Parent and demographic predictors of participant engagement in a parental mHealth intervention: results from the Let’s Grow trial

Johanna Sandborg, Brittany Reese Markides, Savannah Simmons, Katherine L Downing, Jan M Nicholson, Liliana Orellana, Harriet Koorts, Valerie Carson, Jo Salmon, Kylie D Hesketh

Submitted to: JMIR mHealth and uHealth
on: May 13, 2024

Table of Contents

Original Manuscript **5**
Supplementary Files **35**
Figures **36**
Figure 1 .... **37**
CONSORT (or other) checklists **38**
CONSORT (or other) checklist 0 .... **39**

Parent and demographic predictors of participant engagement in a parental mHealth intervention: results from the Let's Grow trial

Johanna Sandborg[1, 2] PhD; Brittany Reese Markides[1] PhD; Savannah Simmons[1]; Katherine L Downing[1] PhD; Jan M Nicholson[3] PhD; Liliana Orellana[4] PhD; Harriet Koorts[1] PhD; Valerie Carson[5] PhD; Jo Salmon[1] PhD; Kylie D Hesketh[1] PhD

[1]Institute for Physical Activity and Nutrition (IPAN) Faculty of Health Deakin University Geelong AU
[2]Institute for Physical Activity and Nutrition (IPAN) Faculty of Health Deakin University Burwood AU
[3]Judith Lumley Centre La Trobe University Bundoora AU
[4]Faculty of Health Biostatistics Unit Deakin University Geelong AU
[5]Faculty of Kinesiology, Sport, and Recreation University of Alberta Edmonton CA

Corresponding Author:
Johanna Sandborg PhD
Institute for Physical Activity and Nutrition (IPAN)
Faculty of Health
Deakin University
221 Burwood Highway
Burwood
AU

Abstract

Background: Parents are integral in shaping early childhood health behaviors, and mobile health (mHealth) interventions offer an accessible method of supporting them in this role. Optimizing participant engagement is acknowledged to be key to mHealth effectiveness and impact; however, research examining personal predictors of engagement is largely lacking.

Objective: The aims of this study were to i) describe participant engagement with a novel parental mHealth intervention (Let's Grow) during the first 25 weeks of use, and ii) investigate whether engagement levels varied by family demographics and parent characteristics.

Methods: This observational study utilized data from parents in the intervention group in the Let's Grow trial (n=682). The intervention targeted toddlers' movement behaviors and the program (a purposive-designed progressive web app) was delivered via modules that the parents worked through over time. The content was built around three main components (behavior change activities, information provision, and social support). Engagement data (web app analytics) collected across the first 25 weeks of the intervention were summarized as study specific (time using the app, proportion of accessed features and pages, clicks in the main parts of the app) and overall engagement measures (composite engagement index [EI]) and individual subindices [click depth, loyalty, recency, diversity]). Items measured at baseline included: family demographics (main carer, child and family characteristics, postcode) and parent characteristics (coping, concern, information seeking). Linear regression assessed associations between family demographics and parent characteristics and engagement measures.

Results: Most parents logged in and used at least one app feature (89%). App access declined from 81% in the first week to 28% at 25 weeks. For users who engaged with the app during weeks 12-25, EI remained consistent and was virtually the same as the average EI over the assessed time period (28%, range: 3-50%). More work hours, parents living together, having siblings in the family and living in a regional/remote area were associated with lower engagement on 10 out of 12 indicators (all P?.046). Higher education level was associated with higher engagement on 9 indicators (all P?.020). Of the parent characteristics, only higher parent coping was positively associated with engagement (P=.003).

Conclusions: Our findings indicate that time and sociodemographic factors might be most relevant to predicting engagement and highlight the characteristics of parents who may benefit from more active strategies to support their engagement with digital interventions. The uptake and continued engagement with this app were higher than what is reported for apps more generally, but it is unknown whether this is sufficient for behavior change. Individual and composite measures of engagement yielded similar results, indicating that simpler metrics which might be more feasible for researchers to use compared to complex EIs, can be useful for reporting engagement in digital interventions. Clinical Trial: ACTRN12620001280998; U1111-1252-0599

(JMIR Preprints 13/05/2024:60478)
DOI: https://doi.org/10.2196/preprints.60478

Preprint Settings

1) Would you like to publish your submitted manuscript as preprint?
✓ **Please make my preprint PDF available to anyone at any time (recommended).**
Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users.
Only make the preprint title and abstract visible.
No, I do not wish to publish my submitted manuscript as a preprint.
2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?
✓ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**
Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain v
Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <a href="http

Original Manuscript

Parent and demographic predictors of participant engagement in a parental mHealth intervention – results from the *Let's Grow* trial

Johanna Sandborg[1], Brittany R Markides[1], Savannah Simmons[1], Katherine L Downing[1], Jan M Nicholson[2], Liliana Orellana[3], Harriet Koorts[1], Valerie Carson, Jo Salmon[1], Kylie D Hesketh[1]

[1]Institute for Physical Activity and Nutrition, Faculty of Health, Deakin University, Geelong, Victoria, Australia

[2]Judith Lumley Centre, La Trobe University, Bundoora, Victoria, Australia

[3]Faculty of Health Biostatistics Unit, Deakin University, Geelong, Victoria, Australia

[4]Faculty of Kinesiology, Sport, and Recreation, University of Alberta, Edmonton, Alberta, Canada

Journal: JMIR mHealth uHealth

Corresponding author: Johanna Sandborg, Institute for Physical Activity and Nutrition, Deakin University Faculty of Health, Geelong, Victoria, Australia, +46733285912, johanna.sandborg@ki.se

Abstract

Background: Parents are integral in shaping early childhood health behaviors, and mobile health (mHealth) interventions offer an accessible method of supporting them in this role. Optimizing participant engagement is acknowledged to be key to mHealth effectiveness and impact; however, research examining personal predictors of engagement is largely lacking.

Objective: The aims of this study were to i) describe participant engagement with a novel parental mHealth intervention (*Let's Grow*) during the first 25 weeks of use, and ii) investigate whether engagement levels varied by family demographics and parent characteristics.

Methods: This observational study utilized data from parents in the intervention group in the *Let's Grow* trial (n=682). The intervention targeted toddlers' movement behaviors and the program (a purposive-designed progressive web app) was delivered via modules that the parents worked through over time. The content was built around three main components (behavior change activities, information provision, and social support). Engagement data (web app analytics) collected across the first 25 weeks of the intervention were summarized as study specific (time using the app, proportion of accessed features and pages, clicks in the main parts of the app) and overall engagement measures (composite engagement index [EI]) and individual subindices [click depth, loyalty, recency, diversity]). Items measured at baseline included: family demographics (main carer, child and family characteristics, postcode) and parent characteristics (coping, concern, information seeking). Linear regression assessed associations between family demographics and parent characteristics and engagement measures.

Results: Most parents logged in and used at least one app feature (89%). App access declined from 81% in the first week to 28% at 25 weeks. For users who engaged with the app during weeks 12-25, EI remained consistent and was virtually the same as the average EI over the assessed time period (28%, range: 3-50%). More work hours, parents living together, having siblings in the family and living in a regional/remote area were associated with lower engagement on 10 out of 12 indicators (all $P \leq .046$). Higher education level was associated with higher engagement on 9 indicators (all $P \leq .020$). Of the parent characteristics, only higher parent coping was positively associated with engagement ($P = .003$).

Conclusion: Our findings indicate that time and sociodemographic factors might be most relevant to predicting engagement and highlight the characteristics of parents who may benefit from more active strategies to support their engagement with digital interventions. The uptake and continued engagement with this app were higher than what is reported for apps more generally, but it is unknown whether this is sufficient for behavior change. Individual and composite measures of engagement yielded similar results, indicating that simpler metrics which might be more feasible for researchers to use compared to complex EIs, can be useful for reporting engagement in digital interventions.

Trial registration number ACTRN12620001280998; U1111-1252-0599

Keywords (3-10): digital intervention; parenting; movement behaviors; sleep; screen time; early childhood

Introduction

Early childhood (0-5 years) has been identified as a key time to promote health behaviors (e.g., physical activity) [1]. In the early years, parents play an important role in providing opportunities for these behaviors, and parental encouragement and support has been shown to positively influence children’s health behaviors [2,3]. Parental involvement in childhood interventions has also been shown to be effective at promoting a healthy diet and physical activity in children [4], with greater effects from interventions including parenting skill training and behavior change strategies [5]. Mobile health (mHealth) interventions (e.g., mobile apps, websites, or messaging services) offer a convenient and accessible way to provide support and timely information to parents and can enable participation regardless of geographic location. This delivery mode has been shown to be well accepted among parents, and to be effective at promoting health behaviors in children [6–8].

