912439, https://clinicaltrials.gov/study/NCT05912439

Introduction

Emotional disorders, along with significantly disabling though sub-clinical emotional problems, are among the most common cause of developmental and psychiatric distress in adolescents (Erskine et al., 2017; Philipp et al., 2018). Global prevalence estimates of psychiatric disorders in children and adolescents in recent systematic reviews are in line with estimated rates from international health organizations, which vary from nearly 7% to considerably higher pooled rates of roughly 14% (Erskine et al., 2017; Hossain et al., 2022; Katzmarzyk et al., 2014; Polanczyk et al., 2015; Silva et al., 2020). Over 6% of US children from twelve to seventeen years old have been diagnosed with clinical depression according to the Centers for Disease Control and Prevention (CDC) and over 10% with anxiety disorders (CDC, 2019). Anxiety and depression are in fact so common that they make up nearly half of mental disorders in adolescent populations (Barker et al., 2019; Sacco et al., 2022; Shorey et al., 2022). Following the coronavirus pandemic, a growing body of empirical support has revealed the broad adverse effects the pandemic has had on mental health in adolescent populations (Thorisdottir et al., 2023). There among is increased prevalence of sleep disorders, depression and anxiety disorders (Jahrami et al., 2022; Jones et al., 2021; Kauhanen et al., 2023; Samji et al., 2023; Thorisdottir et al., 2023).

Smartphone access and ownership rapidly grew throughout the past decade among adolescents and youth worldwide (Pew Research Center, 2015; Pew Research Center, 2019). In fact, smartphone ownership or access among US adolescents was 95% four years ago and had increased by 23% in the four years prior (Pew Research Center, 2015; Pew Research Center, 2019). Similar development has been evident elsewhere and youth smartphone access and ownership is above the 90th percentile in majority of developed economies (Kliesener et al., 2022; Pew Research Center, 2019). Smartphones are widely distributed and used, with modest estimated average daily usage among adolescents being above 240 minutes (Ceci, 2023; Chaffey, 20016; Kliesener et al., 2022). However, a large proportion of adolescents spends significantly more time on their mobile devices and 45% of the adolescent population is in fact nearly constantly online (Anderson & Jiang, 2018).

Excessive smartphone usage among adolescents is an extensively documented problem (Anderson & Jiang, 2018; Harris et al., 2020; Sahu et al., 2019). Many adolescents use online providers to seek mental health information and clinical help providing ample opportunities to reach at risk adolescents with science-based methods focusing on mental health (Birnbaum et al., 2017; Lawlor A. & Kirakowski, 2014; Pretorius et al., 2019). Since mental health problems disproportionally burden minority and lower-socioeconomic status (SES) groups in terms of limited access to science-based interventions, smartphones could be a key tool in diminishing such inequalities since smartphone access and ownership is not related to SES status, gender or race in diverse economies (Center, 2019; McLaughlin et al., 2012; Radomski et al., 2019). The number of mHealth apps has ballooned in recent years, with over 90.000 new applications introduced in the year 2020 and estimated 350.000 mHealth applications currently on the market (IQVIA, 2021). Further, it is estimated that up to roughly 22.750

mental health application are in the market (Torous & Roberts, 2017). Nevertheless, relatively few adolescents seem use health applications to improve their health (Chan et al., 2017; Maenhout et al., 2022; Wu et al., 2014; Yardley et al., 2016).

Mobile health interventions have shown encouraging results regarding lowered depression and anxiety symptoms in different youth populations, though attrition rates seem to dampen effectiveness of these interventions (Adelman et al., 2014; Eysenbach, 2005; Maenhout et al., 2022; Meyerowitz-Katz et al., 2020; Mohr et al., 2013; Radomski et al., 2019; Topooco et al., 2019). Attrition is here defined as leaving treatment before obtaining a required level of improvement or completing intervention goals, though varying definitions of the term has challenged concentrated research on the matter (Melville et al., 2010; Mitchell & Selmes, 2007; Twomey et al., 2014). Research on mHealth interventions targeting emotional disorders, or significant emotional symptoms among adolescents, have often lacked detailed time related attrition data alongside accurate definitions and analysis of attrition reasons though recent studies have focused on these matters (Maenhout et al., 2022; Radomski et al., 2019; Vigerland et al., 2016). Attrition in these studies is often reported at two distinct points of time; beginning and end of intervention. An improved depiction of attrition rates from mHealth interventions for adolescent populations should perhaps be through continuous measures of usage vs. non-usage while simultaneously obtaining detailed usage data to prevent or delay exact times of attrition in future interventions (Egilsson et al., 2021, 2023). Interventions targeting mental health issues have shown attrition rates that are up to twice as high compared to other health areas (Mitchell & Selmes, 2007). Attrition rates from cognitive behavioral therapy (CBT) interventions have for instance been reported up to nearly 44%, though these rates seem to be somewhat lower in group therapy format (Hans & Hiller, 2013). Online and mobile CBT interventions have been found to be effective in treating adolescent anxiety and depression symptoms, though attrition rates from these interventions were problematic (Clarke et al., 2015; Radomski et al., 2019; Richardson et al., 2010; Rooksby et al., 2015). A better understanding of actual attrition reasons in adolescent sub-groups, i.e. anxious or depressed, is needed to decrease attrition rates from mHealth interventions targeting clinical emotional symptoms in adolescent populations. One of those aspects is to gain better knowledge about what motivates usage in these different groups of adolescents and why they become and stay interested in using mHealth applications to improve their health. Systematic reviews on the matter point for example to app customization, functional user support, gamification of health tasks and immediate visual but simplified feedback on user action (Bear et al., 2022; Jeminiwa et al., 2019). The purpose of this study was firstly to build on authors' prior work on time-based attrition rates from a mHealth intervention among adolescents with significant anxiety and depression symptoms and to seek better understanding of continuous attrition rates (Egilsson et al., 2021, 2023). Secondly, the aim was to examine effectiveness of the mHealth intervention among adolescents with anxiety and depressive symptoms.

Methods

Participants

Participants were 121 individuals, 67 girls and 54 boys. The participants' age ranged from 13 to 15 years old and all attended one of three elementary schools in the greater capital area of Iceland. Mean age was 13.88 (SD=.87) at baseline. All children attending the oldest 3 classes in three participating public elementary school in Iceland's capitol area were eligible participants. Further, each participant was a native Icelandic speaker and all participants owned smartphones at baseline. It is of importance to note that all students in the participating schools are equipped with an iPad from 10 years of age. Children with severe mental retardation and/or physical-, developmental- and mental illness significantly restricting ability to use mobile apps were excluded from participating in the study. Furthermore, this study is a part of a larger adolescent mHealth attrition research. Not showing significant anxiety and/or depressive symptoms was regarded as an exclusion criterion from data analysis in this paper. Based on the exclusion criteria stated above, 183 individuals were excluded from data analysis. Research specifications and mobile app introduction were sent to legal guardians and parents of all eligible partakers through elementary school officials via email, including confirmative survey link, regarded as informed consent when answered, along with parental information about possible exclusion criteria. A participatory flowchart is displayed in figure 1. The study was approved by the National Bioethics Committee (license number: VSNb2015060065/03-01) and registered at ClinicalTrials.gov (ID: NCT05912439).

Measurements

The frequency, time and total amount of daily health activity measured through completion of in-app health exercises, energy levels, sleep quality and self-reported stress levels as well as gratitude levels were primary outcome measures. Cronbach's α for all in-app measured health activity for the current sample was .909.

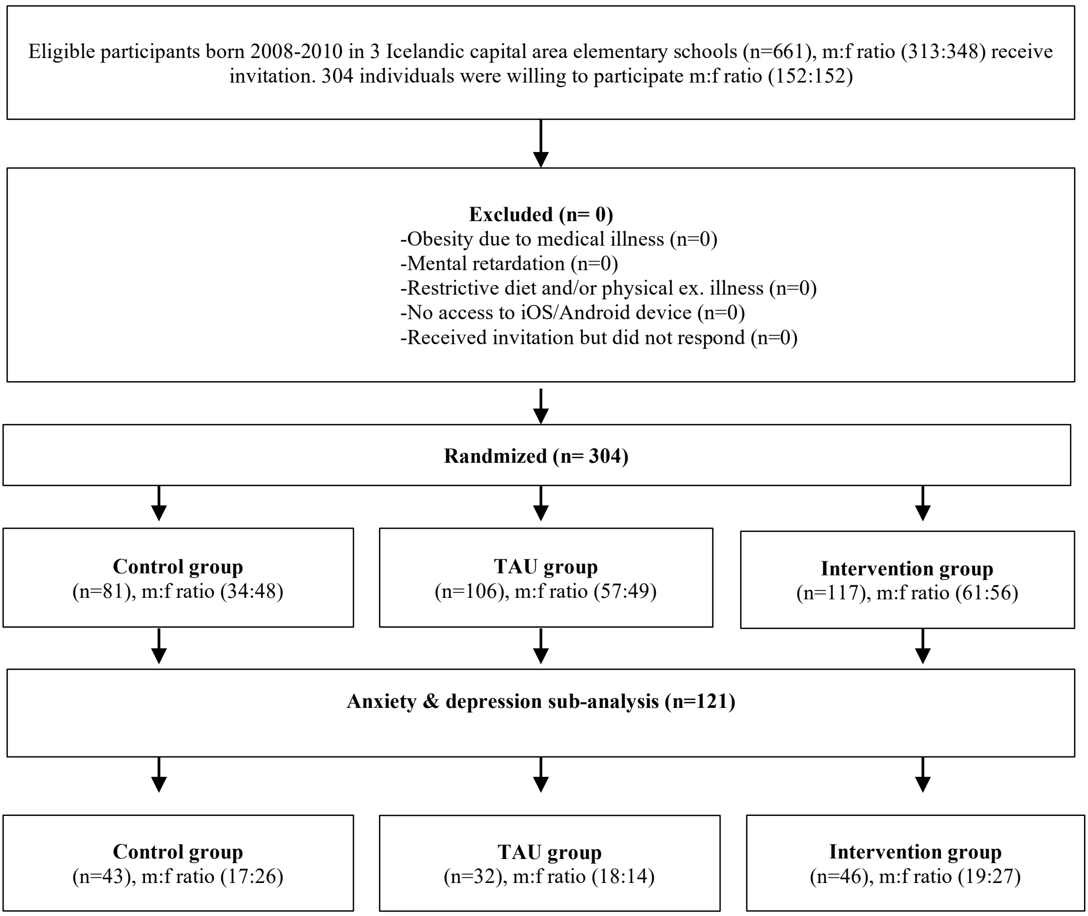
Revised Children´s Anxiety and Depression Scale (RCADS) was used assess anxiety and depressive symptoms. RCADS is a self-report assessment tool for children and youth on a four-point Likert scale. It is divided into 6 subscales and entails 47 questions. Subscales are separation anxiety symptoms, general anxiety symptoms, obsessive-compulsive symptoms, social anxiety symptoms, panic symptoms, depression symptoms. A t-score over 65 marked a clinical cut-off point. RCADS´s psychometrics has been assessed with acceptable findings in both US and Icelandic pediatric populations (Chorpita et al., 2000; Gisladottir, 2014). Cronbach's α for the current sample was .948.