The digital format of mHealth interventions also enables the use of built-in tools for the objective measurement of user engagement (i.e., *how* and *to what extent* users engage with the intervention) which is directly linked to intervention effectiveness [9]. Examining user engagement is a critical component of evaluating mHealth interventions as it provides information on levels of intervention exposure and uptake and can facilitate identification of factors that may optimize engagement [10]. Understanding who and how participants engage with digital interventions can also provide insight into the mechanisms driving intervention effectiveness and contribute to the design of more impactful interventions. However, there is a notable lack of reporting on participant engagement and its predictors in mHealth interventions targeting parents of young children, with only a few studies presenting parental engagement using objective data rather than parent report (e.g., [11–15]). Of the studies that have investigated predictors of engagement in mHealth parental interventions [11–14], only family demographics (parental education [11–14], number of children in the household [11,13], and work status [12]) have been examined. No previous studies have investigated parental beliefs and behaviors despite evidence that parental constructs such as parental confidence, can predict dropout rate in traditional family-based interventions [16]. Hence, little is known about how parents of young children engage with mHealth interventions, nor of the potential influence that family demographics and parent characteristics may have on parents’ engagement with mHealth interventions.

Let's Grow is a novel mHealth intervention designed to support parents in improving the movement behaviors (i.e., physical activity, sedentary behavior, sleep) of their 2-year-old children via a purpose-built app [17]. The program is delivered via modules that parents work through over time, and the content is built around three main components, i.e., behavior change activities, information provision, and social support, all of which have been identified as key strategies to promote health behaviors [18]. To the best of our knowledge, no previous study has comprehensively investigated engagement and predictors of engagement in a parental mHealth intervention. Thus, we utilized data from the *Let's Grow* trial [17] to examine how parents engaged with the intervention and factors associated with app usage.

Objectives

The aims of this study were to: i) describe parental engagement with the *Let's Grow* app during the first 25 weeks of use, and ii) investigate whether engagement levels varied by family demographics and parent characteristics.

Methods

Study design

This observational study utilized data from the *Let's Grow* randomized controlled trial (trial registration nr: ACTRN12620001280998; U1111-1252-0599) [17]. The trial design and rationale have been described previously [17]. In brief, the trial investigated a 12-month mHealth intervention (delivered through a progressive web app, the *Let's Grow* app) aimed at supporting parents of 2-year-old children to improve their child's movement behaviors [17]. The *Let's Grow* trial received ethical approval by the Deakin University Human Research Ethics Committee, Australia (2020-077). The main carer provided consent for their own participation and that of their child via an online form. This study is reported according to the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) checklist.

Recruitment, randomization, and procedures

Participants were recruited through social media (e.g., Facebook, parenting blogs) between March 2021 and June 2022. Parents aged 18 years or older, residing in Australia, owning a mobile phone, having internet access, literate in English, and with a child aged 18-35 months walking independently, were eligible. Following baseline assessment, participants were randomized in a 1:1 ratio stratified by geographical location (urban or outer/remote), yielding 16 strata across the eight Australian states/territories. The intervention group (n=682) were then provided access to the *Let's Grow* app. The baseline survey data and app analytics metrics of intervention group participants collected during the first 25 weeks of app access was used for this study.

The Let's Grow app

The development and content of the *Let's Grow* app has been described in detail elsewhere [17]. In short, the app was built around three main components including active learning targeting changes in specific combinations of movement behaviors (learning modules), general information provision (toolkit) and social support (community chat forum) to help parents improve their child's physical activity, sedentary behavior (including screen time), and sleep. The active learning component consisted of eight modules, each containing information and strategies (in text, pictorial, podcast, and video format) on child sleep, play, screen time and general parenting, as well as a set of behavior change activities including both online and offline components. To further support parents, each module also included SMS messaging (e.g., interactive messages facilitating goal setting and self-monitoring).

While parents could complete the modules in any order, they were only able to access one module at a time and were required to complete all activities within that module before moving onto another. As activities took varying amounts of time to complete (e.g. self-monitoring occurred across a week), the minimum amount of time to complete a module before moving onto the next ranged from 2-5 weeks. Completed modules remained accessible for participants to revisit information. However, if participants did not complete a module, information contained in the other modules would not be available to them. The intervention duration was 12 months; the minimum timeframe to complete all eight modules was 22 weeks but participants were not expected to complete all modules in this time. Upon completion of all modules, participants received SMS notifications once a week to refresh knowledge and encourage revisiting of the app. The toolkit and community chat forum remained freely accessible throughout the intervention period. The toolkit included resources such as outdoor and indoor play ideas, screen free activities, podcast providing help with children's common sleep issues, videos explaining different parenting strategies in relation to managing difficult child behavior. The forum provided parents with the opportunity to anonymously share ideas and connect with other participants. Parents were prompted with text message reminders to reengage with the app if no activity was detected for an extended period of time (e.g. if the app had not been opened for 3 weeks).

Factors related to engagement

At baseline, the main carer completed an online survey (using REDCap) capturing family demographics and parent characteristics. Main carer characteristics considered in this study included age (years), relationship with the child (mother/father), birth country (Australian born, yes/no), education level (university degree vs no university degree), and work status (currently working, yes/no). Participant child characteristics included sex, and temperament in comparison to other children (single item; scale 1-5 ranging from much easier than average to much more difficult than average) [19]. Family characteristics included parents living together (yes/no), siblings in the family (yes/no). Postcode was used to derive information on remoteness, i.e., major cities vs inner/outer regional or rural Australia which was based on the Australian Bureau of Statistics Australian Statistical Geography Standard Remoteness Structure [20], as well as area-level socioeconomic status derived using the Australian Bureau of Statistics Socio-Economic Indexes for Areas (SEIFA) Index of Relative Socio-economic Advantage and Disadvantage (IRSAD) [21].

Three parent characteristics relevant to the intervention were considered, parent coping in general, concern about the targeted topic (movement behaviors) and information seeking related to the targeted topic. Parents reported using a 5-point scale (1=not at all, 5= extremely well, possible range 0-5) how they were coping with life at present [22]. In terms of concern with child movement behaviors, parents reported about their child's sitting time, physical activity/active play, screen use, and sleep to indicate whether they considered it a problem using a 5-point scale (1= not a problem at all to 5 = a serious problem) [23]. A combined movement behavior concern score was calculated as the sum of the individual scores (possible range 4-20, higher scores indicating greater concern) [23]. Finally, parents reported how much time in a usual week they spend using apps or websites to access information on children’s physical activity, sitting time or screen use, and sleep, respectively. The total reported time searching information on child movement behaviors and child health topics was calculated (hours/week, possible range 0-40 hours/week).

Metrics of engagement

Data on users' activities and actions in *Let's Grow* were logged to a dedicated database connected to the app's backend system. These data were used to report user engagement descriptively, such as the proportion of participants who initiated app usage (i.e., intervention uptake), the types of features they used (i.e., learning modules, toolkit, community chat forum), the number of modules they completed, total time spent in the app (minutes), total days app of use, and proportion of pages (%) and features (%) visited at least once throughout the 25 weeks, and number of actions (posts, likes and comments) in the community chat forum.

To assess overall engagement among *Let's Grow* users, an adapted version of a previously developed engagement index (EI) [11,24] was calculated. As per previous studies [11,14,24], the four subindices relevant to this program, from the original seven comprised in the index, were utilized. These included: (1) click depth (average number of app pages viewed per day), (2) loyalty (total days with any usage data for a participant), (3) recency (average number of days between app use; reversed so higher score indicates greater engagement), and (4) diversity (the number of different app features used per day, i.e., activities within modules, toolkit, community chat forum, FAQ). Subindices were normalized by rescaling values between 0 and 100% to assign equal weight to each of the subindices. The EI was calculated as the average of the four subindices. In addition, a weekly EI (range 0 to 100%) was calculated for those with engagement data in any particular week, to enable more granular investigation into participant engagement over the 25 weeks. All calculations were carried out using Python 3.

Covariates

The *Let's Grow* trial was conducted during the Covid-19 pandemic (baseline data collection from March 2021 to June 2022; data for this paper collected to January 2023). There were varying pandemic restrictions across different states and territories in Australia, which potentially impacted the everyday life of the participating families and their ability to engage with the program. Thus, data on the number of days in lockdown during the 6-month engagement period was calculated based on individual postcode and publicly available data on local restrictions. In addition, due to technical issues the app was not functioning at certain periods, but due to the staggered recruitment not all participants experienced equal app downtime which might have differentially affected engagement. App downtime was calculated for each participant using web app analytics.