General Self Efficacy Scale (GSE) was used to measure self-efficacy levels with higher score signifying increased self-efficacy (Schwarzer & Jerusalem, 1995). GSE is a 10 item self-report questionnaire with ranging total scores from 10 to 40. Acceptable psychometric properties for the questionnaire have been obtained and the inventory used globally in youth populations (Luszczynska et al., 2004). Cronbach's α for the current sample was .916.

Sleep impairment among participants was assessed with the *BEARS* sleep screening algorithm. BEARS is a sleep screening instrument for children from 2 to 18 years old and divided into five domains; bedtime problems, excessive daytime sleepiness, awakenings during night, regularity and duration of sleep and snoring (Owens & Dalzell, 2005). The screening tool´s psychometrics has been studied with acceptable findings in pediatric populations (Owens & Dalzell, 2005). Cronbach's α for the current sample was .732.

Figure 1

Procedural flowchart of participants

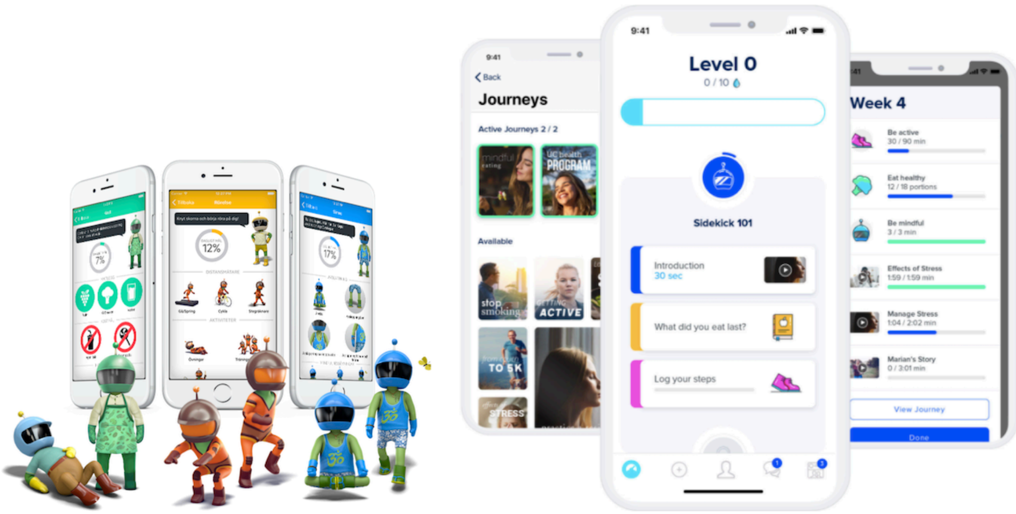


mHealth application

The application used for the intervention is called SidekickHealth and has been comprehensively described in the research group´s prior work (Egilsson et al., 2021, 2023). A visual depiction of the app´s function is portrayed in figure 2. SidekickHealth supports the user to set goals and complete health tasks (gamification of tasks), in three main categories; physical activity (e.g. body-weight exercises, logged minutes of sports activity), food and drink (e.g. encouraging consumption of fruits, vegetable and water intake and avoiding consumption of sugary soda or energy drinks), and mental health exercises (e.g. improving sleep habits, reducing stress and exercising expressed gratitude). Completion of health tasks and participation in friendly competitions with peers, users earn points which are turned into altruistic real-life rewards (e.g. liters of water for children in need or polio vaccinations that are sent in their name to children in need through UNICEF). The app operates on Android and iOS platforms and focuses on education and simple health behavior changes through the benefits of increased physical activity, healthier diet trough appetite awareness training (AAT) and completion of daily mental health exercises (Bloom et al., 2013; Gunnarsdottir et al., 2012). In the intervention realm, participants were randomly assigned to groups consisting of 6-8 individuals that collectively and individually competed in point collection through completion of in-app health tasks. Each of the 6 weeks of the trial began with in-app messages to the intervention group, introducing weekly competitions and tasks at both individual and group levels, with altruistic rewards. From weeks 2 to 6, active participants could also receive altruistic rewards for their efforts from the previous week, independent of the competitions and tasks. Competition winners received confirmation that UNICEF had sent Polio vaccinations to children in need in their name. Further, through completion of in-app health exercises participants collected liters of water that was sent in their name to children in need through UNICEF. The total cost for the altruistic rewards, paid for by the first author, for of all in-app rewards throughout the treatment period was roughly 53 US dollars or 56 US cents per participant.