Data analysis

All statistical analyses were carried out using the statistical software R version 4.0.3 (R Foundation for Statistical Computing). Chi-square tests for categorical and t-test for numerical variables were used to investigate differences between those who logged in at least once and used at least one app feature (i.e., users, n=609) and those who never logged in or logged in but never used an app feature (i.e., non-users, n=73). Associations between potential predictors (family demographics and parent characteristics) and individual (clicks in the main parts of the app: learning modules, toolkit, and community chat forum) and overall measures of engagement (EI and subindices) at 25 weeks were estimated using linear regression. Sensitivity analyses were performed adjusting for lockdown and app downtime by including number of days in lockdown and total app downtime (days) in the models. Estimates from sensitivity analyses are presented alongside the main analyses where results differed.

Results

Participant characteristics

Baseline characteristics of the 682 participants randomized to the intervention group are reported in *Table 1*. Participants were on average 34.9 (SD 4.5) years (range: 21-48 years) old, the majority were mothers (98%), Australian born (77%), university educated (72%), lived in major cities (72%), and lived together with a partner/spouse (92%). In terms of intervention uptake, 67 participants never logged in, and a further six did not progress past the log in page to use any of the app features. The 609 participants who logged in at least once and used at least one app feature were referred to as "users" and are included in subsequent analyses. Users did not differ from non-users in terms of key baseline characteristics, with the exception of reporting higher coping score (mean score 3.2 vs 3.0, P=.01) and a higher level of concern with their child's movement behaviors (mean score 7.4 vs 6.8, P=.04).

Table 1. Family demographics and parent characteristics of the participants in the intervention group in the *Let's Grow* trial (n=682) [a].

	Value [b]
Parent demographics and characteristics [c]	
Age (years) (mean, SD)	34.9 (4.5)
Mother	670 (98.2)
Australian born	522 (76.7)
University degree	490 (71.8)
Currently working	442 (64.9)
Parent coping (mean, SD)	3.2 (0.7)
Concern with child movement behaviors (mean, SD)	7.3 (2.6)
Information seeking (hours/week) (mean, SD)	2.2 (4.6)
Child	
Female	337 (49.4)
Child temperament	
Much easier/easier	221 (32.4)
Average	361 (52.9)
More/much more difficult	100 (14.7)
Family	
Living with a partner/spouse	629 (92.4)
Siblings in the family	361 (58.8)
Living area and area level socioeconomic status	
Remoteness level	
Major cities	490 (71.8)
Inner regional Australia	131 (19.2)
Outer regional/remote Australia	61 (8.9)
Socio-Economic Indexes for Areas category	
Low advantaged/high disadvantaged	136 (20.0)
Middle advantaged/disadvantaged	223 (32.8)
High advantaged/low disadvantaged	321 (47.2)

[a] Due to missing data, n varied slightly for some variables with missing data for individual variables ranging from n=0-68 missing.

[b] Data presented as n (%) unless otherwise stated.

[c] These data are from the self-selected main carer of the child.

User engagement with the *Let's Grow* app

Table 2 presents different measures of engagement for those classified as users, including overall use and engagement with the different components of the app. Across the 25 weeks users spent on average a total of 31 minutes (SD 36 minutes) in the app and accessed the app on an average of 18 separate days (SD 15 days) over this time. The users visited on average 13% [SD 13%] of the pages and 40% [SD 18%] of the app features, noting that a large proportion of the content was contained within the learning modules and hence remained inaccessible until modules were completed.

The highest level of engagement was observed in the learning modules (83% accessed a module at least once), and the average number of completed modules was 2.4 (SD 3.0; range 0-8) out of the possible eight. More than half (54%) completed at least one module: 18% completed one module; 8% two modules; 8% three modules; 6% four modules; 7% five modules; 4% six modules; 2% seven modules, and 1% completed all eight modules by 25 weeks (the mid-intervention point). The information provision component was the second most used part of the app (55% accessed the toolkit at least once). The lowest level of engagement was observed in the social support component which 29% of users accessed at least once. Users of the social support feature made between 0-37 posts (mean 0.5 [SD 2.7], 0-96 likes (mean 0.5 [SD 4.6]), and 0-17 comments (mean 0.4 [SD 1.7]).

The average EI over the 25-week time period was 28% (SD 7%) out of 100%. In terms of patterns of engagement, the level of engagement (EI) varied throughout the 25 weeks (*Figure 1*). For those who progressed past the log in page, engagement was highest after initial access to the app (91% accessed the app in the first week; average EI in the first week was 34% [SD 12%], n=552) and declined during the first 25 weeks of the intervention period (36% of users accessed the app at 12 weeks and 31% at 25 weeks) although in a non-linear fashion. For users with engagement data at 12- and 25 weeks, EI was similar at the two time points, (mean 28% [SD 7%], n=217, and mean 28% [SD 9%], n=190, respectively).

Table 2. Objective measures of app engagement after 6-months in participants defined as app users (n=609).

	Value[a]	Range
Individual engagement metrics		
Overall use		
Total time spent in the app (minutes)	31 (36)	0-270
Days using the app	18 (15)	1-82
Proportion of content viewed (%)		
Pages visited	12.8 (13.0)	1-77
Features visited	39.6 (18.5)	5-100
Engagement in the main parts of the app		
At least one time access (n, %)		
Learning modules	505 (82.9)	-
Toolkit	335 (55.0)	-
Community chat forum	177 (29.1)	-
Number of clicks		
Learning modules	58.8 (74.8)	0-497
Toolkit	17.6 (40.2)	0-356
Community chat forum	1.8 (4.8)	0-42
Composite engagement metrics		
Total engagement index	28.0 (6.6)	3.2-50.0
Subindices		
Click-depth	2.4 (2.4)	0.1-17.8
Loyalty	9.2 (7.6)	0-46.4
Recency	87.4 (14.9)	0-100
Diversity	13.0 (9.5)	0-66.7

[a] Data reported as mean (SD) unless otherwise stated.

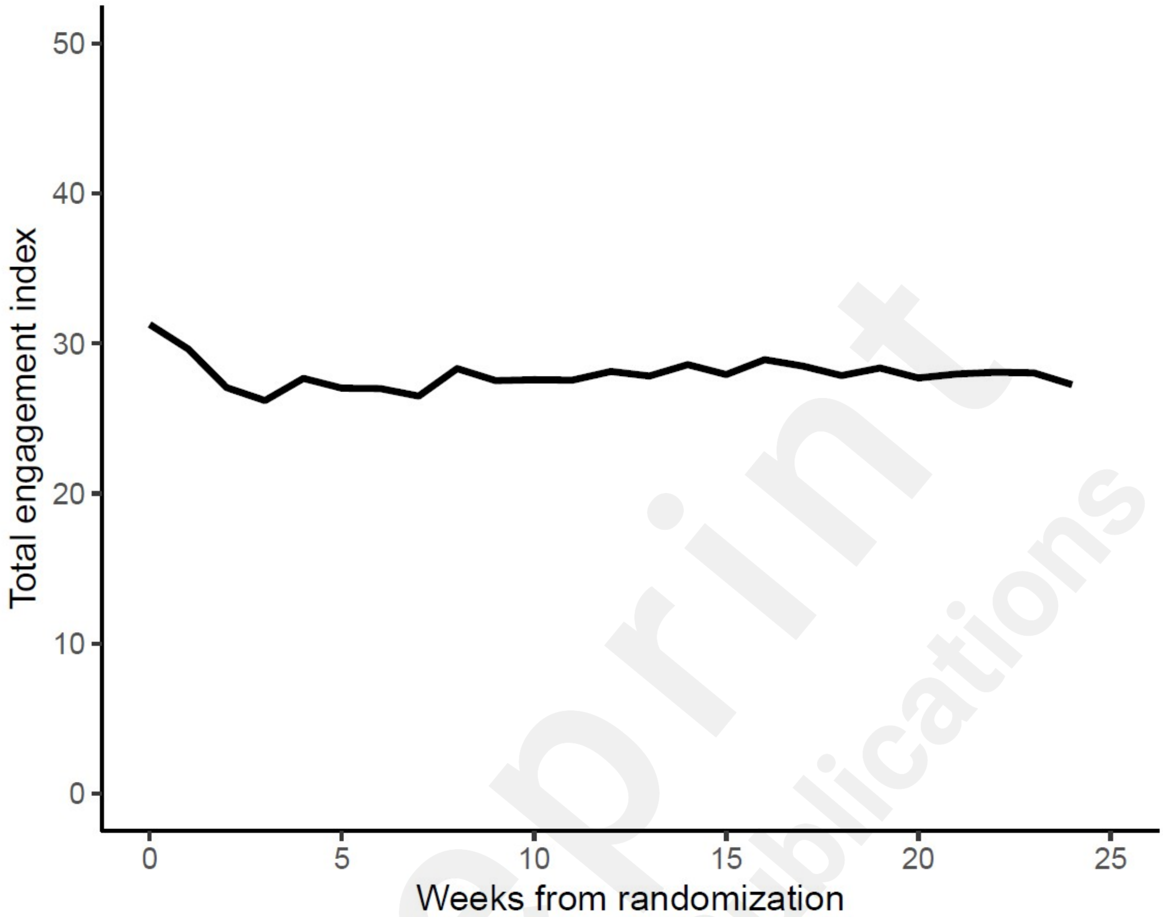


Figure 1. Average weekly engagement index (EI) over the usage period for participants defined as users (n=609). The EI comprises of four subindices: click depth (the average number of app pages viewed per day), loyalty (the total number of days a user engaged with the app), recency (the average number of days between app use: reversed so higher score indicates greater engagement), and diversity (the number of different app features used per day). Subindices were normalized by rescaling values between 0 and 100 to assign equal weight to each of the subindices (each element was equally important in contributing to the measurement of engagement). The EI was then calculated as the athematic mean of the four subindices (click depth, loyalty, recency, and diversity).

Associations between predictors and user engagement

Estimated associations between potential predictors and individual (time spent in the app, proportion of pages visited, clicks in the main parts of the app) as well as composite (EI and subindices) indicators of engagement from the unadjusted regression models are presented in *Table 3-4* and *Table 5*, respectively. Overall, the same pattern of associations was seen for individual and composite measures of engagement.

Higher education level was associated with higher levels of engagement on 4 of the 7 individual indicators, and all 5 of the composite indicators. Higher education level was associated with more days of app use (β=3.14 ,95% CI: 0.50 to 5.78, *P*=.020), accessing a higher proportion of pages (β= 3.27, 95% CI: 0.96 to 5.59, *P*=.006) and features (β= 4.33, 95% CI: 1.05 to 7.61, *P* =.010), more clicks in the modules (β = 18.59; 95% CI: 5.33 to 31.86; *P* =.006), as well as higher EI (β=2.61; 95% CI: 1.46 to 3.77; *P* <.000), click-depth (β=0.77; 95% CI: 0.36 to 1.19; *P* <.000), loyalty (β=2.48; 95% CI: 1.14 to 3.83; *P* <.000), recency (β=4.64; 95% CI: 2.00 to 7.27; *P* =.001), and diversity index (β=2.56; 95% CI: 0.89 to 4.24; *P* =.003). Parent coping score was positively associated with engagement on 1 composite indicator (i.e., loyalty score, β=1.25; 95% CI: 0.43 to 2.08; *P*=.003).

In contrast, higher working hours was associated with lower levels of engagement on 4 of the individual indicators, and 1 of the composite indicators. Number of working hours was inversely associated with total time spent in the app (β= -0.24, 95% CI: -0.43 to -0.05, *P*=.013), proportion of pages visited (β= -0.08, 95% CI: -0.15 to -0.01, *P*=.023), clicks in the modules (β= -0.40; 95% CI: -0.79 to -0.01; *P*=.046) and toolkit (β= -0.27; 95% CI: -0.48 to -0.06; *P*=.012), as well as click-depth index (β = -0.01; 95% CI: -0.03 to -0.00; *P*=.046). Parents living together was associated with lower levels of engagement on 5 individual indicators. Parents living together with a partner spent less time (β=-13.58, 95% CI: 24.39 to 2.77, *P*= .014) and days using the app (β= -5.07, 95% CI: -9.531 to -0.6, *P*= .026), accessed a lower proportion of pages (β= -4.30, 95% CI: -8.22 to -0.38, *P*= .031), and on average clicked less times in the modules (β= -31.37; 95% CI: 53.79 to 8.95; *P*=.006) and toolkit (β=-12.72; 95% CI: 24.82 to 0.63; *P*=.039). Having siblings in the family was associated with lower engagement on 5 individual indicators, and 4 of the composite indicators. Having siblings in the family was inversely associated with total time spent in the app (β= -7.11, 95% CI: -13.40 to 0.82, *P*=.027), number of days of app use (β= -3.04, 95% CI: -5.59 to -0.49, *P*=.019), clicks in the toolkit (β =-7.75; 95% CI: -14.82 to -0.68; *P*=.032) as well as lower EI (β= -1.56, 95% CI: -2.65 to -0.48, *P*=.005), click-depth (β= -0.43, 95% CI: -0.83 to -0.04, *P*= .031), loyalty (β= -2.4, 95% CI: -3.68 to -1.12, *P*= <.000), and recency index (β= -2.77, 95% CI: -5.17 to -0.36, *P*= .024). Living outside a metropolitan area was associated with lower engagement on 1 composite indicator (i.e., click-depth index, β = -0.47; 95% CI: -0.88 to -0.05; *P*=.027).

No associations were observed between any of the predictor variables and clicks in the community chat forum. Parent characteristics (age, birth country), information seeking and concern as well as area-level socioeconomic status were not associated with any of the considered indicators of engagement.

Sensitivity analyses results were the same with a few exceptions. Associations between education level and total time spent in the app were significant after adjustment for app downtime (β= 6.61, 95% CI: 0.21 to 13.00, *P*=.043) and days in lockdown (β=6.75, 95% CI: 0.35 to 13.16, *P*=.039). In contrast, associations between work status and click-depth index (β=-0.01; 95% CI: -0.02 to -0.00; *P*=.050), siblings in the family and the proportion of features visited (β = -2.90, 95% CI: -6.00 to 0.24, *P*=.071) as well as between remoteness (major city vs regional/remote area) and click-depth index (β=-.0.32; 95% CI: -0.73 to 0.10; *P*=.137) were attenuated after adjustment for app downtime and days in lockdown.

Table 3. Associations between family demographics and parent characteristics with individual engagement indicators for overall use (n=609) [a].

Predictor variables	Total time spent in the app (minutes) β (95% CI)	Days of app use β (95% CI)	Proportion of pages visited β (95% CI)	Proportion of features visited β (95% CI)
Parent age (years)	0.45 (-0.19 to 1.09)	0.10 (-0.16 to 0.37)	0.13 (-0.10 to 0.36)	0.12 (-0.21 to 0.45)
Australian born	-0.91 (-7.71 to 5.90)	0.22 (-2.58 to 3.03)	-0.14 (-2.61 to 2.32)	0.64 (-2.84 to 4.13)
University degree [b]	6.30 (-0.11 to 12.71)	*3.14 (0.50 to 5.78)*	*3.27 (0.96 to 5.59)*	*4.33 (1.05 to 7.61)*
Work status (h/week)	*-0.24 (-0.43 to -0.05)*	-0.04 (-0.12 to 0.04)	*-0.08 (-0.15 to -0.01)*	-0.08 (-0.18 to 0.02)
Parents living together	*-13.58 (-24.39 to -2.77)*	*-5.07 (-9.53 to -0.61)*	*-4.30 (-8.22 to -0.38)*	-4.51 (-10.06 to 1.05)
Siblings in the family	*-7.11 (-13.4 to -0.82)*	*-3.04 (-5.59 to -0.49)*	*-2.66 (-4.92 to -0.40)*	*-3.22 (-6.38 to -0.07)*
Living in a regional area [c]	-1.62 (-7.97 to 4.72)	-0.95 (-3.57 to 1.66)	-1.00 (-3.29 to 1.30)	-1.49 (-4.75 to 1.76)
SEIFA score	0.01 (-0.04 to 0.05)	0.01 (-0.01 to 0.02)	0.01 (-0.01 to 0.02)	0.01 (-0.01 to 0.03)
Parent coping	1.70 (-2.23 to 5.62)	0.99 (-0.62 to 2.61)	0.32 (-1.11 to 1.74)	0.56 (-1.45 to 2.58)
Concern with child MB	-0.53 (-1.61 to 0.55)	-0.20 (-0.65 to 0.24)	-0.20 (-0.59 to 0.19)	-0.28 (-0.01 to 0.30)
Information seeking	0.33 (-0.31 to 0.98)	-0.04 (-0.31 to 0.23)	-0.03 (-0.21 to 0.26)	-0.06 (-0.39 to 0.27)

[a] Due to missing data, n varied slightly for some models; ranging from 1 to 62 missing observations. β, unstandardized regression coefficient; SEIFA, Socio-Economic Indexes for Areas; MB, movement behaviors.
[b] University degree or higher education vs no university degree.
[c] Major cities vs inner/outer regional and remote Australia.