Figure 2

Application function



Procedure

The study is a multi-centered randomized controlled study. Group randomization was used to distinguish three participating schools into control, treatment-as-usual (TAU) and intervention groups. Research specifications and introduction to the application was sent via email to parents and legal caretakers of all eligible participants through school officials along with confirmative survey link. If the link was answered it yielded confirmation for informed participation allowance. Measures were obtained at baseline, continuously throughout trial period and 42 days later. Participants in both the TAU group and intervention group received an approximately 10 minutes long introduction to the study specifications and the application. The control group received no further contact or information until study-end measures. Participants were randomly assigned to teams consisting of 6-8 individuals that collectively and individually competed in point collection through completion of in-app health tasks. Participation in the TAU group and intervention group was defined as downloading the Sidekick app and completing at least 3 health exercises within it. Time of attrition was defined as the time stamp of last completing health exercise within the Sidekick within intervention period.

Statistical analysis

Descriptive characteristics of partaking adolescents along with attrition reason are reported. Mean differences from baseline to trial's end between and within research groups on primary and secondary outcome measures were obtained with Pearson's correlation coefficient, independent samples t-tests, repeated measures ANOVAs with adjusted alpha levels, and $\chi 2$

tests. Time of attrition and likely significant differences between and within research groups was assessed with Kaplan-Meier survival analysis plots and logrank tests (Clark et al., 2003; Van der Mispel et al., 2017). Beginning of the trial was defined as time of first in-app health exercise completion and the trial period was six weeks, or 42 days, from that moment. The event, or simply time of attrition, was defined as the exact time of participants' last completed health exercise in SidekickHealth. Cases were evaluated as censored when participants were still using the app 42 days after study start. Cox proportional hazard regression models with interacting covariables using research groups as clusters was used to examine attrition prediction based on usage of in-app health exercises between time, type and frequency of exercises as well as sociodemographic variables (age, gender) (Bradburn et al., 2003). Multiple regression models were used to assess predictor variables for primary mean change from baseline to trial's end in anxiety and depressive symptoms based on significant correlations to prevent overfitting the regression models (Tabachnick, 2019). Significance was defined at $p < .05$. Data was analyzed using IBM SPSS Statistics, Release Version 29.0.1.0 (SPSS, Inc., 2022, Chicago, IL, USA, http://www.spss.com).

Results

Participant characteristics are portrayed in Table 1. Results indicate a significant difference in amount of logged health exercises between research groups, where individuals in the intervention group (*m*=245.790, *SD*=211.845) conducted on average a significantly greater number of exercises than the TAU group (*m*=17.630, *SD*=17.848) over the study period; $t(58)$=-1,930, p<.05. Examination of logged health exercises within the app in all exercise categories reveal that there was a significant difference between the intervention group (*m*=23.07, *SD*=35.21) and the TAU group (*m*=7.94, *SD*=6.92); $t(221)$=-1,31, p<.05. Significant baseline differences were only obtained between research groups in perceived sleep problems; $F(2,118)=5.718$, $p=0.004$.

Table 1

Baseline Participants Characteristics

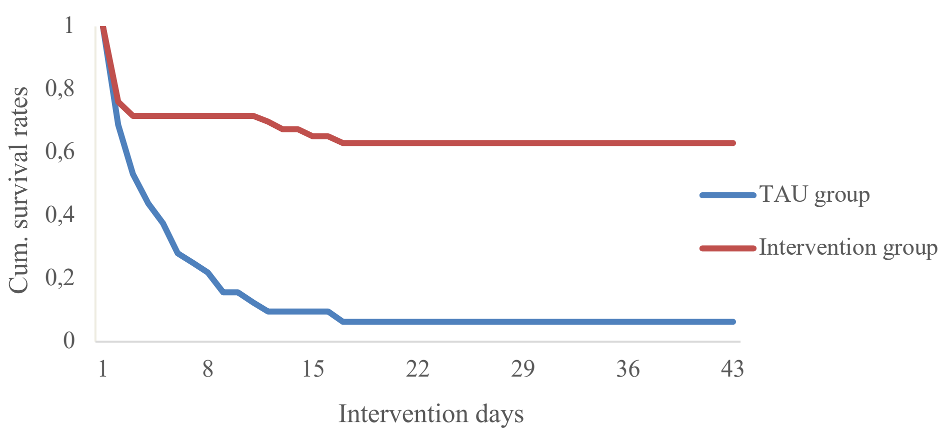
Characteristic	Control (n=43)	TAU (n=32)	Intervention (n=46)	*p* values
Age (years), mean (SD)	13.77 (.43)	13.19 (.59)	13.52 (.62)	
Male:female ratio	17:26	18:14	19:27	
Native Icelandic Speakers, n (%)	43 (100)	32 (100)	46 (100)	
Sleep Impairment, n (%)	22 (51.16)	10 (31.25)	16 (33.33)	.004**
Anxiety Symptoms				
OCD Symptoms, n (%)	20 (46.51)	11 (34.38)	19 (43.30)	.706
Social Anxiety Symptoms, n (%)	21 (48.84)	14 (43.75)	17 (36.95)	.524
Panic Symptoms, n (%)	6 (13.95)	0 (0)	6 (13.04)	.090
Generalized Anxiety Symptoms, n (%)	23 (53.49)	13 (40.63)	25 (54.35)	.433
Seperation Anxiety Symptoms, n (%)	14 (32.56)	9 (28.13)	13 (28.26)	.175
Depression symptoms, n (%)	12 (27.91)	5 (15.63)	7 (15.22)	.447
RCADS Total Score, mean (SD)	59.67 (12.77)	57.81 (8.04)	58.61 (13.12)	.867
General Self-Efficacy, mean (SD)	16.26 (4.07)	15.16 (6.37)	14.85 (6.68)	.501

** Significant at $p< .01$

Attrition rates during the 42 days trial period between research groups are displayed in figure 3. Results reveal a significant difference in completion rates between intervention group (63%) and TAU group (6.3%) according to logrank tests; $X^2(1)= 27.11$, $p<.01$. Mean survival time was 6.31 (95% CI 2.90-9.73) among participants in TAU group while the mean survival time in intervention group was 29.96 (95% CI 22.58-33.34).

Figure 3

Days of Attrition Between Research Groups



As displayed in table 2, a significant difference between intervention and TAU groups was observed in mean number of in-app health exercises during all weeks of the trial period. In fact, throughout the trial mean in-app health exercise completion was tenfold in the research group compared to TAU group. Among members in the TAU group there was a significant mean drop (13.469, SD 15.486) in usage from the first week of the trial period the second one; t_{31}=4.920, p<.01. Such a drop in usage was not evident in the intervention group and usage rose slightly (7.954%), though insignificantly, from the first week to the second. In the intervention group, mean number of completed health exercises was significantly higher in the last week of the trial compared to the 5^{th} week (m=35.261, SD=72.013); t_{45}=2.344, p<.05. Such an increase was not observed among the TAU group members.

Table 2

Weekly comparison of usage and attrition

Week	In-app health exercises completed, n (M:F)	TAU Group M (SD)[1]	Intervention Group M (SD)[1]	*p* values
1	2627 (1768:859)	15.28 (15.625)	46.48 (49.126)	.030*
2	2373 (1818:555)	1.81 (5.012)	50.33 (67.453)	.003**
3	770 (371:399)	1.88 (8.816)	15.43 (40.164)	.005**
4	865 (540:325)	.31 (1.768)	18.59 (32.495)	.001**
5	951 (768:183)	.00 (.00)	20.67 (44.608)	.001**
6	2601 (1882:719)	.88 (4.434)	55.93 (96.439)	.002**
Total	10187 (7147:3040)	20.16 (19.869)	207.43 (331.316)	.006**

[1]Average frequency of weekly exercise completion, **Significant at p< .01, *significant at p< .05

Correlations between time of exercise and exercise category is shown among anxious and depressed participants in table 3, while mean differences between measures at baseline and study end are depicted in table 4.

Table 3

Correlations between time of exercise and exercise category among anxious and depressed participants

Exercise Category	0:01 to 6:00	6:01 to 12:00	12:01 to 18:00	18:01 to 0:00
Anxious participants				
Physical Health	.833**	.346**	.864**	.846**
Mental Health	.043	.705**	.137	.160
Nutrition	-.041	.480**	.130	.225*
Depressed participants				
Physical Health	.960**	.877**	.245	.540*
Mental Health	.429	.841**	.664**	.648**
Nutrition	0.017	.204	.122	.814**

** Significant at $p< .01$, *significant at $p< .05$

Table 4

Pre- and post-measures differences in self efficacy, emotional- and sleep problems

Characteristic	Control Mdiff (SD)	TAU Mdiff (SD)	Intervention Mdiff (SD)	*p* values
Sleep Problems	-16.283%	6.25%	6.521%	.292
Anxiety Symptoms				
OCD Symptoms	.907 (10.330)	-1.401 (11.854)	-.327 (14.321)	.905
Social Anxiety Symptoms	-2.605 (4.425)	-7.812 (16.177)	-2.935 (7.630)	.412
Panic Symptoms	-2.326 (9.553)	2.219 (13.626)	-4.174 (9.656)	.293
General Anxiety Symptoms	-3.861 (10.427)	-2.688 (8.695)	-7.022 (11.259)	.612
Separation Anxiety Symptoms	-1.372 (12.299)	-6.906 (12.074)	-3.217 (10.073)	.471
Depression symptoms	-3.120 (7.408)	.00 (4.516)	-2.739 (8.618)	.706
RCADS Total Score	-2.70 (11.11)	-3.41 (6.607)	-5.37 (11.736)	.814
General Self-Efficacy	.0910 (4.530)	.120 (5.713)	-2.670 (4.564)	.330