Table 4. Associations between family demographics and parent characteristics with individual indicators for engagement in the main parts of the app (i.e., clicks in the modules, toolkit, and community chat forum) (n=609) [a].

Predictor variables	**Learning module clicks** β (95% CI)	**Toolkit clicks** β (95% CI)	**Community chat forum clicks** β (95% CI)
Parent age (years)	0.71 (-0.62 to 2.04)	0.64 (-0.08 to 1.35)	0.00 (-0.08 to 0.09)
Australian born	-3.22 (-17.4 to 10.9)	-0.40 (-8.00 to 7.21)	-0.01 (-0.92 to 0.90)
University degree [b]	*18.59 (5.32 to 31.86)*	5.34 (-1.83 to 12.51)	0.74 (-0.12 to 1.60)
Work status (h/week)	*-0.40 (-0.79 to -0.01)*	*-0.27 (-0.48 to -0.06)*	-0.02 (-0.04 to 0.01)
Parents living together	*-31.37 (-53.79 to -9.00)*	*-12.72 (-24.82 to -0.63)*	-0.50 (-1.95 to 0.95)
Siblings in the family	-10.92 (-23.76 to 1.92)	*-7.75 (-14.82 to -0.68)*	-0.58 (-1.41 to 0.24)
Living in a regional area [c]	-6.37 (-19.55 to 6.81)	-3.51 (-10.60 to 3.58)	-0.13 (-0.98 to 0.72)
SEIFA score	0.03 (-0.05 to 0.12)	0.01 (-0.04 to 0.05)	0.00 (-0.00 to 0.01)
Parent coping	5.89 (-2.26 to 14.03)	-2.00 (-6.39 to 2.39)	-0.10 (-0.63 to 0.42)
Concern with child MB	-1.07 (-3.31 to 1.17)	-0.63 (-1.84 to 0.58)	0.01 (-0.14 to 0.15)
Information seeking	0.46 (-0.88 to 1.80)	0.04 (-0.65 to 0.73)	0.01 (-0.07 to 0.10)

[a] Due to missing data, n varied slightly for some models; ranging from 1 to 62 missing observations. β, unstandardized regression coefficient; SEIFA, Socio-Economic Indexes for Areas; MB, movement behaviors.

[b] University degree or higher education vs no university degree.

[c] Major cities vs inner/outer regional and remote Australia.

Table 5. Associations of family demographics and parenting characteristics with composite indicators of engagement (n=609)[a].

Predictor variables	**Total score** β (95% CI)	**Click-depth** β (95% CI)	**Loyalty** β (95% CI)	**Recency** β (95% CI)	**Diversity** β (95% CI)
Parent age (years)	0.07 (-0.05 to 0.18)	0.02 (-0.02 to 0.06)	0.04 (-0.10 to 0.17)	0.11 (-0.16 to 0.38)	0.10 (-0.07 to 0.27)
Australian born	-0.99 (-2.21 to 0.23)	-0.32 (-0.77 to 0.12)	-0.99 (-2.43 to 0.44)	-1.87 (-4.62 to 0.88)	-0.78 (-2.56 to 1.00)
University degree[b]	*2.61 (1.46 to 3.77)*	*0.77 (0.36 to 1.19)*	*2.48 (1.14 to 3.83)*	*4.64 (2.00 to 7.27)*	*2.56 (0.89 to 4.24)*
Work status (h/week)	-0.02 (-0.06 to 0.01)	*-0.01 (-0.03 to -0.00)*	-0.03 (-0.07 to 0.02)	-0.04 (-0.12 to 0.04)	-0.02 (-0.07 to 0.03)
Parents living together	-0.29 (-2.27 to 1.68)	-0.44 (-1.15 to 0.27)	-2.15 (-4.43 to 0.15)	1.55 (-2.94 to 6.04)	-0.14 (-2.99 to 2.71)
Siblings in the family	*-1.56 (-2.65 to -0.48)*	*-0.43 (-0.83 to -0.04)*	*-2.40 (-3.68 to -1.12)*	*-2.77 (-5.17 to -0.36)*	-0.65 (-2.24 to 0.93)
Living in a regional area[c]	-0.20 (-1.36 to 0.95)	*-0.47 (-0.88 to -0.05)*	0.07 (-1.27 to 1.41)	-0.14 (-2.77 to 2.48)	-0.27 (-1.93 to 1.40)
SEIFA score	-0.00 (-0.01 to 0.01)	0.00 (-0.00 to 0.00)	-0.00 (-0.01 to 0.01)	0.00 (-0.01 to 0.02)	-0.00 (-0.02 to 0.01)
Parent coping	0.56 (-0.15 to 1.27)	0.13 (-0.13 to 0.39)	*1.25 (0.43 to 2.08)*	0.62 (-1.01 to 2.24)	0.24 (-0.79 to 1.27)
Concern with child MB	0.03 (-0.17 to 0.23)	0.00 (-0.07 to 0.08)	-0.07 (-0.30 to 0.16)	-0.06 (-0.50 to 0.39)	0.25 (-0.04 to 0.53)
Information seeking	0.04 (-0.08 to 0.16)	0.03 (-0.02 to 0.07)	-0.04 (-0.17 to 0.10)	0.07 (-0.20 to 0.34)	0.09 (-0.08 to 0.26)

[a] Due to missing data, n varied slightly for some models; ranging from 1 to 62 missing observations. β, unstandardized regression coefficient; SEIFA, Socio-Economic Indexes for Areas; MB, movement behaviors.
[b] University degree or higher education vs no university degree.
[c] Major cities vs inner/outer regional and remote Australia.

Discussion

Principal Findings

To the best of our knowledge, this is the first study to examine user engagement and predictors of engagement, including both family demographics and parent characteristics, with a mHealth intervention targeting parents of young children. Use of the *Let's Grow* app was initially high, with declining levels; however, among those who continued to use the app across the 25-week period, the level of engagement remained consistent across this period. We identified several demographics predictors of engagement. More work hours, parents living together, having siblings in the family and living in a regional/remote area were associated with lower engagement, while having higher education level were associated with higher engagement. Of the parent characteristics examined, higher parent coping was positively associated with engagement, while parent concern and information seeking in relation to child movement did not appear to impact engagement.

Comparison with previous findings

User engagement in digital interventions has gained more interest in recent years and the link between intervention uptake and efficacy has been established [25]. However, the conceptualization and reporting of engagement in digital interventions targeting parents and other populations (e.g., [26]) is scarce, and there are no universal criteria for defining "good" engagement. Nevertheless, engagement has been the focus of commercial app and website companies for a long time. A report on engagement in all available apps in the Apple and Google Play stores suggests that 25% of all downloaded apps are engaged with just once in the first six months [27], and an engagement rate between 1-5% has been described as acceptable app engagement [28]. In contrast, attendance rate in group-based face-to-face programs typically ranges from 35-50% [29]. In that context, initial engagement in our study can be described as high, which is also similar to what has been observed in previous studies investigating engagement in digital health interventions (e.g., [30,31]). Moreover, overall engagement with our app, as assessed by the mean composite EI (four subindices) was moderate and almost identical to that reported in two other studies which investigated engagement in the *Growing Healthy* app among expectant parents and parents with an infant [11] and in the *Milk Man* app among fathers with an infant [14]. Both *Growing Healthy* and the *Milk Man* study also used an adapted version of the Web Analytics Demystified visitor index (five subindices), and reported a composite mean EI of 30% (SD 12%, range 2-58%)

and 30% (SD 20%, range 1-80%), respectively. Similarily, a study in parents to 2-5-year-olds (n=42) reported a slightly higher index score (median 56 [SD 21], range 4-81, scale 0-100) with an mHealth parent-training program (*ezPARENT* tablet app); however, they used a different index based on only three engagement measures (i.e., the completion of app modules, number of visits and time between visits) [12].