Multiple linear regression models were used to examine possible significant predictors for pre- and post-measure differences in anxiety symptoms, depressive symptoms and total score on the RCADS. As shown in table 5, results indicate that days of active app usage significantly predicted differences in pre- and post-measures on RCADS total score (β = -.252, p<.01), anxiety symptoms (β = -.334, p<.05) as well as depressive symptoms (β = -.307, p<.05). The amount of mental health exercises participants carried out was also significantly predictive of pre- and post-measures on RCADS total score (β = .215, p<.01), anxiety symptoms (β = -.382, p<.01) and depressive symptoms (β = -.271, p<.04).

Table 5

Multiple Regression Models

Pre- Post Measure Differences	β (SE)	B (95% CI)	*t*	*p value*
RCADS Total Score				
Predictor Variables				
Usage Days	-.252 (.088)	-.410 (-.428-.076)	-2.858	<.001
Gender	4.161 (2.440)	.179 (-.709-9.030)	1.705	.093
Total Exercise Amount	-.232 (.107)	-8.285 (-.447-.018)	-2.162	<.05
Mental Health	.215 (.072)	-.638 (.071-.359)	2.978	<.01
Nutrition	-.080 (.078)	-.212 (-.075-.235)	1.026	.308
0:01 to 6:00 Exerc.	.263 (.106)	4.410 (.052-.475)	-2.481	<.05
6:01 to 12:00 Exerc.	.051 (.135)	.209 (-.219-.320)	.374	.710
12:01 to 18:00 Exerc.	.302 (.104)	4.338 (0.94-.510)	2.895	<.01
18:01 to 0:00 Exerc.	-.089 (.133)	.796 (-.176-.353)	.669	.506
G-Self Difference	-.283 (.137)	.231 (.010-.557)	2.066	<.01
R^2=.327, F(10,77)=3.255, P<.01				
Anxiety Symptoms				
Predictor Variables				
Usage Days	-.334 (.150)	-.337 (.034-.634)	-2.225	<.05
Gender	-3.063 (4.156)	-.082 (-11.355-5.230)	-.737	.464
Total Exercise Amount	-.248 (.183)	5.482 (-.117-.613)	1.356	.180
Mental Health	.382 (.123)	-.702 (-.627-.136)	-3.106	<.01
Nutrition	-.093 (.132)	-.153 (-.357-.171)	-.701	.485
0:01 to 6:00 Exerc.	-.281 (.181)	-2.910 (-.641-.080)	-1.551	.125
6:01 to 12:00 Exerc.	.047 (.230)	.120 (-.412-.506)	.203	.840
12:01 to 18:00 Exerc.	.302 (.104)	4.338 (0.94-.510)	2.897	<.01
18:01 to 0:00 Exerc.	-.335 (.178)	-2.978 (-.689-.020)	-1.884	.064

G-Self Difference	-.530 (.232)	.268 (-.993-.068)	-2.289	<.01
R^2=.284, $F(10,77)=2.363$, $P<.05$				
Depression Symptoms				
Predictor Variables				
Usage Days	-.307 (.140)	-.344 (.028-.586)	2.199	<.05
Gender	-2.718 (3.866)	-.080 (-10.431-4.996)	-.703	.484
Total Exercise Amount	.195 (.170)	4.780 (-.145-.535)	1.146	.256
Mental Health Exerc.	-.271 (.114)	-.552 (-.499-.043)	-2.368	<.05
Nutrition Exerc.	-.037 (.123)	-.068 (-.283-.209)	-.303	.763
0:01 to 6:00 Exerc.	-.223 (.168)	-2.566 (-.559-.113)	-1.326	.189
6:01 to 12:00 Exerc.	.007 (.214)	.019 (-.420-.434)	.032	.975
12:01 to 18:00 Exerc.	-.261 (.165)	-2.574 (-.591-.069)	-1.578	.119
18:01 to 0:00 Exerc.	-.070 (.210)	-.433 (-.489-.349)	-.334	.739
G-Self Difference	-.813 (.201)	-.455 (-1.214-.413)	-4.053	<.001
R^2=.319, $F(10,77)=3.138$, $p<.01$				

Table 6 reveals Cox proportional hazard regression models results. The research group that participants were assigned to (hazard ratio 0.299, 95% CI .208-.429) is significantly negatively related to attrition ($p<.01$). Total amount of exercises completed throughout the trial was significantly negatively related to time of attrition in both TAU group (hazard ratio 0.959, 95% CI .930-.989) and in the intervention group (HR 0.960, 95% CI .922-.999). An interesting finding was that frequency of in-app exercises completed from 6AM to noon was significantly negatively related to time of attrition in both the TAU group (HR 1.209, 95% CI 1.008-1.451) and intervention group (HR 0.924, 95% CI .858-.996). Such findings were not obtained regarding other time periods of exercise completion in the TAU group while a significant relationship was found between amount of exercises between noon and 6PM and time of attrition among members in the intervention group (HR 0.931, 95% CI .872-.993). Further, a significant negative relationship was obtained between amount of nutrition exercises completed in the intervention group (HR .926, 95% CI .858-1.000) as well as the interaction between mental health exercises and usage days (HR .891, 95% CI .801-.991).

Table 6

Results of Cox proportional hazard regression model

Factor	Coefficient (SE)	HR (95% CI)	*p* value	Coefficient (SE)	HR (95% CI)	*p* value
Research Group	-1.208 (.185)	.299 (.208 - .429)	.001**			
		TAU Group			Intervention	
Sociodemographics						
Gender	.603 (.402)	1.827 (.831-4.020)	.134	.573 (.542)	1.773 (.613-5.132)	.291
Age	-.196 (.331)	.822 (.430-1.572)	.553	-.047 (.420)	.954 (.419-2.173)	.910
Exercise Type						
Physical Health	-.909 (3.028)	.403 (.083-.152.311)	.764	-.073 (.085)	.930 (.787-1.098)	.392
Mental Health	-.512 (3.047)	.599 (.002-.235.06)	.867	-.094 (.066)	.910 (.799-1.037)	.157
Nutrition	-.464 (3.025)	-.629 (.002-235.964)	.878	-.077 (.039)	.926 (.858-1.000)	<.05
Exercise Frequency						
W 1*	-1.062 (.727)	.346 (.83-.1.438)	.144	.648 (.884)	1.911 (.338-10.799)	.464
Week 1	.425 (3.035)	1.529 (.004-586.18)	.889	-.007 (.026)	.993 (.944-1.045)	.798
Week 2	.071 (3.035)	1.074 (.003-411.028)	.981	-.183 (.144)	.832 (.627-1.105)	.204
Week 3	.007 (.027)	1.007 (.956-1.061)	.794	-.338 (.232)	.713 (.453-1.123)	.145
Week 4	-.978 (5.193)	.376 (.00-9898.76)	.851	-.011 (.117)	.989 (.786-1.244)	.924
Week 5	-	-	-	.277 (.580)	1.320 (.423-4.114)	.633
Week 6	-.263 (2.671)	.789 (.004-144.497)	.922	-2.006 (1.151)	.134 (.014-1.283)	.081
Total Exercises	-.042 (.016)	.959 (.930-.989)	<.01	-.041 (.020)	.960 (.922-.999)	<.05
Time of Exercise						
0:01 to 6:00	.025 (.421)	1.025 (.449-2.340)	.954	-.377 (1.309)	.686 (.053-8.921)	.773
6:01 to 12:00	-.190 (.093)	1.209 (1.008-1.451)	<.05	-.079 (.038)	.924 (.858-.996)	<.05
12:01 to 18:00	.160 (.117)	1.174 (.934-1.475)	.170	-.072 (.033)	.931 (.872-.993)	<.05

18:01 to 0:00	-	-	-	-.077 (.043)	.926 (.851-1.008)	.076
Psychometrics Pre-Post						
Self Efficacy	.001 (.033)	1.001 (.939-1.067)	.987	-.011 (.052)	.989 (.893-1.095)	.834
RCADS Total	-.102 (307)	.903 (495-1.647)	.739	.052 (.089)	1.053 (.885-1.254)	.558
Social Anxiety	.038 (0.37)	1.039 (.864-1.250)	.683	-.011 (.052)	.989 (.893-1.095)	.834
Separation Anx.	.000 (.037)	1.000 (.929-1.076)	.998	.003 (.029)	1.003 (.947-1.062)	.931
General Anxiety	.007 (.064)	1.007 (.888-1.141)	.918	-.014 (.033)	.986 (.924-1.052)	.667
Panic Symptoms	.029 (.071)	1.030 (.897-1.183)	.676	-.069 (.042)	.933 (.859-1.014)	.105
OCD Symptoms	.019 (.051)	1.019 (.922-1.127)	.708	.015 (.021)	1.015 (.973-1.059)	.486
Depression Sym.	.009 (.081)	1.009 (.861-1.184)	.908	-.008 (.035)	.992 (.927-1.063)	.828
Interaction UsageDays						
12:01-18:00*UD	-.074 (.027)	.929 (.880-.980)	<.01	-.111 (.035)	.895 (.835-.959)	<.01
18:01-0:00*UD	-	-	-	-.098 (.047)	.907 (.828-.993)	<.05
Nutrition*UD	.02	1.02 (.99-1.06)	.17	-.077 (.033)	.926 (.869-.987)	<.05
MentalHealth*UD	.01	1.01 (.99-1.04)	.26	-.115 (.054)	.891 (.801-.991)	<.05