Considering the differences in intervention design and thus purposive tailoring and calculation of these engagement indices, direct comparison between studies is impractical. Instead, it can be argued that a composite EI can be seen as a study specific indicator of user engagement which can be a valuable tool for statistical analysis purposes (e.g., investigating intervention effects) but requires careful deliberation of the most relevant indicators to include for that intervention. Individual indicators of engagment that can be more consistently applied across interventions may be better for direct comparison, such as total time spent using the app. A further complication is that some apps, such as the *Let's Grow* app, act as tools to promote offline engagement in behavior change which is not measurable by app usage metrics. For example, most of the activities contained within the behavior change component of the app were designed to prompt parents to engage their children in active play opportunities offline. Engagement in these offline components of the intervention which are likely to impact efficacy are not captured in app engagement statistics. Thus, future studies should aim to develop and assess measures beyond objective engagement metrics to enable complete assessment of engagement in mHealth interventions promoting offline activities.

Another important aspect of participant engagement is use over time, and retaining user's engagement in digital health interventions has been reported to be challenging [32,33]. Our patterns analyses indicate that usage was not linear. Rather, we found an initial decline during the first few weeks followed by steady levels of engagement among the subgroup who were still using the intervention at 12- and 25 weeks. In contrast, Taki et al. [11] showed a downward trend in engagement subindices score from 12- and 25 weeks, which is in line with studies in other populations where continual linear decline in usage over time has been reported [34,35]. One possible reason for the difference between our findings and the consistent declines reported for *Growing Healthy* [11] and other mHealth interventions (e.g., the *HealthyMoms* app [36]) may rest with a key design difference. To illustrate, in the *Growing Healthy* app, all content was freely available whenever the user wished to access it [37], and new intervention content was delivered regularly (i.e., biweekly) in the

HealthyMoms app regardless of participant use [36]. In contrast, *Let's Grow* participants had to work through modules to unlock the next one. This may have encouraged more regular ongoing use amongst those highly engaged parents with continued use across the study, and could be viewed as a form of gamification (users were encouraged to keep coming back to unlock new content) which has been described to have some success in achieving maintained parental engagement in child health promotion apps [33]. However, it is also possible that not having all content freely available or the need to undertake behavior change activities (rather than just view content) in *Let's Grow* may have been a barrier to engagement for some participants. A better understanding of engagement with these and other app designs such as individually tailored apps (e.g., using a just-in-time adaptive intervention design) is needed. Moreover, formal testing is required to understand what format best optimizes engagement, as well as development of implementation strategies to support and sustain user engagement.

Furthermore, a better understanding of the participant characteristics that impact engagement in parental interventions can assist in clarifying how to design interventions to maximize behavior change. Nevertheless, few previous studies have reported predictors of engagement in parental mHealth interventions, and they have mostly focused on parent and family demographic characteristics [11–14]. In our study, we expanded this to include three measures of parent characteristics including parent coping in general as well as concern and information seeking specific to the targeted topic (child movement behaviors). We identified several predictors related to time and socioeconomic pressures (education level, work hours, remoteness, family structure) as well as parent coping in general (not specific to the targeted intervention topic). In more detail, socioeconomic pressures such as lower education level, working more hours, and living in a remote/outer regional area as well as family structure (living with a partner/spouse and siblings in the family) were associated with *lower* engagement. This is similar to previous studies investigating predictors of engagement in parental mHealth interventions which have shown lower levels of engagement among parents with lower education level [13] and parents with more than one child [11,13]. Indeed, more work hours and having more than one child could be seen as indicators of less available time, which previously has been described as a barrier to app engagement [34]. Moreover, poorer parent coping in general was identified as a predictor of *lower* engagement. Similar to lack of available time, this could reflect a lack of parent capacity to take on new learning when they are struggling to cope with their daily commitments. In contrast, perceived need and motivation as well as utility have been described to promote engagement in health apps for adults [38–40]. Similarly, a mixed-methods assessment in a sub-sample from the *Growing Healthy* study showed that participants defined as having low or moderate engagement felt they had sufficient knowledge and the app did not provide further information [41]. In our study, parents who did not engage with the app (defined as non-users) reported lower coping score and concern with movement behaviors compared to those defined as users. Unexpectedly, and notably, parent concern about child movement behaviors and parent information seeking about topics related to the intervention content were also not associated with engagement in our study. This indicates that being concerned and coping with life may predict actually starting the intervention (i.e. initial engagement), but beyond enrolling in the study it seems that other factors drive how much parents engage. Altogether, this suggests that time and other pressures outweigh the content relevance when it comes to actual engagement with the intervention, and parents under time or other pressures might need more support to initiate and sustain engagement.

Strengths and limitations

This study has several strengths including the objective and accurate assessment of the outcome (i.e., participant engagement) and the relatively large sample size. In addition, the use of several engagement metrics provides a more comprehensive understanding of how users interact with mHealth interventions [42–44], and greater insights into engagement can be achieved by aggregating data across different domains (i.e., frequency, intensity, time, and type) [44]. Thus, another strength of the study is the reporting of both individual measures of engagement (representing engagement in three key strategies for promoting health behaviors: behavior change, information provision, and social support), as well as overall engagement (EI). The study also has some limitations to acknowledge. First, we utilized mid-intervention data and thus, our results do not capture engagement for the entire intervention period (i.e., 12 months). However, the actual minimum time to complete the intervention program was 22 weeks, which is a similar intervention duration compared to previous studies (e.g., [13]). Second, data on potential predictors were self-reported and some measures e.g., parent concern, were subjective and thus results may be subject to reporting biases (i.e., social desirability). However, we observed a wide variation in the sample in terms of outcomes and predictor variables. In similarity to many previous studies (e.g., [13]), another limitation in the study is that the majority of the participants were mothers (98%). Although the majority of participants lived in major cities (72%), inner regional (19%) and outer regional/remote

Australia (9%) were also represented, as well as representation across different socioeconomic areas. In addition, a larger proportion of the participants in the study had a university degree or higher level of education compared to women in the same age group (25-44 years) in the general population (72% vs 50%) [45]. Nevertheless, our study sample was similar to the general population in terms of birth country (77% vs 71% Australian born) [46], as well as work status among women in this age group (65% vs 58%) [45]. Moreover, we did not measure enactment (i.e., participants 'real-world' use of intervention skills) and thus we have no information on intervention engagement beyond usage within the app, which was actually designed to encourage parents to enact changes offline. Future studies should aim to capture offline engagement as well, potentially using check-in questions during the intervention period. Finally, *Let's Grow* had a non-linear dynamic intervention design with parents able to choose the order and timing of their progress and not all content was freely available at once. This is different compared to most previously reported studies; hence some engagement measures may not readily apply. On the same note, engagement scores need to be tailored for individual interventions, and consequently results are not directly comparable across studies. In summary, our results are limited to mothers, and topics for future research should aim to engage fathers to a higher extent, as well as include measures of enactment to identify intervention engagement beyond direct app usage.

Implications and Clinical relevance

Although the use of mHealth to deliver parental interventions is an established field, and the importance of engagement in interventions has been recognized, engagement in parental mHealth interventions is rarely measured. Thus, our study adds to the scarce literature in several aspects. First, to the best of our knowledge, there is no best practice to assess engagement in digital interventions and considering the heterogeneity of intervention designs and delivery, a universal approach might not be feasible. Moreover, although the digital format offers a great opportunity to objectively assess engagement, it also represents challenges in deciding which metrics are of importance. In that sense, our study reports two different approaches to assess participant engagement using both individual metrics and an overall engagement index, as well as highlights the importance of not only investigating total engagement but also looking at usage patterns over time. This information will be useful when investigating potential intervention effects (e.g., dose-response relationship), for future refinement of *Let's Grow* and development of similar mHealth interventions, as well as development of guidelines for the assessment and evaluation of user engagement in parental mHealth interventions. Second, reporting of participant engagement and predictors of engagement is important to inform the design and tailoring of future interventions to assist in them being used to a higher extent. Moreover, this information can provide a better understanding of the effect or lack of effect on the targeted outcomes. Altogether, our study provides valuable evidence in the field of intervention engagement which can be of use for the evaluation and design of future parental mHealth interventions.

Conclusions

This study provides novel data on engagement and predictors of engagement in a parental digital intervention. While engagement data were comparable to other published data, a key difference was the relatively consistent level of engagement noted for those showing continued use across the period under investigation rather than the typically seen continued decline. Our findings show that both family demographics and parent characteristics can influence engagement, and time and socioeconomic pressures might outweigh content relevance when it comes to engagement, although content relevance appears important to initial uptake. Our results highlight the characteristics of parents who may benefit from more active engagement strategies to support their use of digital interventions, specifically those with time and capacity stressors. Finally, our results showed similar results for individual and composite measures of engagement, indicating that simpler engagement metrics which might be more feasible and attainable for researchers to collect, process and analyze, can be useful in the reporting of engagement in digital interventions. Altogether, our findings will be useful when investigating intervention effects (dose-response relationship) and might be important to consider for future refinement of *Let's Grow* and development of similar interventions.