*Exercised after 1st day

Discussion

Most adolescents in developed economies own smartphones and roughly 45% of them are nearly constantly online (Anderson & Jiang, 2018; Center, 2015; Center, 2019). Adolescents are likely to seek information on mental health and clinical mental help through their smartphones, which highlights the need for science-based cost-effective mental mHealth interventions. The number of mHealth apps on the market has sharply increased in recent years with an estimated 350.000 mHealth applications on the market and roughly 22.750 application focusing on mental health (IQVIA, 2021; Torous & Roberts, 2017). However, exceedingly small percentage of adolescents use mHealth applications or partake in mHealth interventions (Chan et al., 2017; Maenhout et al., 2022; Wu et al., 2014; Yardley et al., 2016). In this study, we aimed to obtain a deeper understanding of what motivates mHealth usage among adolescents through analyses of in-app usage by measuring time and frequency of nutritional-, physical activity and mental health exercise completion within the application. In our previous prior work on the matter, we concluded that a better understanding of what occurs among adolescent participants in mHealth intervention from treatment instigation to time of attrition was direly needed (Egilsson et al., 2021). Studies focusing on attrition in mHealth interventions targeting adolescent populations commonly present attrition rates in a two-point fashion, from initiation of intervention to the end of treatment though we are beginning to witness methodological changes in that regard.

This study offers insight into daily attrition rates among adolescents with clincal anxiety and depressive symptoms. A significant difference between the research groups was observed in attrition rates, where attrition was nearly 94% in the TAU group compared to 37% in the intervention group. These attrition rates are comparable to our previous research on the matter where attrition rates in intervention arms were 35% and 44,4%, respectively (Egilsson et al., 2021, 2023). The intervention therefore shows promise in engaging adolescents with anxiety and/or depression, as well as those without these conditions. The sole difference between research groups was additional support in form of weekly feedback on progress, friendly individual and group health task competitions along with altruistic reward schedules. Motivational support appears to be a critical factor that could enhance the effectiveness of mHealth interventions for adolescents since mean time of active usage was roughly six days (95% CI 2.90-9.73) among participants in TAU group while the time in intervention group was fivefold or nearly 30 days (95% CI 22.58-33.34).

Results revealed significant differences in the frequency and amount of health tasks completed between research groups. Adolescents in the intervention group completed a greater number of health exercises overall and in each of the health categories, nutrition, physical activity and mental health. In fact, the intervention group conducted on average ten times as many in-app health exercise as the TAU group throughout the trial. The results show a significant decrease in usage from the 1st week of the intervention to the 2nd one among the TAU group members, which was not evident in the intervention group. Furthermore, completion rates of in-app health exercises rose from the 5th trial week to the last week of the trial in the intervention group. Such increase was not observed in the TAU group. This suggests there is a sensitive period shortly after instigation of mHealth interventions and towards the end. Further, it underlines the importance of support and motivational program features to maintain or increase health behavior and counter attrition. A significant negative relationship was found between amount of nutrition exercises completed in the intervention group (HR .926, 95% CI .858-1.000) as well as the interaction between mental health exercises and days of active usage (HR .891, 95% CI .801-.991) while such findings were not found between physical activity and days of usage. These findings highlight the importance of a broad range of health exercise categories in mHealth adolescent intervention to motivate usage and hinder attrition.

According to multiple linear regression results, days of active usage significantly predicted differences in anxiety symptoms as well as depressive symptoms throughout the trial period. Time of daily usage and completion of in-app health exercises can provide some insight into possible differences in usage between adolescents with anxiety symptoms compared to those who suffer from significant depression symptoms. Anxious participants were most active in all exercise categories, i.e. nutrition, physical activity and mental health exercises, between 6 o´clock in the morning to noon. Participants with depressive symptoms were, however, more likely to complete health exercises in all health categories between 6 o´clock in the evening until midnight. An interesting yet a confounding finding was that the frequency of in-app exercises completed from 6 o'clock in the morning to noon was significantly negatively related to time of attrition in both the TAU group (HR 1.209, 95% CI 1.008-1.451) and the intervention group (HR 0.924, 95% CI .858-.996). This suggests that there is a daily sensitivity usage period that differs between anxious adolescents and those facing depression symptoms. Future interventions that target these groups of adolescents could benefit from aiming application support in form of incentives, notification or initiation of new intervention period to those time frames in order to reduce attrition. In conclusion, this RCT was designed to obtain knowledge on time specific attrition rates in a mHealth intervention for adolescents with anxiety and depressive symptoms and increase understanding of attrition through focus on how, when and to what extent these adolescents take part in the program, through either motivational support or on their own. Sizable and significant differences in attrition rates between the groups were evident and motivational support of key importance to ultimately lower attrition. The question remains, how can we mitigate the decline in usage following the initiation of an intervention to further reduce attrition rates? Additional research on the matter is called for as this could be examined in relation to app features and design of motivational support for adolescents with anxiety and depression.

Acknowledgments

The authors wish to thank part-taking elementary school officials. The authors wish to thank Icelandic Research Fund (IRF 141381051) for partially funding the study through research grant.

Conflicts of Interest

First author is a minority shareholder in SidekickHealth AB and former employee.

Abbreviations

AAT: Appetite Awareness Training

CDC: Centers for Disease Control and Prevention

CBT: Cognitive Behavioural Therapy

GSE: General Self Efficacy Scale

mHealth: Mobile Health

RCADS: Revised Children´s Anxiety and Depression Scale

RCT: Randomized Controlled Trial

TAU: Treatment As Usual

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