Acknowledgements

The authors would like to gratefully thank all the participating families in the *Let's Grow* trial, as well as the members of the *Let's Grow* team for their invaluable work with recruitment and data collection. KDH is the principal investigator of the *Let's* Grow trial. KDH, KLD, and JN contributed to development of the intervention content. BRM analyzed the app analytics to produce an engagement index and contributed to the data analysis planning and interpretation together with JS, SS, LO, VC, and KDH. JS analyzed the data and drafted the manuscript and all authors have approved of the final draft and submitted manuscript. The *Let's Grow* trial was supported by the National Health and Medical Research Council (GNT 1162980). In addition, KDH is supported by a Heart Foundation Future Leader Fellowship (105929). JS is supported by two post-doctoral fellowships from the Henning and Johan Throne-Holst Foundation and the Erik and Edith Fernström Foundation for Medical Research.

Conflict of interest

The authors declare no conflict of interest. BRM owns a private company (Digital Health Promotion) that works with the development of digital wellness products. Digital Health Promotion was not involved in this study.

References

1. World Health Organization. *Guidleines for Physical Activity, Sedentary Behaviour, and Sleep for Children under 5 Years of Age*.; 2019. Accessed February 3, 2022. https://apps.who.int/iris/handle/10665/311664
2. Xu H, Wen LM, Rissel C. Associations of parental influences with physical activity and screen time among young children: a systematic review. *J Obes*. 2015;2015. doi:10.1155/2015/546925
3. Lee EY, Hesketh KD, Rhodes RE, Rinaldi CM, Spence JC, Carson V. Role of parental and environmental characteristics in toddlers' physical activity and screen time: Bayesian analysis of structural equation models. *Int J Behav Nutr Phys Act*. 2018;15(1). doi:10.1186/s12966-018-0649-5
4. Yavuz HM, Van Ijzendoorn MH, Mesman J, Van Der Veek S. Interventions aimed at reducing obesity in early childhood: a meta-analysis of programs that involve parents. *J Child Psychol Psychiatry*. 2015;56(6):677-692. doi:10.1111/JCPP.12330
5. Ling J, Robbins LB, Wen F, Zhang N. Lifestyle Interventions in Preschool Children: A Meta-analysis of Effectiveness. *Am J Prev Med*. 2017;53(1):102-112. doi:10.1016/J.AMEPRE.2017.01.018
6. Ajay K, Azevedo LB, Haste A, et al. App-based oral health promotion interventions on modifiable risk factors associated with early childhood caries: A systematic review. *Front oral Heal*. 2023;4. doi:10.3389/FROH.2023.1125070
7. Nyström CD, Sandin S, Henriksson P, et al. Mobile-based intervention intended to stop obesity in preschool-aged children: The MINISTOP randomized controlled trial. *Am J Clin Nutr*. 2017;105(6):1327-1335. doi:10.3945/ajcn.116.150995

8. Bonvicini L, Pingani I, Venturelli F, et al. Effectiveness of mobile health interventions targeting parents to prevent and treat childhood Obesity: Systematic review. *Prev Med reports*. 2022;29. doi:10.1016/J.PMEDR.2022.101940
9. Yardley L, Spring BJ, Riper H, et al. Understanding and Promoting Effective Engagement With Digital Behavior Change Interventions. *Am J Prev Med*. 2016;51(5):833-842. doi:10.1016/j.amepre.2016.06.015
10. Schoeppe S, Alley S, Van Lippevelde W, et al. Efficacy of interventions that use apps to improve diet, physical activity and sedentary behaviour: a systematic review. *Int J Behav Nutr Phys Act*. 2016;13(1). doi:10.1186/S12966-016-0454-Y
11. Taki S, Lymer S, Russell CG, et al. Assessing User Engagement of an mHealth Intervention: Development and Implementation of the Growing Healthy App Engagement Index. *JMIR mHealth uHealth*. 2017;5(6). doi:10.2196/MHEALTH.7236
12. Breitenstein SM, Brager J, Ocampo E V., Fogg L. Engagement and Adherence With ezPARENT, an mHealth Parent-Training Program Promoting Child Well-Being. *Child Maltreat*. 2017;22(4):295-304. doi:10.1177/1077559517725402
13. Laws RA, Cheng H, Rossiter C, et al. Perinatal support for breastfeeding using mHealth: A mixed methods feasibility study of the My Baby Now app. *Matern Child Nutr*. 2023;19(2). doi:10.1111/MCN.13482
14. Røed M, Nordgård Vik F, Rudjord Hillesund E, van Lippevelde W, Christine Medin A, Cecilie Øverby N. Process Evaluation of an eHealth Intervention (Food4toddlers) to Improve Toddlers' Diet: Randomized Controlled Trial. *JMIR Hum factors*. 2020;7(3). doi:10.2196/18171
15. Gunnarsdottir T, Njardvik U, Olafsdottir AS, Craighead LW, Bjarnason R. The role of parental motivation in family-based treatment for childhood obesity. *Obesity (Silver Spring)*. 2011;19(8):1654-1662. doi:10.1038/OBY.2011.59
16. Hesketh KD, Downing KL, Galland BC, et al. Protocol for the Let's Grow randomised controlled trial: examining efficacy, cost-effectiveness and scalability of a m-Health intervention for movement behaviours in toddlers. *BMJ Open*. 2022;12(3):e057521. doi:10.1136/BMJOPEN-2021-057521
17. Michie S, Richardson M, Johnston M, et al. The behavior change technique taxonomy (v1) of 93 hierarchically clustered techniques: Building an international consensus for the reporting of behavior change interventions. *Ann Behav Med*. 2013;46(1):81-95. doi:10.1007/s12160-013-9486-6
18. Prior M, Sanson A, Smart D. *Pathways from Infancy to Adolescence: Australian*

Temperament Project 1983–2000.; 2001.

19. Australian Bureau of Statistics. 1270.0.55.005 - Australian Statistical Geography Standard (ASGS): Volume 5 - Remoteness Structure, July 2016. Published March 16, 2018. Accessed September 25, 2023. https://www.abs.gov.au/ausstats/abs@.nsf/mf/1270.0.55.005
20. Australian Bureau of Statistics. 2039.0 - Information Paper: An Introduction to Socio-Economic Indexes for Areas (SEIFA), 2006. Published March 26, 2008. Accessed September 25, 2023. https://www.abs.gov.au/ausstats/abs@.nsf/mf/2039.0
21. Haines J, Downing KL, Tang L, Campbell KJ, Hesketh KD. Associations between maternal concern about child's weight and related behaviours and maternal weight-related parenting practices: a cross-sectional study. *Int J Behav Nutr Phys Act*. 2018;15(1). doi:10.1186/S12966-018-0738-5
22. Maher CA, Lewis LK, Ferrar K, Marshall S, De Bourdeaudhuij I, Vandelanotte C. Are health behavior change interventions that use online social networks effective? A systematic review. *J Med Internet Res*. 2014;16(2):e2952. doi:10.2196/jmir.2952
23. Saleem M, Kühne L, de Santis KK, Christianson L, Brand T, Busse H. Understanding Engagement Strategies in Digital Interventions for Mental Health Promotion: Scoping Review. *JMIR Ment Heal*. 2021;8(12). doi:10.2196/30000
24. Statista. Percentage of mobile apps that have been used only once from 2010 to 2019. https://www.statista.com/statistics/271628/percentage-of-apps-used-once-in-the-us/
25. Team Storyly. App Engagement. Published 2023. https://www.storyly.io/glossary/app-engagement
26. Heinrichs N, Bertram H, Kuschel A, Hahlweg K. Parent recruitment and retention in a universal prevention program for child behavior and emotional problems: barriers to research and program participation. *Prev Sci*. 2005;6(4):275-286. doi:10.1007/S11121-005-0006-1
27. Røed M, Medin AC, Vik FN, et al. Effect of a Parent-Focused eHealth Intervention on Children's Fruit, Vegetable, and Discretionary Food Intake (Food4toddlers): Randomized Controlled Trial. *J Med Internet Res*. 2021;23(2). doi:10.2196/18311
28. Edney S, Ryan JC, Olds T, et al. User engagement and attrition in an app-based physical activity intervention: Secondary analysis of a randomized controlled trial. *J Med Internet Res*. 2019;21(11):e14645. doi:10.2196/14645
29. Henriksson P, Migueles JH, Söderström E, Sandborg J, Maddison R, Löf M. User engagement in relation to effectiveness of a digital lifestyle intervention (the

HealthyMoms app) in pregnancy. *Sci Rep*. 2022;12(1). doi:10.1038/S41598-022-17554-9
30. Szinay D, Jones A, Chadborn T, Brown J, Naughton F. Influences on the Uptake of and Engagement With Health and Well-Being Smartphone Apps: Systematic Review. *J Med Internet Res*. 2020;22(5). doi:10.2196/17572
31. Sandborg J, Henriksson P, Larsen E, et al. Participants' Engagement and Satisfaction With a Smartphone App Intended to Support Healthy Weight Gain, Diet, and Physical Activity During Pregnancy: Qualitative Study Within the HealthyMoms Trial. *JMIR mHealth uHealth*. 2021;9(3):e26159. doi:10.2196/26159
32. Guertler D, Vandelanotte C, Kirwan M, Duncan MJ. Engagement and nonusage attrition with a free physical activity promotion program: The case of 10,000 steps Australia. *J Med Internet Res*. 2015;17(7):e4339. doi:10.2196/jmir.4339
33. Denney-Wilson E, Laws R, Russell CG, et al. Preventing obesity in infants: the Growing healthy feasibility trial protocol. *BMJ Open*. 2015;5(11):e009258. doi:10.1136/BMJOPEN-2015-009258
34. Wei Y, Zheng P, Deng H, Wang X, Li X, Fu H. Design Features for Improving Mobile Health Intervention User Engagement: Systematic Review and Thematic Analysis. *J Med Internet Res*. 2020;22(12). doi:10.2196/21687
35. Anderson K, Burford O, Emmerton L. Mobile Health Apps to Facilitate Self-Care: A Qualitative Study of User Experiences. *PLoS One*. 2016;11(5). doi:10.1371/JOURNAL.PONE.0156164
36. Taki S, Russell CG, Lymer S, et al. A Mixed Methods Study to Explore the Effects of Program Design Elements and Participant Characteristics on Parents' Engagement With an mHealth Program to Promote Healthy Infant Feeding: The Growing Healthy Program. *Front Endocrinol (Lausanne)*. 2019;10(JUN). doi:10.3389/FENDO.2019.00397
37. Perski O, Blandford A, West R, Michie S. Conceptualising engagement with digital behaviour change interventions: a systematic review using principles from critical interpretive synthesis. *Transl Behav Med*. 2017;7(2):254-267. doi:10.1007/S13142-016-0453-1
38. Pham Q, Graham G, Carrion C, et al. A Library of Analytic Indicators to Evaluate Effective Engagement with Consumer mHealth Apps for Chronic Conditions: Scoping Review. *JMIR Mhealth Uhealth 2019;7(1)e11941 https//mhealth.jmir.org/2019/1/e11941*. 2019;7(1):e11941. doi:10.2196/11941

39. Short CE, DeSmet A, Woods C, et al. Measuring Engagement in eHealth and mHealth Behavior Change Interventions: Viewpoint of Methodologies. *J Med Internet Res*. 2018;20(11). doi:10.2196/JMIR.9397
40. Australian Bureau of Statistics. Australia's Population by Country of Birth, 2021 | Australian Bureau of Statistics. Published 2021. Accessed August 22, 2023. https://www.abs.gov.au/statistics/people/population/australias-population-country-birth/latest-release
41. Australian Bureau of Statistics. Australia's Population by Country of Birth, 2021 | Australian Bureau of Statistics. 2021. Accessed August 22, 2023. https://www.abs.gov.au/statistics/people/population/australias-population-country-birth/latest-release

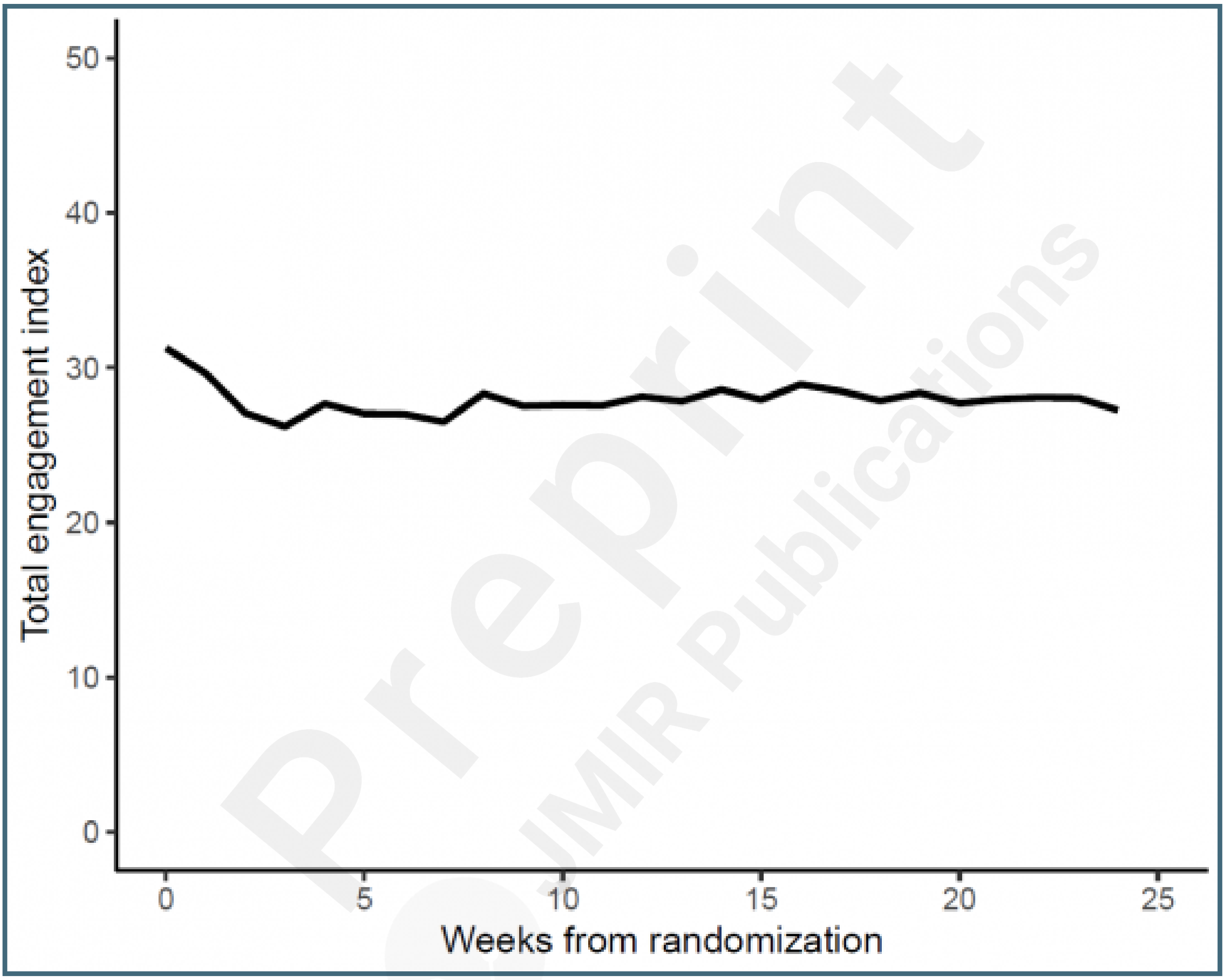
Abbreviations

BMI, body mass index
EI, engagement index
MB, movement behaviors
MVPA, moderate-to-vigorous physical activity
SD, standard deviation
SEIFA, socio-economic indexes for areas

Supplementary Files

Figures

Average weekly engagement index (EI) over the usage period for participants defined as users (n=609). The EI comprises of four subindices: click depth (the average number of app pages viewed per day), loyalty (the total number of days a user engaged with the app), recency (the average number of days between app use: reversed so higher score indicates greater engagement), and diversity (the number of different app features used per day). Subindices were normalized by rescaling values between 0 and 100 to assign equal weight to each of the subindices (each element was equally important in contributing to the measurement of engagement). The EI was then calculated as the athematic mean of the four subindices (click depth, loyalty, recency, and diversity).



CONSORT (or other) checklists

Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) checklist.
URL: http://asset.jmir.pub/assets/71cc3dc9aa6f1d6aa01f083a323a6b60.pdf